DYNAMIC RESCUE IN FLAMES: REAL-TIME STRUCTURAL FIRE RESPONSE PREDICTION AND ADAPTIVE INDOOR RESCUE PATH PLANNING

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Dynamic Rescue in Flames:

Real-Time Structural Fire Response Prediction and Adaptive Indoor Rescue Path Planning

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CERTIFICATE OF ORIGINALITY

I hereby declare that this thesis is my own work and that, to the best of my knowledge and belief, it reproduces no material previously published or written, nor material that has been accepted for the award of any other degree or diploma, except where due acknowledgement has been made in the text.

YE Zhongnan

To my family,

ABSTRACT

Fire emergencies in buildings present substantial challenges to firefighters and rescue teams due to their rapidly evolving nature and potential compromise of structural safety. In such high-risk environments, timely and accurate information about the building's structural safety and efficient rescue path planning is crucial for the success of firefighting operations and the safety of both occupants and firefighters. However, the dynamic behavior of fire propagation and the intricate processes involved in fire-induced structural degradation present substantial challenges in predicting structural fire responses and determining corresponding safe and efficient rescue paths. Traditional methods, such as finite element models (FEM) and computational fluid dynamics (CFD), may provide accurate predictions of structural responses to fire, but their computational complexity and time-consuming nature make them unsuitable for real-time applications. Additionally, existing path planning algorithms may not be well-adapted to the dynamic and uncertain conditions of building fire environments, potentially leading to suboptimal or even dangerous route recommendations for firefighters. While significant progress has been made in the field of machine learning (ML), computational modeling, and numerical simulation techniques for fire emergencies, efficient and effective solutions remain limited for real-time structural fire response prediction and adaptive fire rescue path planning.

This study aims to facilitate efficient and safe fire rescue operations under time-varying building fire environments by exploring the dynamics of structural fire responses and corresponding fire rescue paths with higher efficiency but lower risk for firefighters. A data-driven approach is employed to address the challenges of dynamic behaviors of fire propagation and fire-induced structural degradation, by integrating data analytics, computational simulation, and mathematical modeling within the context of building fire emergencies. The primary research objectives are twofold: (1) to develop an ML-based model for real-time prediction of structural fire responses by integrating FEM and CFD databases, and (2) to develop an adaptive indoor fire rescue path planning model that considers the time-varying structural safety conditions. The models developed through this research are designed to provide reliable and timely predictions of structural responses and suggest efficient and safe rescue paths, ultimately contributing to the safety and effectiveness of firefighting operations in dynamic building fire environments.

In the realm of real-time structural fire response prediction, a FEM-based ML framework is developed to predict structural displacement using temperature field data as input. This framework combines the precision of FEM with the efficiency of ML techniques to enable real-time predictions of structural responses during fire emergencies. Utilizing a virtual case of a single-story, two-bay, 3D steel frame structure, four distinct ML models are trained based on a FEM numerical database of structural responses under various fire scenarios derived from parametric fire curves. Among these models, the Random Forest (RF) and Gradient Boosting (GB) models demonstrate superior performance in terms of predictive accuracy and model robustness. The Coefficient of Determination (R^2) value of the predictive mid-span displacement reaches up to 0.99 when 1000 fire scenarios are included in the training dataset. Additionally, all models exhibit robustness against noise in temperature data when the signal-to-noise ratio exceeds 15. The developed FEM-based ML framework shows considerable promise for real-time structural response prediction during building fires.

To enhance the realism of the fire scenarios in the numerical database, the FEM-based ML structural response prediction framework is augmented by incorporating CFD for fire simulation. The integration of CFD and FEM enables the CFD/FEM-based ML framework to capture the intricate and dynamic interactions more comprehensively between fire-induced temperature fields and structural deformation, resulting in more precise and reliable predictions of the structural behavior during fire emergencies. With numerical cases of an 8m×8m×0.6m steel roof structure under 1200 virtual fire scenarios, various ML models are developed to predict the vertical displacement in real-time and in the near future (e.g., 10 seconds) using temperature field data as input. The RF and GB models demonstrate considerable effectiveness in predicting real-time displacement, with R^2 values reaching up to 0.97 when the number of fire scenarios in the training dataset is 200 or more. In contrast, the Long-Short Term Memory (LSTM) model displays competitive performance in predicting displacement for the subsequent 10 seconds, with a maximum Mean Squared Error (MSE) less than 0.05 when the epoch exceeds 200. The proposed CFD/FEM-based framework can offer reliable and precise predictions of structural responses in a real-time manner, aiding firefighting teams in making informed decisions and optimizing their response strategies.

Building upon reliable and timely predictions of structural fire responses, an adaptive path planning model has been developed to recommend efficient and safe rescue paths under dynamic building fire environments. The model considers time-varying structural safety conditions as a dynamic risk map, optimizing rescue paths to minimize overall cost in terms of time, distance, and risk. A dynamic grid-based search algorithm is specifically developed to generate a sequence of path segments connecting the firefighting agent's current location to the destination while considering time-varying structural safety conditions incorporated into a dynamic risk map. The model is tested using a case of a single-story office building, measuring 30m×30m, and involving 50 random fire scenarios. The rescue paths suggested by the proposed model are found to be adaptive to the updated risk map of the environment, attempting to avoid paths with a high risk of structural component failure or collapse. In comparison to the traditional non-adaptive path suggested by the Dijkstra algorithm, the proposed adaptive model results in an average of 12.94% longer travel time. However, the adaptive model demonstrates a significant advantage in reducing the time duration that firefighters are exposed to high-risk areas with severe damage or worse. Specifically, the rescue paths suggested by the adaptive model decrease such exposure by 45.45% compared to those suggested by the non-adaptive model, which is of critical importance in ensuring the safety of firefighters during fire rescue operations. Furthermore, with a noise level of 20% in the risk map, the proposed adaptive model remains robust enough to suggest rescue paths with substantially lower risk exposure durations than the non-adaptive model. The proposed model helps firefighters in fire rescue tasks by recommending optimal paths that adapt to dynamic building fire environments, addressing both efficiency and safety concerns.

The main contribution of this thesis lies in developing data-driven methodologies for real-time structural fire response prediction and adaptive fire rescue path planning in dynamic building fire environments. By providing robust and efficient frameworks and models, this research addresses critical gaps in the available tools and methodologies for firefighting teams during building fire emergencies. Furthermore, the integration of FEM, CFD, and ML techniques offers valuable insights and advancements for future research in structural fire safety, smart firefighting, and emergency response planning. Ultimately, the developed frameworks and models serve as a prototype for practical tools to enhance the safety and effectiveness of firefighting operations, reducing the risks to firefighters during building fires.

LIST OF PAPERS

The thesis is based on the following papers:

I. **Ye, Z.**, Liu, X., Hsu, S. C.* (2023). Adaptive Indoor Fire Rescue Path Planning under Time-varying Structural Safety Conditions. *Automation in Construction.* (Under Review)

II. **Ye, Z.**, & Hsu, S. C.* (2022). Predicting real-time deformation of structure in fire using machine learning with CFD and FEM. *Automation in Construction.* 143, 104574.

III. **Ye Z.**, Hsu S. C.*, Wei H. H. (2022). Real-time Prediction of Structural Fire Responses: A Finite Element-Based Machine-Learning Approach. *Automation in Construction*. 136, 104165.

Other papers of the author during the Ph.D. program not included in this thesis:

IV. **Ye, Z.**, Heidarpour, A., Jiang, S.*, Li, Y., & Li, G. (2022). Numerical study on fire resistance of cyclically-damaged steel-concrete composite beam-to-column joints. Steel and composite structures. 43(5), 673-688.

V. **Ye Z.**, Cheng K., Hsu S. C.*, Wei H. H., & Cheung, C. M. (2021). Identifying critical building-oriented features in city-block-level building energy consumption: A data-driven machine learning approach. Applied Energy, 301, 117453.

VI. Yuan, Z., **Ye, Z.**, Zhang, Y., & Hsu, S. C. (2023). Identifying potential superspreaders of airborne infectious diseases in construction projects. Journal of Management in Engineering, 39(6), 04023039.

VII. Kang, Z., **Ye, Z.**, & Hsu, S. C.* (2023). Developing an hourly-resolution well-to-wheel carbon dioxide emission inventory of electric vehicles. Resources, Conservation and Recycling, 190, 106819.

VIII. Wang, R., **Ye, Z.**, Lu, M.*, & Hsu, S. C. (2022). Understanding post-pandemic work-from-home behaviours and community level energy reduction via agent-based modelling. Applied Energy. 322, 119433.

IX. Wang, R., **Ye, Z.**, Hsu, S. C.*, & Chen, J. H. (2022). Photovoltaic rooftop's contribution to improve building-level energy resilience during COVID-19 work-from-home arrangement. Energy for Sustainable Development. 68, 182-191.

X. Li, Y., Du, Q*., Zhang, J., Jiang, Y., Zhou, J., & **Ye, Z.** (2023). Visualizing the intellectual landscape and evolution of transportation system resilience: A bibliometric analysis in CiteSpace. Developments in the Built Environment. 14, 100149.

XI. Chen, J. H., Wei, H. H.*, Chen, C. L., Wei, H. Y., Chen, Y. P., & **Ye, Z.** (2020). A practical approach to determining critical macroeconomic factors in air-traffic volume based on K-means clustering and decision-tree classification. Journal of Air Transport Management. 82, 101743.

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
BIM	Building Information Modeling
CART	Classification and Regression Tree
CFD	Computational Fluid Dynamics
CNN	Convolutional Neural Network
DQL	Deep Q-Learning
DT	Decision Tree
FDS	Fire Dynamic Simulator
FEM	Finite Element Method
GB	Gradient Boosting
LSTM	Long-Short Term Memory
ML	Machine Learning
MSE	Mean Square Error

NN	Neural Network
PDE	Partial Differential Equation
R^2	Coefficient of Determination
RBF	Radial Basis Function
RC	Reinforced Concrete
RF	Random Forest
RL	Reinforcement Learning
RMSE	Root Mean Square Error
SNR	Signal-to-Noise Ratio
SVM	Support Vector Machine

* in alphabetical order

CHAPTER 1 INTRODUCTION

1.1 Research Background

Fire hazards pose great threats to the life, structural, and property safety in a building (Kodur et al., 2019). Building Fire Disasters have been a growing concern in recent years under significant transformation in terms of the severity and versatility of the fire (Khan et al., 2021b). A total of more than 86.1 million fire incidents have caused more than one million deaths in the past two decades (Brushlinsky et al., 2016). The total annual loss from fire hazards is estimated to account for about 1% of the global gross domestic product (GDP) (Geneva Association, 2014). Public fire departments across the U.S. attended more than 499,000 fires in buildings annually, leading to around 3000 deaths and 13,000 injuries (U.S. Fire Administration, 2021). In Hong Kong, with numerous tall buildings and extremely high population density, around 16,631 building fires and 1558 fire-induced casualties are recorded from 2017 to 2021(Hong Kong Fire Service Department, 2022).

Structural fire engineering aims to tackle this global issue. Advanced numerical approaches, including Computational Fluid Dynamics (CFD) and Finite Element Methods (FEM), have provided valuable insights into fire behaviors and structural responses under high temperatures (de Boer et al., 2019, Bernardi et al., 2020, Janardhan et al., 2022). They offer comprehensive characterizations of fire development and structural behavior, enabling a detailed understanding of the interplay between fires and the built environment. Despite their utility, these models are computationally intensive, often requiring significant computational resources and time, which challenges their feasibility for real-time fire emergency responses (Ye et al., 2022, Ye and Hsu, 2022, Khan et al., 2021b).

Recent advances in machine learning (ML) have sparked new possibilities in this domain. Researchers have utilized ML to estimate various fire dynamics, including the occurrence of flashover points in compartments, the evolving temperature distribution during a fire, and the ignition locations and fire intensities (Wu et al., 2021, Wu et al., 2020). However, these advances in ML are often explored independently or combined with either CFD or FEM, leaving a considerable gap for a comprehensive integration of these powerful tools.

The structural fire response prediction, while being critical, is only part of the challenge. Firefighters face the additional task of navigating safely and efficiently in these highly volatile and dangerous environments (Chou et al., 2019). Traditional path-planning algorithms, which have been successful in static environments, show suboptimal performance under the dynamic conditions of building fires (Lei et al., 2018, Wang et al., 2021). When firefighters arrive at fire locations and conduct firefighting and rescue operations (i.e., to search and save the trapped occupants and to put out the fire), the situation may continuously change. These algorithms often fail to consider the changing structural integrity and safety conditions, which can have severe implications on rescue operations.

There is a pressing need for an integrative and dynamic solution that can address these complexities in a holistic manner. This requires a system that combines real-time structural fire response prediction with dynamic path optimization, providing firefighters with reliable information and safe paths for evacuation and rescue.

To bridge these gaps, this research proposes a novel integration of CFD, FEM, and ML into a unified framework for real-time prediction of structural fire responses. This comprehensive approach seeks to harness the respective strengths of each method, offering high-resolution, timely, and reliable predictions under various fire scenarios. Moreover, this research presents an adaptive path planning model that considers the dynamic and unpredictable nature of fire environments and the time-varying structural safety conditions. These proposed solutions aim to significantly enhance fire safety management, potentially transforming fire rescue operations and ultimately reducing the devastating losses associated with building fires. The primary application of this research is for the response phase of a building subjected to a fire scenario. This phase encompasses the period during a fire emergency when immediate actions are required to ensure the safety of both trapped occupants and firefighters. The proposed solutions are particularly crucial in providing essential guidance for navigating firefighting agents through fire-affected structures safely and efficiently.

1.2 Research Objectives

The overarching goal of this thesis is to utilize data-driven methodologies to create adaptive, real-time solutions that enhance the efficiency and safety of fire rescue operations in buildings experiencing fire emergencies. By integrating the power of machine learning (ML) with computational simulations (Finite Element Method - FEM, and Computational Fluid Dynamics - CFD), this research aims to provide a more comprehensive understanding of structural fire responses and the dynamic conditions of building fires. These insights will be used to guide the design of adaptive fire rescue path planning under time-varying structural safety conditions. Specifically, the research aims to achieve the following three primary objectives:

1. **Development of a ML-based Real-Time Structural Fire Response Prediction Model:** this objective aims to develop an ML-based model capable of predicting real-time structural fire responses. This model will be developed by integrating and processing data from numerical databases from FEM. The resulting model should provide firefighters with timely and accurate predictions about how the building's structural components are likely to behave in response to the fire. This data-driven approach can potentially help to enhance the efficiency of firefighting efforts by ensuring that actions are based on the most up-to-date and accurate information available.
2. **Integration of CFD and FEM in Data-Driven Structural Fire Deformation Prediction:** This objective seeks to augment the ML framework from the first objective by incorporating CFD simulations for fire propagation. The aim is to capture the dynamic interactions between fire-induced temperature fields and structural deformation more accurately. The resulting integrated CFD/FEM-based ML model should provide precise, real-time predictions of structural behavior during fire emergencies. This capability will be crucial in enabling firefighting teams to make informed decisions and implement appropriate response strategies.
3. **Adaptive Indoor Fire Rescue Path Planning under Time-Varying Structural Safety Conditions:** The final objective involves the development of an adaptive indoor fire rescue path planning model. This model will factor in the dynamic and

uncertain conditions typical of building fire environments and provide safe, efficient rescue paths. The model will use real-time data about the structural safety conditions of the building to optimize rescue paths, striking a balance between speed, distance, and risk. The development of this tool will contribute to the body of knowledge on how to design optimal paths that adapt to the dynamic conditions of building fires, thereby enhancing the safety and efficiency of rescue operations.

Through the achievement of these objectives, this thesis aims to make a significant contribution to the field of fire safety engineering, by providing practical tools and methodologies that can enhance the safety and effectiveness of firefighting operations.

1.3 Organization of the Thesis

This thesis is organized into six comprehensive chapters, each dedicated to a specific aspect of the study.

Chapter 1: Introduction provides the foundation for the thesis. It offers an overview of the research background, clearly articulating the research objectives and the importance of the study in the context of fire safety engineering.

Chapter 2: Literature Review offers a thorough examination of existing knowledge in the areas relevant to the thesis, such as structural fire engineering with CFD and FEM, real-time prediction of dynamic building fire environments, adaptive indoor path planning in fire emergencies, and emerging techniques and applications in fire safety. This review provides a basis for the methodologies applied in this research.

Chapter 3: Real-Time Prediction of Structural Fire Responses: A FEM-Based Machine-Learning Approach focuses on the first research objective. This chapter details the methodology, model development, and validation for the proposed FEM-based ML approach. It provides extensive analyses of the case results, highlighting the predictive performance, computational efficiency, robustness, and sensitivity of the developed models.

Chapter 4: Towards Fire Dynamics: Integrating CFD and FEM with Data-Driven Structural Fire Deformation Prediction is dedicated to the second research objective. Here, the integration of CFD and FEM with the ML model is described, providing a more comprehensive tool for predicting structural fire deformation. Similar to Chapter 3, it presents a thorough discussion of the case results, addressing the predictive performance and robustness of the models.

Chapter 5: Adaptive Indoor Fire Rescue Path Planning under Time-Varying Structural Safety Conditions addresses the third research objective. This chapter details the development of an adaptive indoor fire rescue path planning model considering time-varying structural safety conditions. It also provides an analysis and discussion of the proposed model's performance in comparison to traditional non-adaptive models.

Finally, **Chapter 6: Conclusions and Future Works** brings the thesis to a close, offering a comprehensive summary of the research findings, contributions, and potential future work. This chapter emphasizes the impacts of the study and provides insights into further research that could enhance the scope and applicability of the proposed models.

Each chapter provides a complete yet concise exploration of the research objectives, contributing to the overarching goal of enhancing efficiency and safety in firefighting operations in building fire emergencies. The overall organization of the chapters in this thesis is shown in Fig. 1-1.

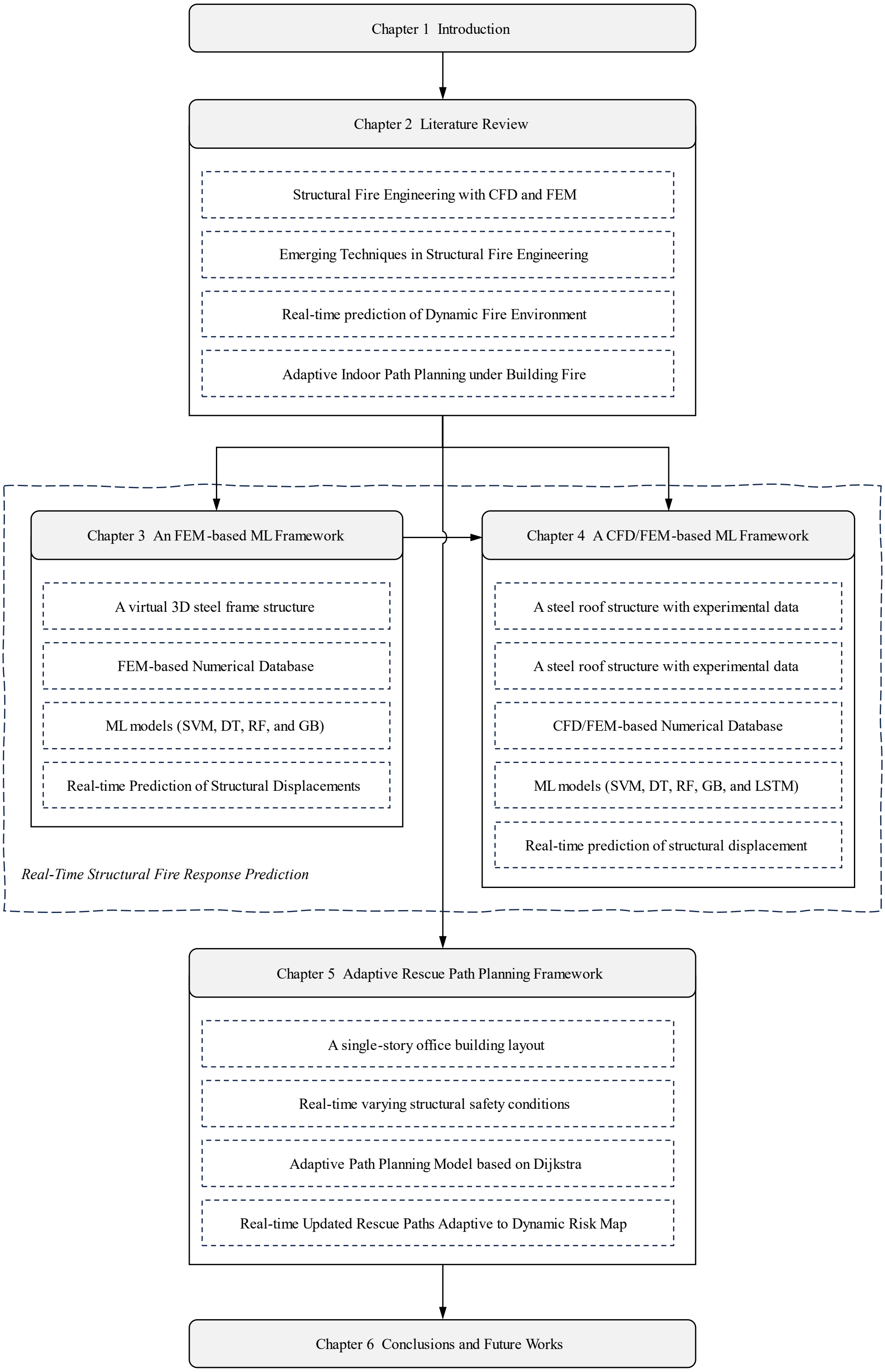


Fig. 1-1 Organization of the chapters in this thesis

CHAPTER 2 LITERATURE REVIEW

2.1 Introduction

The resilience and safety of built environments, particularly under unexpected and catastrophic scenarios like fire, are of paramount importance. Building fire safety is a complex subject that intersects various domains, including engineering, firefighting, and computer science (Khan et al., 2022). This complexity brings numerous challenges, ranging from the technical specifics of fire engineering and the unpredictable nature of fire scenarios to the computational efficiency and accuracy of predictive models(Kodur et al., 2019).

The advent of advanced simulation tools and computational methods like Finite Element Method (FEM) and Computational Fluid Dynamics (CFD) has facilitated more precise fire scenario modeling, but these methods are inherently resource-intensive, and their practical application for real-time response and decision-making remains a challenge (Malendowski and Glema, 2017, Feenstra et al., 2018). This is particularly true given the increasing scale and complexity of modern buildings.

Simultaneously, the application of Machine Learning (ML) and Artificial Intelligence (AI) in fire safety is an emerging field of research (Ye et al., 2022, Fu, 2020, Kim et al., 2020). These techniques have shown potential in various aspects, such as fire detection, fire behavior prediction, and structural response modeling, offering a possible path toward overcoming some of the limitations of traditional approaches.

Finally, the dynamic and unpredictable nature of fires presents significant operational challenges for firefighters, highlighting the need for adaptive indoor path planning strategies that can respond in real-time to changing fire conditions (Lei et al., 2018, Ding et al., 2016, Wang et al., 2021). While the application of AI techniques such as reinforcement learning has shown promise in other dynamic environments, its applicability and effectiveness in firefighting operations require further exploration.

In light of these developments and challenges, this literature review provides a critical survey of the state-of-the-art in structural fire safety analysis, focusing particularly on traditional structural fire engineering approaches, emerging techniques in structural fire safety analysis, real-time prediction of dynamic building fire environments, and adaptive indoor path planning in building fire emergencies. In doing so, it aims to provide an overview of current knowledge, identify gaps in the literature, and highlight potential areas for future research.

2.2 Traditional Structural Fire Engineering with CFD and FEM

Since the collapse of the World Trade Tower due to fire after terrorist attacks, increasing attention has been paid to understanding structural failure or collapse of buildings in fire (Domada et al., 2020, Yarlagadda et al., 2018, Jiang et al., 2014). Structural fire designs are traditionally based on standard fire tests conducted on individual structural members (e.g., beams, columns, and slabs) with preassigned boundary and loading conditions. These fire tests performed on an individual-member level failed to consider the real fire scenarios and neglected the mechanical support and/or restraint from other structural members, which would be less realistic in simulating the fire-resistance performance of the tested member at a structural level (Sun et al., 2012, Bresler, 1985). The fire-resistance performance of steel-framed composite buildings in a real fire is reported to be much better than it is in a standard fire test for an individual structural member (Lou et al., 2018). To integrally consider structural performances in fire conditions, performance-based design approaches have been applied in structural fire design, which takes into account the specific characteristics of the target building under various fire scenarios (Kodur et al., 2013, Jiang and Usmani, 2013, Jiang and Li, 2017, Izzuddin et al., 2000). Apart from using traditional standard fire curves, previous studies have adopted various fire models in terms of natural fire, localized fire, and traveling fire to represent complex fire scenarios in a more realistic manner (Khan et al., 2021b).

Experimental and numerical approaches are widely adopted in the investigation of structural fire analysis. Experimental programs on structural fire analysis generally require sophisticated equipment (e.g., furnace) and are usually time-consuming and costly (Li et al., 2021, Wang et al., 2008). As complementary, numerical approaches such as FEM analyze structural performance numerically in a mathematical way and cost less in the physical world. Still, developing comprehensive numerical models requires professional knowledge of mathematics and mechanics (Guillaume et al., 2019) and it could be computationally expensive to get numerical results, especially for complicated building structures. Therefore, neither an experimental nor numerical approach can be practically suitable to predict the real-time structural response in building fire emergencies, as fire scenarios are unpredictable before the fire happens, as well as during the fire evolves, and there is not enough time to wait for the result of numerical analysis from the advanced FEM model.

Recent studies have noticed the necessity of real-time monitoring and in-time warning of fire-induced structural failures or collapses, while efficient and feasible solutions are still limited. Most structural fire safety warnings and predictions were conducted based on structural deformation or vibration characteristics (Duron et al., 2005a). Traditional instruments such as displacement gages or vibration sensors are vulnerable to elevated temperature and, thus, limit the application of most tools in real fire scenarios. To fill this gap, some studies tried to predict structural safety conditions based on temperature data of structural components in a fire. For instance, Madrzykowski and Kent adopted thermal imagers to monitor the temperature of structural wood plates for the prediction of the structural integrity of wood plates under fire (Madrzykowski and Kent, 2011b). However, they concluded that the temperature data from the thermal imager is not accurate enough to reflect the real temperature of the slabs. Alternatively, Jiang et al. developed a fire safety monitoring and predicting system for steel truss structures that monitor the temperature of structural components using thermocouples, capable of recording the precise temperature data of structural members in a fire (Jiang et al., 2020a). A simplified critical temperature method was adopted in their structural safety predicting system to avoid time-consuming computational processes in conducting complex structural analysis, which simplified the load-transferring mechanisms in the structure and might lead to inaccurate results. More attempts are needed to improve the accuracy of the results with acceptable computational efficiency in the prediction of structural safety conditions in both component and structural levels.

2.3 Emerging Techniques in Structural Fire Safety Analysis

With the rapid development of ML and high-performance computing, numerous studies have proposed ML-based models for fire detection and fire prediction. Xue (2010) proposed a classic three-layer artificial neural network for the detection of the occurrence of fire in tunnels with the temperature and density data of smoke and toxic gas. Hodges et al. (2019) adopted a transpose convolutional neural network to predict the steady-state temperature distribution inside a compartment. Wu et al. (2021) developed an artificial intelligence model integrating a long short-term memory model and a transpose convolution neural network model to predict the temperature distribution inside tunnels based on limited temperature sensor data. These models were all trained on numerical databases without real-world on-site fire data, while the predictive performances based on the numerical datasets were still satisfactory. Moreover, the ML models after training and tuning were capable to complete the predictive task in a very short time (Xue, 2010, Wu et al., 2021). Recently, more studies have focused on the applicability of ML techniques in structural engineering. For instance, Thirumalaiselvi et al. adopted ML algorithms to predict load and deflection capacities of laced steel-concrete composite beams with the dataset from validated nonlinear FEM models (Thirumalaiselvi et al., 2018). Kim et al. compared the performance of several ML algorithms in predicting the ultimate load-bearing capacity of steel frames with the dataset obtained from the nonlinear inelastic analysis (Kim et al., 2020). Fu developed an ML framework to predict the failure patterns of steel frame structures under fire based on the dataset obtained from the Critical Temperature Method (Fu, 2020). Still, the application of the FEM-based ML model in real-time structural fire response prediction has not been adequately studied. Given the indications from previous studies, ML is likely to complement the traditional numerical approaches (e.g., FEM) in structural fire engineering to improve the predictive accuracy and/or computational efficiencies.

2.4 Real-time Prediction of Dynamic Building Fire environment

Dynamic building fire environments present significant operational challenges to firefighters due to the rapidly evolving and inherently unpredictable nature of fire incidents (Kodur et al., 2019). Each fire incident typically progresses through four distinct stages: Incipient, Growth, Fully Developed, and Decay, as illustrated in Fig.1. The fire’s growth is divided into two phases: the pre-flashover and post-flashover phases (Buchanan and Abu, 2017). The pre-flashover phase spans from initial smoldering to ignition, followed by a swift temperature escalation until the flashover. The post-flashover phase sees the fire intensifying before gradually decreasing as the fuel is depleted.

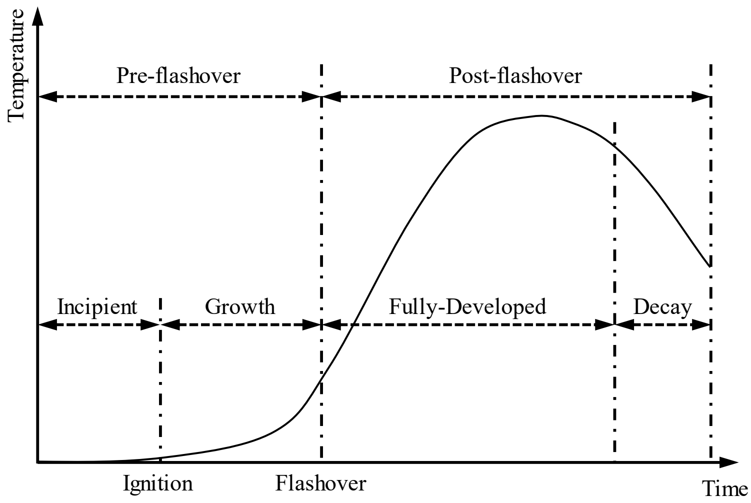


Fig. 2-1 Development process of a fire in a building compartment

The pre-flashover phase is crucial for human life safety, as occupants are generally expected to evacuate successfully during this time (Khan et al., 2022). In contrast, the post-flashover phase is important for structural safety assessment, given the increased likelihood of structural component failure (Jiang et al., 2020b). Firefighters typically initiate their operations slightly later, often during the Fully Developed stage or even after (Chou et al., 2019). This stage is characterized by an environment that becomes increasingly hazardous and unpredictable, signifying the complexity and inherent risks of firefighting operations. The potential for failure in both load-bearing (beams, columns, slabs, and some walls) and non-load-bearing (windows, curtain walls) structural components during these later stages presents a significant obstacle to firefighting efforts (Ye and Hsu, 2022, Khan et al., 2022). Firefighters may be attempting to rescue trapped occupants or control the fire when such failures occur, further complicating the operation and underscoring the need for adaptive and dynamic path planning strategies.

Fire Dynamics Simulator (FDS) is widely recognized and utilized in the field of fire safety engineering. It's a powerful tool for simulating fire spread, smoke movement, and heat transfer in buildings. FDS involves advanced computational techniques that can model complex fire scenarios with a high degree of accuracy. However, these simulations can be computationally intensive, often requiring significant resources and time, which can be a limitation in real-time applications.

Recent literature acknowledged this dynamism and focuses on real-time warning systems for structural failure due to fire and structural fire safety monitoring. The advent of high-performance computing has enabled the development of machine learning (ML)-based models aimed at predicting fire ignition and development (Xue, 2010, Hodges et al., 2019, Wu et al., 2021). Moving the focus from fire dynamics to structural fire responses, Ye et al. (2022) and Ye and Hsu (2022) explored real-time structural displacement prediction in building fire emergencies using Finite Element Method (FEM)-based ML models and Computational Fluid Dynamics (CFD)/FEM-based ML frameworks, respectively (Ye et al., 2022, Ye and Hsu, 2022). All the abovementioned studies have offered substantial benefits in structural fire engineering and fire emergency management, including the potential to provide early detection and predictive analysis of fire dynamics and structural responses. Still, their direct application to dynamic path planning for firefighting operations in fire environments is relatively unexplored.

2.5 Adaptive Indoor Path Planning in Building Fire Emergency

Firefighters operating in building fire scenarios face extreme external conditions, including high temperatures, smoke, and exposure to toxic gases (Horn et al., 2019, Romet and Frim, 1987, Khan et al., 2022). These conditions can severely impair their situational awareness, compromising their ability to make effective and safe decisions and increasing the risk of injuries and fatalities (Fabio et al., 2002, Britton et al., 2013, Li et al., 2014). The operational environment during a building fire is often dynamic and unpredictable, with time-varying structural safety conditions that add a layer of complexity to the decision-making process (Ye et al., 2022, Ye and Hsu, 2022, Jiang et al., 2020a, Jiang et al., 2020b). Moreover, the structural components of a building in a fire scenario can reach exceedingly high temperatures, sometimes over 1,000°C, posing a significant risk to the structural integrity of the building and the safety of firefighters (Kodur, 2014, Li et al., 2003).

The dynamic and unpredictable nature of building fires significantly impacts the efficacy of traditional path-planning strategies. These strategies often assume a stationary or slowly changing fire environment without considering the possibility of building collapse (Jarvis and Marzouqi, 2005, Ranaweera et al., 2018, Liu et al., 2020, Zhong et al., 2020). Such assumptions can lead to suboptimal performance and increased risks in rapidly changing fire scenarios with deteriorating structural fire safety conditions. For instance, Ding and He (Ding et al., 2016) proposed a dynamic method to optimize indoor fire evacuation paths based on the real-time perception of fire situation parameters and the changing indoor environment information. Wang and Wei (Wang et al., 2021) proposed an analytical method of real-time dynamic escape path prediction based on Building Information Modeling (BIM). While such approaches offer valuable insights, their application is limited in dynamic and unpredictable fire scenarios with the risk of structural component failure and collapse. They may not provide optimal paths, or they may fail to adapt quickly to rapidly changing structural fire safety conditions. Thus, there is a clear gap in the literature for an adaptive path planning algorithm for firefighting operations that can dynamically respond to changing structural safety fire conditions.

The rise of artificial intelligence (AI) and big data technologies has sparked novel approaches for dynamic path planning, with Reinforcement Learning (RL) being one of the most promising methods. RL is an AI technique that learns an optimal policy to maximize total expected rewards through interaction with the environment. RL-based path planning has been successfully implemented in various contexts outside of building fire disasters (Xu et al., 2022), such as training autonomous mobile robots to dynamically avoid obstacles (Lin et al., 2006) and motion planning of industrial robots (Meyes et al., 2017). Recent advancements in deep RL have even led to significant breakthroughs in game environments, with AI agents outperforming humans (Mnih et al., 2013, Silver et al., 2017).

Despite these advancements, RL has several limitations when applied to dynamic environments like building fires. RL requires extensive training data and computational resources, which might not be readily available or feasible in real-world firefighting scenarios. Moreover, RL's iterative learning process can be too slow to adapt to rapidly changing environments, and its exploratory nature may produce unpredictable or suboptimal results, which could be catastrophic in high-risk firefighting operations. Furthermore, the application of RL-based path planning in complex, real-world environments like building fires is still in its infancy. While studies have begun to emerge applying deep Q-learning (DQL) to path planning in complex environments (Bae et al., 2019, Lei et al., 2018, Niroui et al., 2019), their application in firefighting or rescue operations remains limited.

In light of these identified limitations within the existing body of literature, this research adopts and builds upon classic path planning algorithms, such as Dijkstra's algorithm, integrating them with data-driven real-time dynamic risk maps. This innovative approach facilitates the adjustment of edge costs in direct response to real-time changes in structural safety conditions for adaptively updating the optimal fire rescue paths.

2.6 Chapter Summary

Through a comprehensive exploration of the existing literature, this review has highlighted the criticality of structural fire safety and response and underscored the importance of adopting a progressive and holistic approach in this field. The strengths and limitations of traditional structural fire safety methodologies, the potential of emerging AI and ML technologies, the dynamics of building fire environments, and adaptive indoor path planning strategies in fire emergencies were meticulously examined.

The landscape of structural fire safety is rapidly evolving, and the review revealed that AI and ML hold substantial potential to augment current methodologies. However, it also brought to light that the direct use of these technologies for real-time structural fire response prediction remains an under-explored research area, thus defining our first research objective.

Furthermore, the complexities of building fire environments were dissected. The review underscored that the unpredictability and inherent risks involved in late-stage fire incidents necessitate the development of dynamic fire safety measures, marking the second research objective. The focus on adaptive indoor path planning for firefighting operations also unveiled a significant need for strategies that can accommodate rapidly changing structural fire conditions, forming our third research objective.

In conclusion, the gaps identified in this literature review reflect the need for innovative and robust solutions to enhance structural fire safety. This review serves as a foundation to guide future research aimed at the outlined objectives. By addressing these gaps, we aim to contribute meaningfully to the field, significantly enhancing fire safety measures, firefighting efficacy, and ultimately, the preservation of lives and infrastructure.

CHAPTER 3 REAL-TIME PREDICTION OF STRUCTURAL FIRE RESPONSES: A FEM-BASED MACHINE-LEARNING APPROACH [1]

3.1 Introduction

Annually, more than 7 million fire accidents happen all over the world, and the number of casualties is up to around 70,000, according to the Centre of Fire Statistics of the International Association of Fire and Rescue Services (Brushlinsky et al., 2016). Among all fire accidents, building fire accidents are the most threatening to mankind (U.S. Fire Administration, 2021). Specifically, the sudden fire-induced failure or collapses of structure members, or even the whole building, will trap people inside the building, which leads to tremendous losses of human lives and properties (Kodur et al., 2019). Even worse, without knowing the real-time safety status of the structure in fire, firefighting instructors would be difficult to make the most efficient rescue decision,

[1] Chapter 3 is based on a published study and being reproduced with the permission of Elsevier. Ye, Z., Hsu, S. C., & Wei, H. H. (2022). Real-time prediction of structural fire responses: A finite element-based machine-learning approach. Automation in Construction, 136, 104165. https://doi.org/10.1016/j.autcon.2022.104165

which may result in secondary casualties of firefighters inside the building. In April 2021, a three-story house in Bangkok was engulfed in flames and abruptly collapsed in about an hour and such unexpected collapse of the building killed five people including four firefighters who were conducting rescue actions and one trapped resident (Reuters, 2021). In this case, the firefighters failed to sense the possible structural collapse in the fire in time, or they might be able to evacuate the building or move to somewhere relatively safer in advance. Therefore, an accurate and timely prediction of structural responses under fire is of great value for guiding the rescuing and firefighting actions in building fire emergencies, which could further contribute to the mitigation of the disastrous consequences caused by building fires.

During the fully developed stage of a building fire, structural materials are subjected to significant degradation in strength and stiffness as the fire temperatures could be higher than 1,000 ºC (Kodur, 2014, Li et al., 2003). Structural members are endangered when carrying designed structural loads under significant material degradation, thus the building structure is exposed to the risk of partial failure or complete collapse during or after the fire (Jiang and Li, 2017). Numerous studies have been conducted in the field of structural fire engineering, most of which aim to investigate the mechanical performance or structural behavior of building structures (Wang, 2000), substructures (Jiang et al., 2020b), or structural members, such as beam, column, slab, wall, and/or joints (Ye et al., 2019, Li et al., 2021). These studies are generally conducted with a series of experimental and/or numerical programs. However, in the context of building fire emergencies, neither experimental nor numerical approach can be particularly suitable for structural response prediction as they are both time-consuming and unable to timely predict the structural response to the real-time varying fire situations.

An efficient approach to capture or predict structural responses to fire in a real-time manner is needed. As an exploratory attempt, Jiang et al. developed a fire safety monitoring system for steel truss structures that judges the safety conditions of the structure member using a simplified critical temperature method (Jiang et al., 2020a). Still, it is difficult to accurately predict the safety conditions of structural members as the response of the structure depends not only on the temperature of the structural components in the fire but also on the applied loads and the effects of any composite action, restraint, and continuity from the remainder of the structure (Bresler, 1985). Due to the complexity of this thermal-mechanical coupled problem, an accurate and efficient solution to this problem has not been fully investigated yet.

With the development of computer science, studies have widely adopted machine learning (ML) models in structural engineering problems, such as the prediction of the ultimate load-bearing capacity of steel frames (Kim et al., 2020), load and deflection capacities of composite beams (Thirumalaiselvi et al., 2018), and mechanical strength of structural materials (Nguyen et al., 2019, Asghari et al., 2020). Recent studies that focused on the fire forecast in building fire emergencies by using ML techniques include the estimation of the occurrence of flashover in a compartment (Dexters et al., 2020), the identification of the size and location of fire inside the tunnel (Wu et al., 2020), and the prediction of the air temperature distribution in a tunnel fire (Wu et al., 2021). These previous studies indicate the high applicability of ML methods in structural engineering, as ML can be found as an accurate and efficient tool in predictive tasks. Analogically, for a specific structure under given load conditions subject to an unforeseen building fire, the problem could be possibly regarded as a predictive problem taking fire scenarios (e.g., development of temperature field) as input and structural responses (e.g., structural member displacement, remaining fire endurance, or structural collapse probability) as output.

This study proposes an FEM-based ML model framework aiming to predict structural responses to fire based on real-time temperature data of structural members. Structural responses to the fire are simulated in ABAQUS using the FEM method. The temperatures and the displacements at specific locations of steel members during the fire processes are recorded in the database. The ML model is trained based on the numerical database with temperature data as input and displacement data as output. After training, the ML model is capable of real-timely predict the displacements at specific locations of the structure under new fire scenarios.

3.2 Methodology

3.2.1 Workflow of the proposed framework

To predict the structural fire response in a real-time manner based on the temperature data of structural members, this chapter proposes a machine learning (ML) framework with datasets generated from numerical models using finite element methods (FEM). The flowchart of the proposed framework is shown in Fig. 3-1, consisting of three main parts: 1) development of FEM model and data generation, 2) development of FEM-based ML model, and 3) real-time prediction using the FEM-based ML model. Firstly, FEM models of the targeted structure are developed with given geometric, material, loading, and boundary specifications. A numerical database of the structure subjected to various fire scenarios is established with the analysis results from the FEM models. The temperatures and structural responses (e.g., displacements, strain, stress) at specific locations of structural members during the fire processes are recorded in the database.

Then, ML models are trained based on the numerical database with temperature data as input and structural response data as output. Four ML algorithms, including support vector machine (SVM), decision tree (DT), random forest (RF), and gradient boosting (GB) are adopted for comparison. Finally, the ML model is trained to predict the displacements in real-time at specific locations of the structure under new fire scenarios, taking real-time temperature data from pre-installed sensors as model input. Detailed descriptions are demonstrated in the following sections. Note that the FEM-based ML framework proposed in this chapter is a general framework for real-time prediction of structural fire response. The framework can be applied to other building structures with required building information.

3.2.2 Theoretical background

1. FEM for structural fire analysis

The Finite Element Method (FEM) is a versatile numerical technique widely utilized in structural fire engineering to predict the performance of a structure under fire conditions. FEM offers the ability to model complex geometries and material behaviors, making it a powerful tool for predicting structural responses under thermal loads.

In a typical FEM-based fire analysis, the structure's geometry is discretized into a finite number of elements, which are interconnected at nodes. Material properties, including thermal conductivity, specific heat, and thermal expansion, among others, are attributed to each element. These elements collectively form the "finite element mesh" of the structure. The thermal properties of the materials allow the FEM to account for the transfer of heat from the fire to the structure and through the structure itself, enabling the determination of temperature distribution within the structure over time.

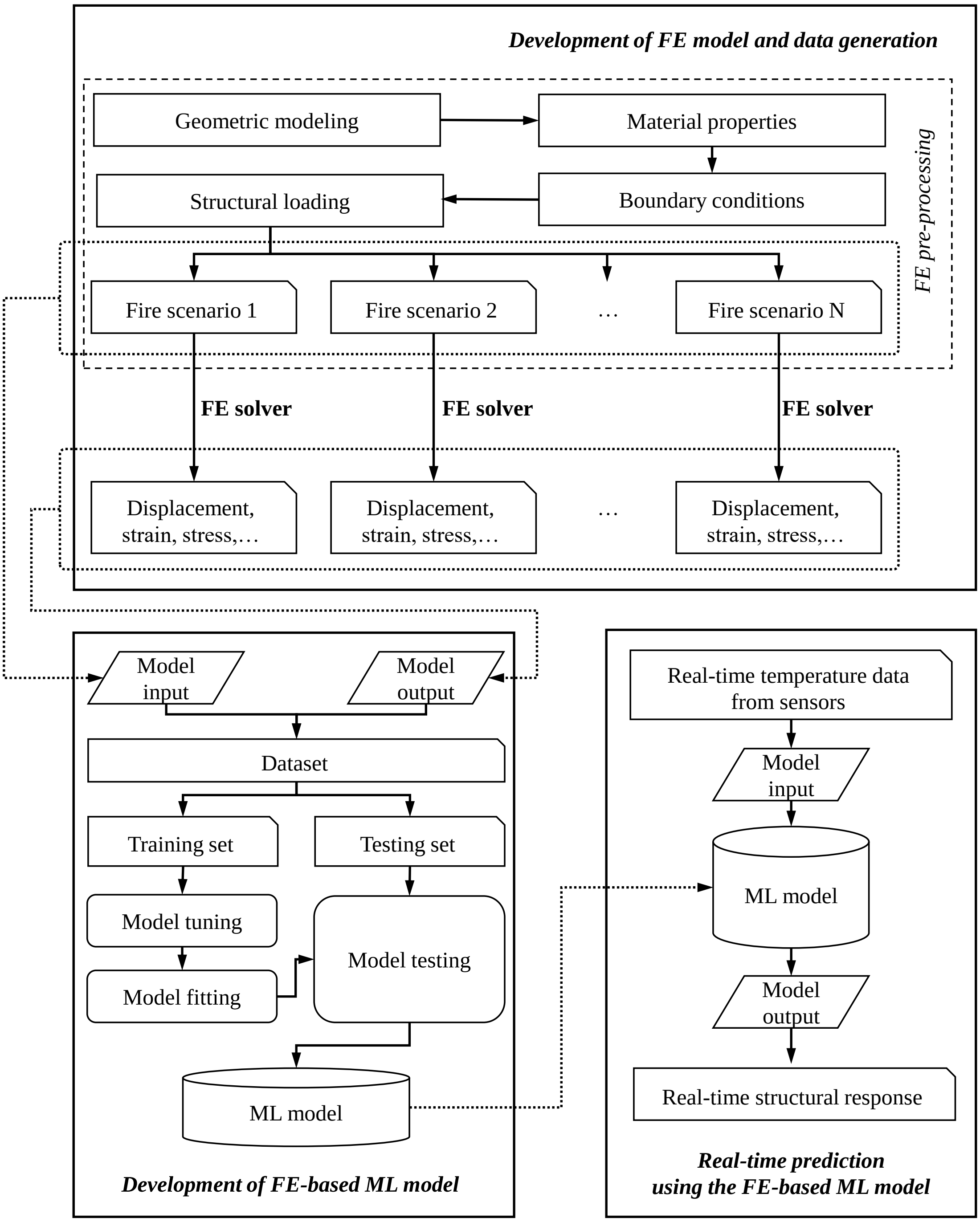


Fig. 3-1 Flowchart of the proposed FEM-based ML framework

Once the thermal analysis is completed, the resulting temperature distribution is used in a structural analysis to determine the structure's response to the fire. This response can include displacements, stresses, and strains in the structure, which are key indicators of its performance under fire.

The strength of FEM lies in its ability to provide detailed information on the structural response to fire at any location within the structure, at any point in time. This detail can be instrumental in understanding the behavior of structures under fire and developing improved design strategies for fire resistance. It’s noteworthy, however, that the accuracy of FEM predictions is highly dependent on the quality of the input data, including material properties, loading conditions, boundary conditions, and the fire scenario, among other factors. Therefore, care must be taken to ensure that these inputs are as accurate and representative as possible.

This study leverages the power of FEM to generate a comprehensive numerical database for various fire scenarios. The FEM models provide temperature and structural response data, which serve as the foundation for our machine learning models in the quest for real-time prediction of structural fire response. Firstly, the data generated by the FEM is meticulously designed to be representative of a wide range of real-world fire scenarios. This includes variations in fire intensity and location. By encompassing a broad spectrum of scenarios, the FEM data effectively simulates the diverse conditions encountered in actual fire incidents, making it a robust foundation for ML training. Secondly, FEM is renowned for its high level of detail and accuracy in simulating structural responses to various stimuli, including fire. The data generated through FEM simulations in this study captures intricate details of temperature distribution and structural deformations, which are crucial for training ML models to predict structural fire responses accurately. Thirdly, the FEM simulations and the resulting data are validated against empirical data from real fire incidents and experimental studies. This validation process ensures that the FEM-generated data is not only theoretically sound but also practically applicable, further reinforcing its suitability for ML model training.

2. ML for structural response prediction

ML is the computational process of revealing patterns from data, which is usually used when it is difficult to model the complex behavior of the system or when computational efficiency is the prime requirement. Structural behavior in building fire emergencies is the complex consequence of fire loads and computational efficiency is an essential concern in the context of a real fire. Therefore, ML could be a possible solution to the real-time structural fire response prediction. Among the commonly used ML algorithms in structural engineering, SVM has been suggested to be powerful in modeling the non-linear relationship in the data with numerous kernel functions, DT is easy to understand with its tree-like decision logic and efficient in model training. As ensemble models, RF and GB are popular in solving both regression and classification problems. As a starting point, these four ML algorithms, i.e., SVM (Noble, 2006), DT (Lewis, 2000), RF (Breiman, 2001), and GB (Friedman, 2001a), are adopted in this chapter to explore the feasibility of real-timely predicting structural fire responses with FEM-based ML models. Brief introductions for the four ML algorithms are summarized as follows.

1) Support Vector Machine

SVM is a powerful and versatile ML model for linear or nonlinear classification, regression, and outlier detection. In this chapter, the SVM regression model will be developed and adopted with the details as follows. SVM model exploits the relationship between observations by arraying predictors in observation space using a set of inner products, as shown in Eq.(3-1):

$$y(x) = b + h(x)^T \omega \tag{3-1}$$

where $h(x)^T$ are the base functions of one or more predictors x with linear or nonlinear transformation, and the factor b and ω are determined by minimizing a regularized error function:

$$\frac{1}{2}\sum_{i=1}^{N}(y_i - t_i)^2 + \frac{\lambda}{2}\|\omega\|^2 \tag{3-2}$$

where N is the number of observations, y_i is the predictive value of the i^{th} observation calculated from Eq.(3-1), t_i is the true value of the i^{th} observation, and λ serves as a regularization coefficient.

The optimization function of SVM regression can be written as:

$$\min C\sum_{i=1}^{N}(\xi_i + \xi_i^*) + \frac{1}{2}\ \|\omega\|^2 \tag{3-3}$$

$$s.t.\ \xi_i \geq 0, and\ \xi_i^* \geq 0 \tag{3-4}$$

where C is a penalty factor, ξ_i and ξ_i^* $(i = 1,2, \ldots, N)$ are slack variables.

The final decision function can be represented as:

$$y(x) = \sum_{i=1}^{N}(\alpha_i - \alpha_i^*)K(x, x_i) + b \tag{3-5}$$

where α_i and α_i^* are the Langrange multipliers, $K(x, x_i)$ is the kernel function. There are several kernel functions for SVM, such as Linear Kernel, Polynomial Kernel, Sigmoid Kernel, and Radial Basis Function (RBF) Kernel. This study uses the RBF kernel considering its capacity to address the nonlinear relationship.

2) Decision Tree

DT employs a tree-like model of decisions and corresponding consequences to make predictions on classification or regression tasks. An oriented graph-like structure is adopted to represent the decision process of DT. The oriented tree-like graph is derived by recursive partitioning based on the attributes in the dataset for maximally reducing the impurity degree (e.g., entropy or Gini Index) in the partitioned groups. In the graph, each root or internal node presents a partitioning attribute, each branch presents the partitioning outcome, and each leaf node presents a predictive label. A path departing from the root node through the internal nodes to the leaf node is regarded as a decision rule. Generally, the impurity degree of end nodes is lower than that of root nodes. A DT model can be mathematically represented as:

$$y(x_i) = r(x_i, \lambda, D) \tag{3-6}$$

where $y(x_i)$ is the final predictive value of x_i, x_i is the i^{th} observation, r is the regression function, λ is a random parameter of partition, and D is the total dataset. A Classification and Regression Trees (CART) algorithm is employed in this chapter, which constructs a decision tree by connecting the internal nodes to leaf nodes with the thresholds of attributes in the observations.

3) Random Forest

RF is a group of unpruned DTs made from the random selection of the training data samples. By aggregating the predictions of the ensemble, the prediction is made. A schematic illustration of an RF is shown in Fig. 3-2.

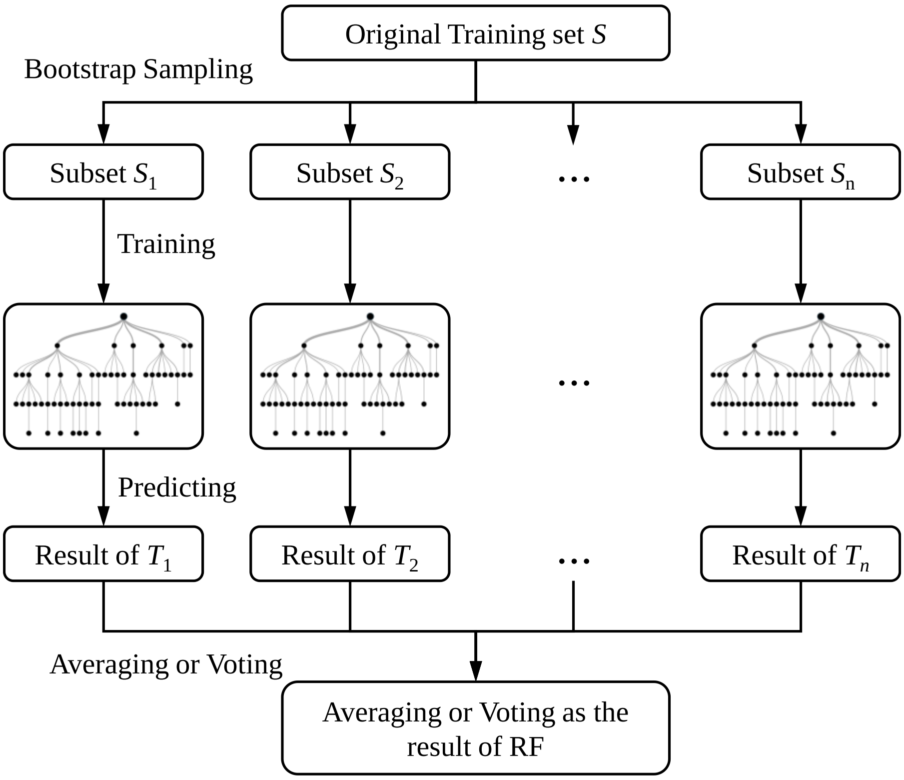


Fig. 3-2 Flowchart of RF algorithm

Firstly, n_{tree} subsets $\{S_1, S_2, \dots, S_{n_{tree}}\}$ are randomly drawn from the original dataset $S = \{(X_i, y_i), | \text{ i} = 1,2, \dots, N,\ X \in R^k, y \in R\}$ with replacement by bootstrap sampling. Then, for each subset S_j, $j = \{1,2, \dots, n_{tree}\}$, a DT model T_j is trained. After n_{tree} trees are established, a forest is established with an ensemble of all trees $\{T_1, T_2, \dots T_{n_{tree}}\}$. Finally, when making predictions, the final decisions are made based on the prediction of each tree by averaging for regression problems or majority vote for classification problems. Eq. (3-7) can be used to predict a new observation X_{new}:

$$y(x_{new}) = \frac{1}{n_{tree}} \sum_{i=1}^{n_{tree}} T_i(x_{new}) \tag{3-7}$$

where $y(x_{new})$ is the final predictive value of x_{new}, $T_i(x_{new})$ is the predictive value resulted from the the i^{th} DT model.

4) Gradient Boosting

The main idea of GB is to compute a sequence of simple DT trees, in which each successive tree is established for the prediction of the residuals of the preceding trees. GB iteratively compares predictions against true observations throughout the analysis to facilitate the correction for previous mistakes in the next iteration. Compared with RF, although GB is also an ensemble of DTs, the distinguishable differences are: 1) GB builds one tree at a time, while RF builds each tree independently, and (2) GB combines results of the ensemble learning throughout the analysis process, while RF combines the outcome of the ensemble learning only at the end of the RF analysis. A schematic illustration of the GB algorithm is shown in Fig. 3-3.

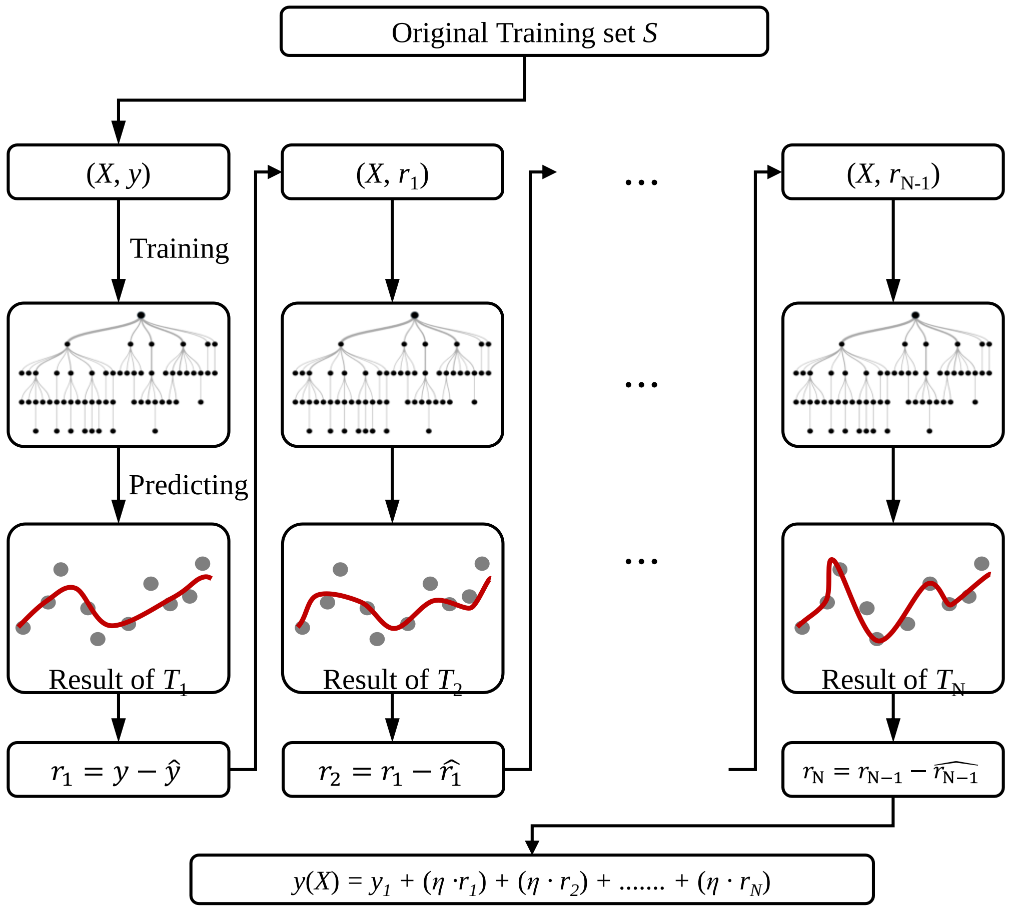


Fig. 3-3 Flowchart of GB algorithm

3.3 Model Development

3.3.1 Development of FEM model

Steel structures are more and more widely used in buildings all over the world because of their high constructional efficiency and outstanding seismic performances. Fire is a great threat to most steel-structure buildings as the mechanical properties (e.g., strength and stiffness) of steel deteriorate significantly at elevated temperatures. These deteriorations may dramatically decrease the load-bearing capacity of structural members under fire, and, thus, lead to partial failure or even progressive collapse of the structure. As a representative example, a single-story two-bay 3D steel frame structure is designed as a simple exemplified case to illustrate the proposed FEM-based ML model for real-time structural fire response prediction, as shown in Fig. 3-4. For the sake of simplicity in FEM modeling, no slabs are included in the virtual case as demonstrated in Section 3.3, while a numerical case with slabs is presented in Section 3.4.6 as a comparative reference for the discussions on the impact of slab on the structural performance of the steel frame when subject to fire. The FEM model is built and analyzed using ABAQUS (Systèmes, 2014) through sequential thermal-mechanical coupling analysis to simulate the structural response to fire.

1. Geometric specifications and material properties

The geometric configuration of the steel frame as shown in Fig. 3-4 is designed based on our previous work (Ye et al., 2019). Given the space requirement (e.g., the height of the column, the distance between the columns) and the corresponding load conditions, the cross-section of the column and the beam were determined by considering the loading bearing capacity of the section, global and local stability of the member, and other construction requirements. The frame is equipped with H-shaped steel beams and columns. All beams are with the cross-section of H300×240×8×12, and all columns are with the cross-section of H240×240×12×14. To keep the numerical case as simple as possible, we approximate the length of the beam from 5.39m as designed in (Ye et al., 2019) to 4m, which is in line with the height of the column. The grade of the steel for all structural members is S355JR. A simplified trilinear model with isotropic hardening is applied to simulate the material property under room temperature. The elastic modulus E_s, yield strength f_y, and ultimate strength fu of the steel members are listed in Table 3-1 according to experimental results from (Ye et al., 2019).

To simulate the structural response under elevated temperature in a building fire, it is necessary to assign the temperature-dependent mechanical properties of the structural material. For steel, the reduction coefficients of strength and Young's modulus of steel at elevated temperatures suggested by Eurocode (EC) 3 (European Committee for Standardisation, 2005a) are adopted and shown in Fig. 3-5. The thermal expansion rate of steel is taken to be zero between the temperatures range from 750 °C to 860 °C, and 1.4×10^{-5}°C^{-1} at other temperatures.

2. Boundary conditions and structural loads

All columns are designed to be rigidly connected to the ground and adjacent members are modeled as rigidly connected. The vertical distributed loads on each beam are assigned as 9.6kN/m. Vertical loads are first applied to the test frame and then remained constant, then the temperatures of the heated structural components are increased according to the fire scenarios specified in the next section to simulate building fires.

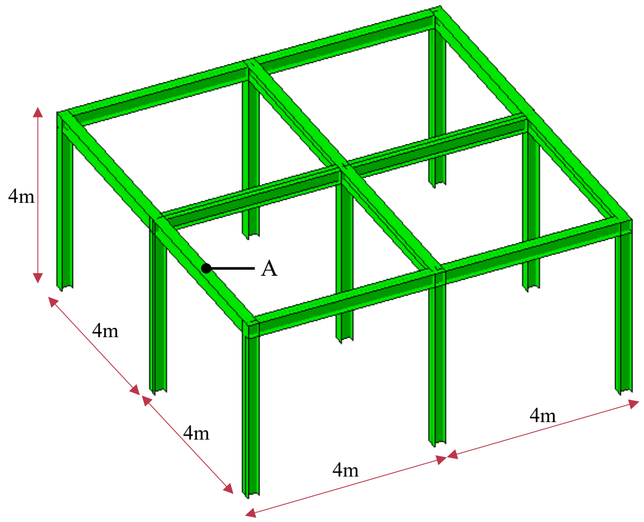


Fig. 3-4 Geometric configuration of the finite element model

Table 3-1 Material properties under room temperature

Material	Property	Value
S355JR (8mm)	E_s	2.1×10^5 MPa
	f_y	350 MPa
	f_u	495 MPa
S355JR (12mm)	E_s	2.1×10^5 MPa
	f_y	323 MPa
	f_u	505 MPa
S355JR (14mm)	E_s	2.1×10^5 MPa
	f_y	309 MPa
	f_u	496 MPa

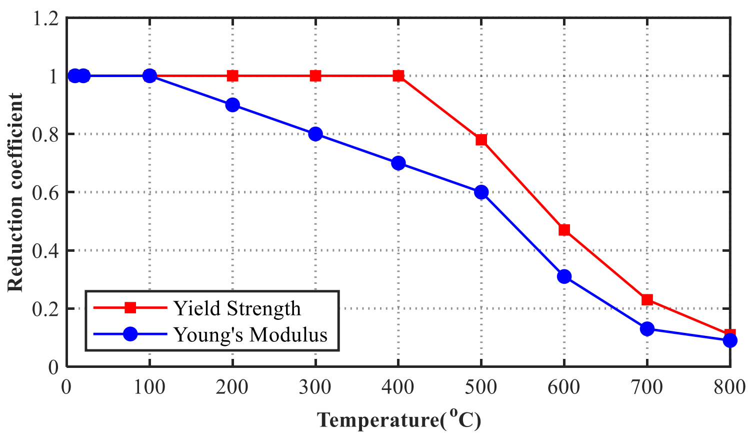


Fig. 3-5 Degradation of mechanical properties of steel at elevated temperatures

3. Fire scenarios

For the sake of simplicity, the numerical model is subjected to compartment fires with fire curves of temperature-time relationship. There are many fire curves in the literature such as ISO 834 Standard Fire (International Organization for Standardization, 1999), and the EC Parametric Fire(European Committee for Standardization, 2004), as shown in Fig. 3-6. The Standard Fire is characterized by its typicalness and simplicity as it ignores the specific characteristics of the building (e.g., geometric specification, ventilation condition, and fuel load density) and considers the heating stage only. The EC Parametric Fire complements the Standard Fire with more parameters concerning building and fire characteristics, as well as taking into consideration both the heating stage and cooling stage. To consider more diversity of fire scenarios, this chapter adopts the EC Parametric Fire, of which the details are described as follows.

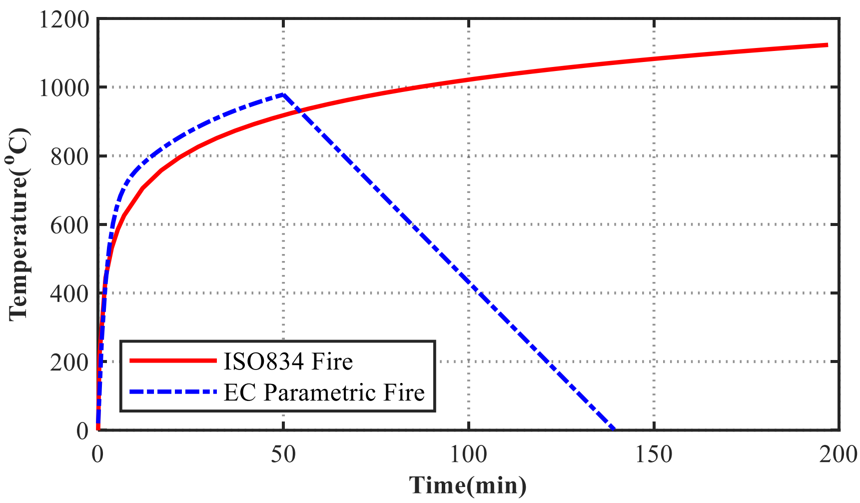


Fig. 3-6 Temperature time curves of ISO Standard fire and EC parametric fire

In the heating stage, the gas temperature is calculated by:

$$\theta_g = 20 + 1325\left[1 - 0.324e^{-0.2(t \cdot \Gamma)} - 0.204e^{-1.7(t \cdot \Gamma)} - 0.472e^{-19(t \cdot \Gamma)}\right] \quad (3\text{-}8)$$

where θ_g is the gas temperature in the fire compartment [°C], t is the heating time [h], and Γ is a dimensionless parameter related to the opening factor O $[m^{1/2}]$ and the thermal absorptivity b $[J/m^2 s^{1/2} K]$ and should be calculated as:

$$\Gamma = \frac{(O/b)^2}{(0.04/1160)^2} \tag{3-9}$$

where O and b are calculated as:

$$\begin{cases} O = \frac{A_v \sqrt{h_{eq}}}{A_t} \\ b = \sqrt{\rho \cdot c \cdot \lambda} \end{cases} \tag{3-10}$$

where A_v is the total area of vertical openings on the surrounding walls, h_{eq} is the average height of windows, A_t is the total area of the enclosure, ρ is the density, c is the specific heat, and λ is the thermal conductivity of the boundary of the enclosure.

In the cooling stage, the gas temperature is calculated by:

$$\begin{cases} \theta_g = \theta_{max} - 625(t - t_{max})\Gamma, & t_{max}\Gamma \leq 0.5h \\ \theta_g = \theta_{max} - 250(3 - t_{max}\Gamma)(t - t_{max})\Gamma, & 0.5h \leq t_{max}\Gamma < 2h \\ \theta_g = \theta_{max} - 250(t - t_{max})\Gamma, & t_{max}\Gamma \geq 2h \end{cases} \tag{3-11}$$

In this chapter, different values of Γ were adopted to simulate the diversity of fire development in the FEM model. As suggested in Eq. (1), a larger Γ indicates a faster increase in gas temperature during the heating stage under fire, while a smaller Γ means a slower increase in gas temperature.

As suggested by EC3, thermal actions are given by the net heat flux to the surface of the structural component subjected to fire, which should be calculated as:

$$\begin{cases} \dot{h}_{\text{net}} = \dot{h}_{\text{net,c}} + \dot{h}_{\text{net,r}} \\ \dot{h}_{\text{net,c}} \ = \alpha_c \cdot (\theta_{\text{g}} - \theta_{\text{m}}) \\ \dot{h}_{\text{net,r}} \ = \Phi \cdot \varepsilon_{\text{m}} \cdot \varepsilon_{\text{f}} \cdot \sigma \cdot ((\theta_{\text{r}} + 273)^4 - (\theta_{\text{m}} + 273)^4] \end{cases} \tag{3-12}$$

where $\dot{h}_{\text{net}}$ is the net heat flux per unit area $[W/m^2]$, $\dot{h}_{\text{net,c}}$ is the net heat flux per unit area due to convection [W/m^2], $\dot{h}_{\text{net,r}}$ is the net heat flux per unit area due to radiation [W/m^2], α_c is the coefficient of heat transfer by convection [W/m^2], θ_{g} is the gas temperature around the component exposed to fire [℃], θ_{m} is the surface temperature of the component exposed to fire [℃], Φ is the configuration factor, ε_{m} is the surface emissivity coefficient of the component, ε_{f} is the emissivity coefficient of the fire, σ is the Stephan Boltzman constant $\left(5.67 \times 10^{-8}\text{W/m}^2\text{K}^4\right)$, and θ_{r} is the effective radiation temperature of the fire environment. Then, assuming a uniform temperature distribution in the cross-section, the increase of temperature in an unprotected steel member during a time interval should be determined as:

$$\Delta\theta_{\text{a,t}} = k_{\text{sh}} \frac{A_{\text{m}}V}{c_{\text{a}}\rho_{\text{a}}} \dot{h}_{\text{net}} \Delta t \tag{3-13}$$

where $\Delta\theta_{\text{a,t}}$ is the increase of temperature in an unprotected steel component, k_{sh} is the correction factor for the shadow effect, A_{m} is the surface area of the component per unit length [m^2/m], V is the volume of the member per unit length [m^3/m], c_{a} is the specific heat of steel [J/kgK], ρ_{a} is the unit mass of steel [kg/m^3], $\dot{h}_{\text{net}}$ is the net heat flux per unit area to the component [W/m^2], and Δt is the time interval [s].

4. Element type and grid mesh

To better capture the local behavior while considering the efficiency of the calculation, shell elements (S4R) are adopted for steel members in the model. Beam elements (e.g., B31) are not able to reflect the detailed responses (e.g., local buckling) of the steel members, while solid elements (e.g., C3D8R) are computationally expensive compared to beam or shell elements (Systèmes, 2014).

The trial results of mesh dependency analysis indicate that the mesh size of 0.1m fails to accurately simulate the failure mode of the steel frame, while the result of mesh size of 0.06m meets well with that of 0.03m. Therefore, to conduct a more efficient calculation, 0.06m is chosen as the basic mesh size in this case as shown in Fig. 3-7.

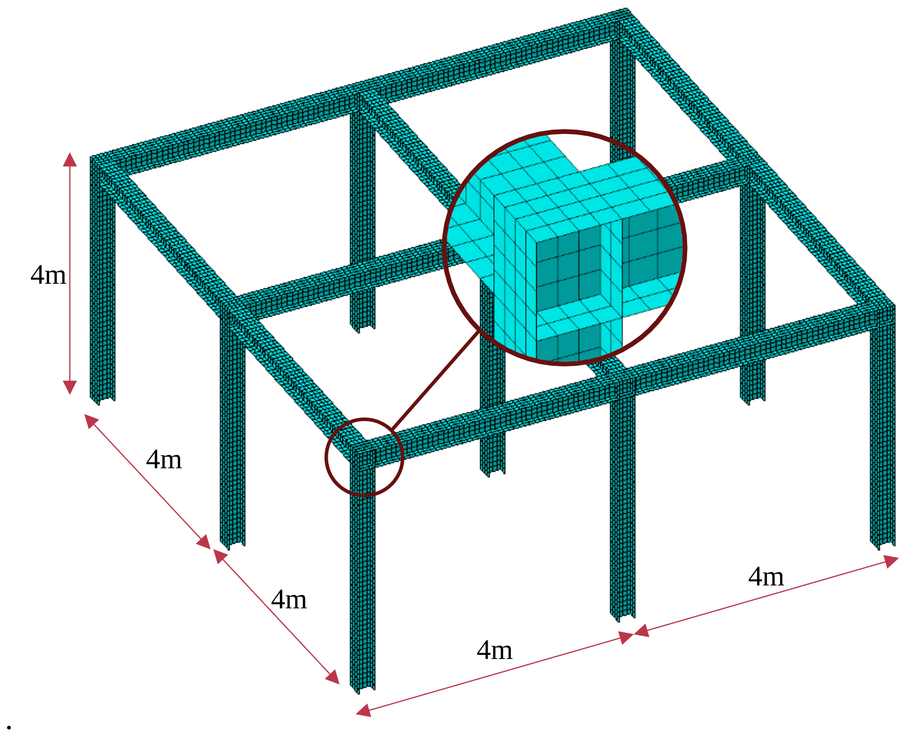


Fig. 3-7 Mesh size of the finite element model (0.06m)

3.3.2 Data generation from FEM models

Generating data from FEM models is a crucial step for the training of ML models. FEM models in ABAQUS are capable of simulating the structural response such as stress distribution and structural deformation displacement at an elementary level and generating a “.odb” file for one fire scenario after FEM analysis. Considering the data requirement of ML models and for the sake of simplicity, this exploratory study firstly focuses on the mid-span displacement of beams, since large beam deformation usually occurs before local or global structural failure. Therefore, the node temperature of the beams and columns at the mid-span points are extracted as the independent variables, and the maximum vertical displacements of the beams are extracted as the dependent variables into the dataset.

For a given fire scenario, a table in the format of Table 3-2 will be generated using Python. In the case of the steel frame shown in Fig. 3-4, the temperature data of 21 structural members (i.e., 12 beams and 9 columns) and the displacement data of 12 beams will be recorded. The data is extracted once every 30 seconds in the fire scenario, which means if a simulated fire lasts for 90 mins, 181 lines of data will be recorded in the datasheet.

Table 3-2 A sample of datasheet extracted from FEM model

No.	Time (min)	Temp-1 (°C)	Temp-2 (°C)	…	Temp-21 (°C)	Disp-1 (mm)	Disp-2 (mm)	…	Disp-12 (mm)
1	0.0	20	20	…	20	-7.0	-6.3	…	-0.3
2	0.5	44	71	…	57	-6.9	-6.1	…	0.3
3	1.0	63	111	…	86	-6.4	-4.9	…	1.29
…	…	…	…	…	…	…	…	…	…
181	90.0	335	758	…	502	-24.9	-993.6	…	9.52

3.3.3 Development of ML models

ML models, including SVM, DT, RF, and GB, are developed after the dataset is generated. In each model, the total number of input variables is equal to the number of temperature data points extracted from the FEM model at a single time step, which is 21 in this case. As a starting point and for the sake of simplicity, the output variable of the ML model is considered as the mid-span displacement of only one beam from the steel frame. Python is employed to develop all the ML models through the open-source software library “sklearn”.

Table 3-3 Search space for parameter tuning of ML models

Model	Parameter	Search space
SVM	C	{0.01, 0.1, 1, 10, 100, 1000, 10000}
	γ	{0.001, 0.01, 0.1, 1, 10, 100}
DT	d_{max}	{3,5,7,9, None}
	s_{node}	{2, 4, 6, 8, 10}
	s_{leaf}	{1, 2 ,3 ,4 ,5}
RF	n_{tree}	{50,100,150,200,250}
	n_{sample}	{20%, 40%, 60%, 80%, 100%}
	m_{try}	{Sqrt, Log2, All}
	d_{max}	{3,5,7,9, None}
	s_{node}	{2, 4, 6, 8, 10}
	s_{leaf}	{1, 2 ,3 ,4 ,5}
GB	n_{tree}	{500,1000,1500,2000,2500}
	η	{0.005, 0.01, 0.02, 0.05, 0.1, 0.2}
	m_{try}	{Sqrt, Log2, All}
	d_{max}	{3,5,7,9, None}
	s_{node}	{2, 4, 6, 8, 10}
	s_{leaf}	{1, 2 ,3 ,4 ,5}

Most ML models are designed with several hyperparameters that need to be tuned before applying the model for general prediction purposes. In SVM, two parameters, i.e., the penalty constant C and the kernel parameter γ for the RBF kernel. In DT, three parameters are taken into account in model tuning, including 1) the maximum depth of the tree d_{max}; 2) the minimum number of samples on a tree node s_{node}, and 3) the minimum number of samples on a tree leaf s_{leaf}. RF is an ensemble model that fits several DT-based models on various sub-samples of the dataset and uses averaging to improve the predictive performance and control over-fitting (Breiman, 2001). Apart from the parameters d_{max} , s_{node} , and s_{leaf} as included in DT model, other hyperparameters could also significantly affect the performance of the RF model, such as 1) the number of trees n_{tree}, 2) the number of samples n_{sample} to draw from the dataset to each tree using bootstrap sampling, and 3) the number of features m_{try} to consider when at each split. GB is another ensemble model using DT as a based model (Friedman, 2001a), where five parameters are taken into account in model tuning, including 1) the number of boosting stages n_{tree}, 2) learning rate η , 3) the maximum depth of the tree d_{max}; 4) the minimum number of samples on a tree node s_{node}, and 5) the minimum number of samples on a tree leaf s_{leaf}. The search space of parameters is listed in Table 3-3, and Grid Search is applied to determine the optimal hyperparameters for each model from search spaces.

3.4 Case Results and Discussions

3.4.1 Validation of FEM modeling approach

FEM models in this chapter intend to capture the structural responses to fire, including the displacement, stress, and/or failure mode. Analyzing structures at elevated temperatures is a complex and challenging process since it involves many factors that may not be considered at ambient temperature such as material nonlinearity, geometric nonlinearity, and time-temperature-varying strength. Therefore, validation is required to show that the results obtained from the modeling approach capture the relevant mechanics. In this chapter, a structural fire experimental program testing a steel frame under local fire in (Jiang et al., 2018) was selected to validate the current modeling approach and to show that the approach captures all the required phenomena at elevated temperatures.

Fig. 3-8 shows the test frame in (Jiang et al., 2018). Rectangular hollow sections are adopted for all steel columns and beams. The column and beam sections are 50×30×3mm and 60×40×3mm, respectively. The steel beams and columns are modeled using shell elements (S4R) in the mesh size of 0.06m. At ambient temperature, the yield strength of the steel columns is 380 MPa while the yield strength of the steel beams is 306 MPa. The elastic modulus of all steel members is 200GPa. A thermal expansion coefficient of 1.4×10^{-5}°C^{-1} was used for all steelworks. Following the application of the gravity loads, the column and parts of the adjacent beams indicated by the shaded area are heated according to the temperature curve as shown in Fig. 3-8.

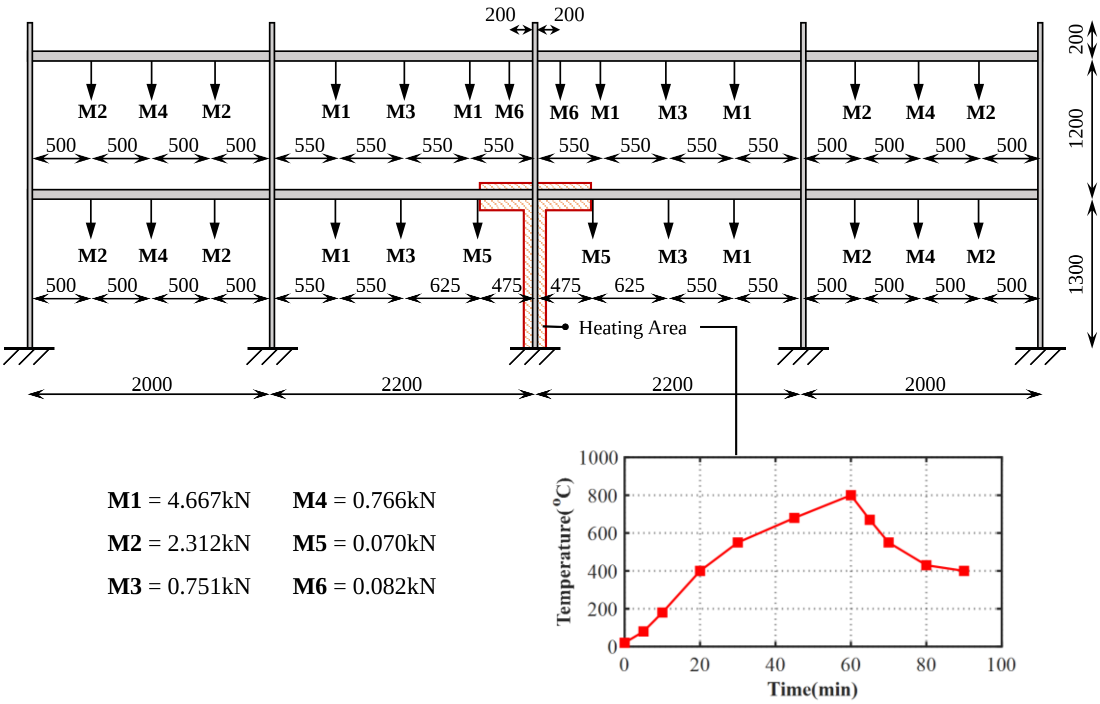
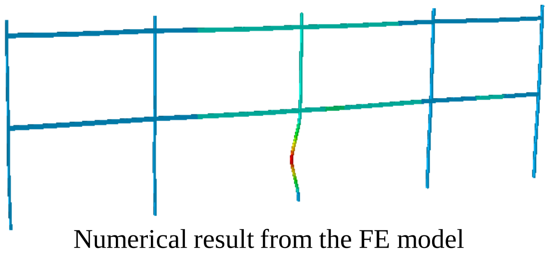


Fig. 3-8 Modeling information of the tested frame

Fig. 3-9 shows the numerical result of the FEM model developed in the present study and the experimental result from the work of (Jiang et al., 2018), indicating a global buckling of the heated column. It can be seen that the FEM result matches well with the experimental result. Moreover, Fig. 3-10 plots the displacement vs. temperature curves of the test frame. The y-axis refers to the displacement at the top of the heated column, and the x-axis refers to the temperature of the heated column. The great agreement between the experimental and numerical results indicates the validity of the proposed FEM approaches in capturing structural responses to fire.



Numerical result from the FE model developed in this study

Experimental result from Jiang et al. (2018)

Fig. 3-9 Deformation patterns of the experimental and numerical result

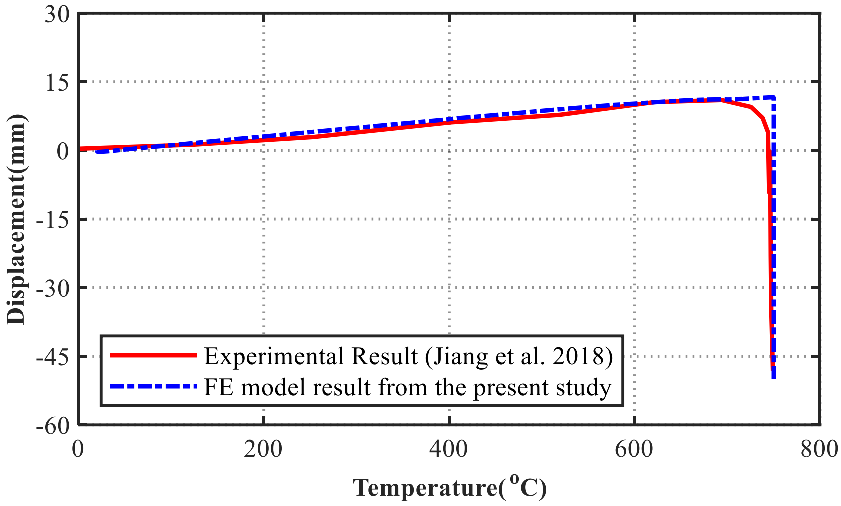


Fig. 3-10 Vertical displacement – temperature curves of the tested frame

3.4.2 Structural fire responses obtained from FEM models

Different combinations of structural members under various fire scenarios are considered and tested on the 3D steel frame structure as shown in Fig. 3-4. EC parametric fires as described in Section 3.3.1 are applied as fire loads in FEM models. 1100 fire scenarios are analyzed in total, including 1000 scenarios as training data and 100 scenarios as testing data for ML models in the next step. Fig. 3-11 shows the deflection pattern of the steel frame model subject to one of the designed fire scenarios, where beams A, B, C, and D are supposed to be in fire conditions. Large deflections are observed for the beams at elevated temperatures, especially for side beams A and C.

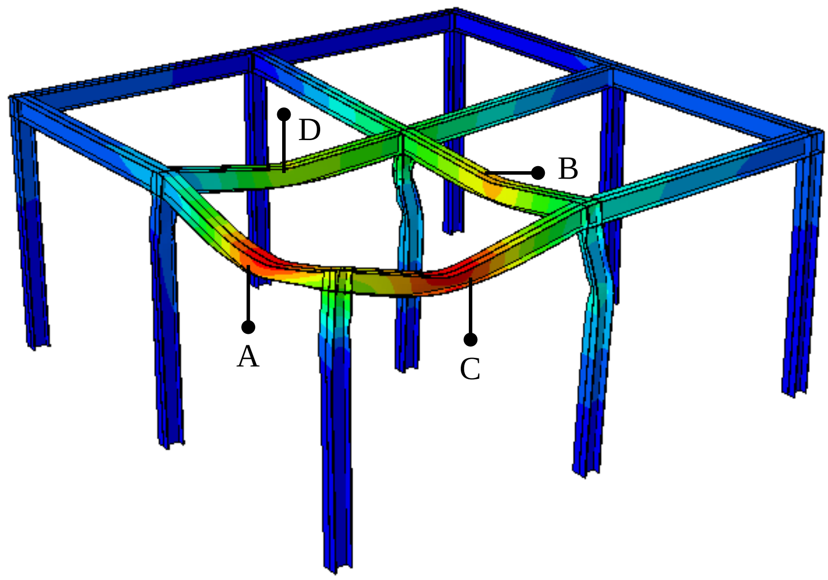


Fig. 3-11 Deflection pattern of the steel frame subject to fire

The temperature-displacement curves for the mid-span point of beams A, B, C, and D as labeled in Fig. 3-11 are plotted in Fig. 3-12. As shown in the figure, the critical temperatures at which the deflection develops rapidly are different for each beam in fire, even though the designed geometry, material, and load properties are the same, which indicates that fire resistance performance varies between structural members with the same configuration. Therefore, to better capture the behavior of structural members under fire conditions in a real building, structural-level fire response analysis is more suitable than individual-member-level analysis as the latter usually fails to consider the supporting and constraint effects from surrounding structural frames.

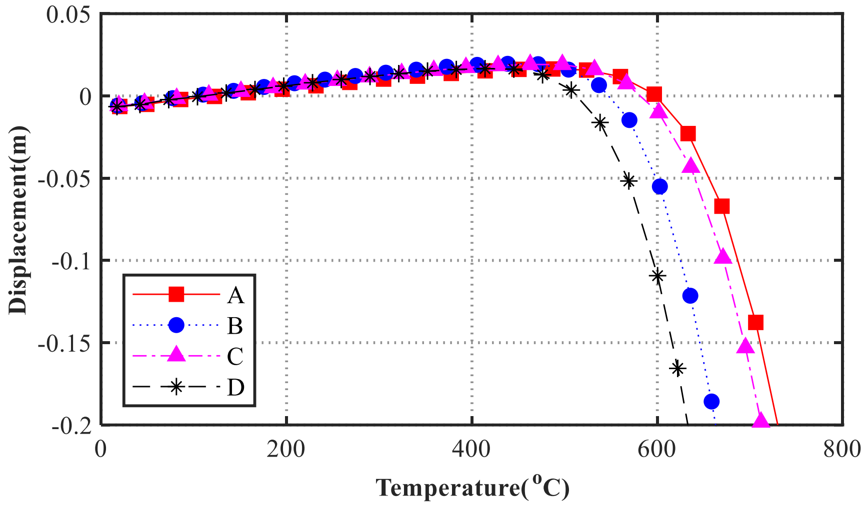


Fig. 3-12 Temperature-displacement curves of the beams in fire

The computational time for getting the numerical result of one fire scenario using ABAQUS on the PC with Intel® Core™ i7-8700 CPU@3.20GHz and 32GB of RAM is shown in Table 3-4. It takes 204 seconds to get the result for one fire scenario. In the case of the simple steel frame designed in this chapter, the number of elements in the FEM model is 5,716. Generally, computational time will increase dramatically as the number of elements increases. Therefore, the time cost indicates that FEM analysis is not suitable for the problem which needs a real-time result.

3.4.3 Predictive performance of FEM-based ML models

The independent variables of the ML model are the temperatures of the mid-span node of each structural component, and the dependent variable of the ML model is the displacement of the mid-span point of beam A as shown in Fig. 3-11. Therefore, the number of independent variables is 21, and the number of the dependent variable is one. Each fire scenario simulates a fire lasting for 90 mins and consists of 181 lines of data.

To facilitate comparisons of the predictive accuracy among all ML models with different numbers of fire scenarios in the training set, the number of fire scenarios in the training samples is chosen as 100, 200, 500, and 1,000, while the number of fire scenarios in the testing samples is 100 in all examples.

Table 3-4 Computational costs for one fire scenario using ABAQUS

Job Time Summary	Time (Second)
User Time	710.60
System Time	111.80
Total CPU Time	822.40
Wall clock Time	204.00

Table 3-5 MSE and R^2 of the predictive result from ML models

Model performance		Number of fire scenarios in the training dataset			
		100	200	500	1000
SVM	MSE	2.5×10^{-3}	1.9×10^{-3}	1.5×10^{-3}	1.3×10^{-3}
	R^2	0.95	0.96	0.97	0.97
DT	MSE	3.4×10^{-3}	2.6×10^{-3}	1.9×10^{-3}	1.6×10^{-3}
	R^2	0.93	0.95	0.96	0.97
RF	MSE	1.5×10^{-3}	1.0×10^{-3}	7.5×10^{-4}	6.2×10^{-4}
	R^2	0.97	0.97	0.98	0.99
GB	MSE	1.2×10^{-3}	8.2×10^{-4}	5.7×10^{-4}	4.9×10^{-4}
	R^2	0.97	0.98	0.99	0.99

Table 3-5 lists the mean square error (MSE) and Coefficient of Determination (R^2) of various ML models for the prediction of structural fire response (i.e., the displacement of the mid-span point of beam A) in the testing set, and Fig. 3-13 depicts the tendency lines of MSE for all ML models. It is found that GB and RF show higher performances than SVM and DT, and, more specifically, GB performs slightly better than RF. With the increase in the number of fire scenarios, the MSE decreases more and more slowly. The predictive performance of all ML models increases at a low convergence rate when the number of fire scenarios exceeds 500.

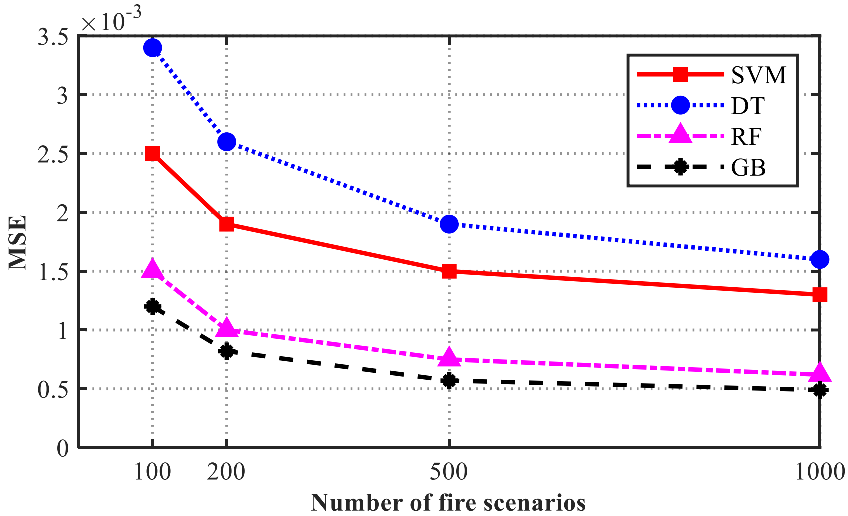


Fig. 3-13 MSE of ML models under different number of fire scenarios

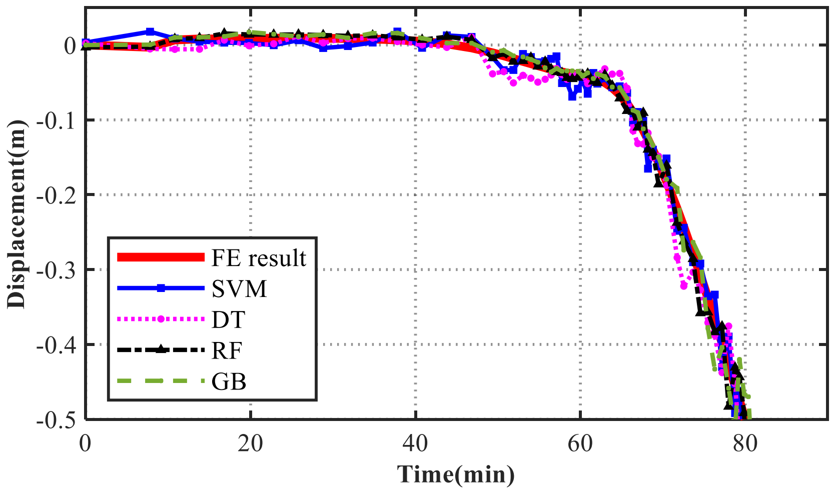


Fig. 3-14 Comparison of the prediction on a fire scenario in the testing set

Fig. 3-14 plots the displacement of the mid-span point of beam A (as shown in Fig. 3-11) obtained from both FEM analysis and ML models for a random fire scenario in the testing set of 100 fire scenarios. It is indicated that RF and GB perform better than SVM and DT, which is in accordance with the result revealed from the MSE evaluation.

3.4.4 Computational efficiency of FEM-based ML models

In addition to predictive accuracy, computational efficiency is another great concern for model selection. Table 3-6 presents the comparison of the running time for training ML models. DT requires the minimum running time and there is a slight increase in the running time of DT when the number of fire scenarios increases. In contrast, SVM requires the maximum running time when the number of fire scenarios is equal to or greater than 200. When the number of fire scenarios is not large, i.e., 100 and 200, GB runs faster than RF, while when the number of fire scenarios reaches up to 500 or 1,000, RF runs faster than GB. Considering both predictive accuracy and computational efficiency, RF and GB outperform DT and SVM. When the number of fire scenarios is equal to or greater than 500, RF shows higher computational efficiency in training the model while GB shows higher predictive accuracy in terms of MSE.

Table 3-6 Comparison of ML model training run times (in seconds)

Model	Number of fire scenarios in the training dataset			
	100	200	500	1,000
SVM	125	2076	8867	34,974
DT	9	12	17	35
RF	185	517	1087	2264
GB	118	452	1390	4135

In terms of the computational cost of the FEM model, a single fire scenario takes around three to four minutes to get the result for one fire scenario under the current setting of the FEM model (as shown in Table 3-4). As for ML models, even though it takes far more time than FEM models in database generation and model training for massive fire scenarios, it only costs less than one second to get the predictive result for a new fire scenario, which means the FEM-based ML model framework is of great possibility to be adopted in a real-time context.

The computational cost of the whole workflow of the proposed FEM-based ML model can be divided into three parts, as shown in Fig. 3-15, namely 1) computational costs of FEM models for generating the database, 2) computational costs of ML model training, and 3) computational cost for structural fire response prediction with the trained model.

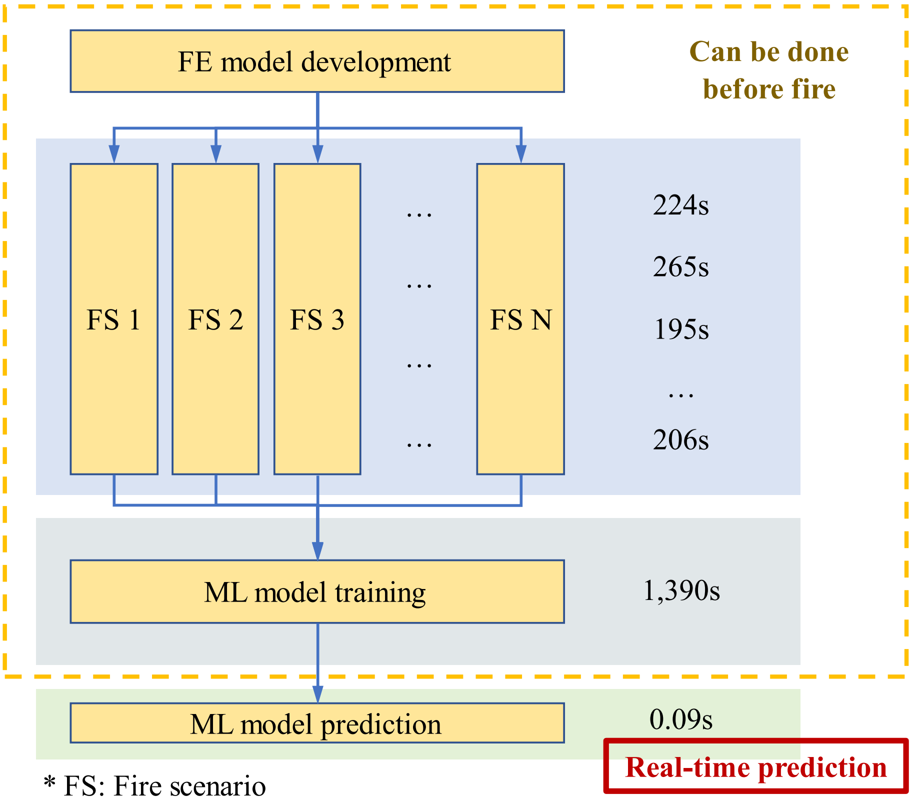


Fig. 3-15 Computational cost of the FEM-based ML model

Generally, the first part regarding the FEM analysis is the most time-consuming as a large number of fire scenarios will be included in the FEM models. In the simple case as demonstrated in this paper, it takes 3~8 min to get the result for one fire scenario using ABAQUS under the current setting. Even though it can be done simultaneously in different computers to accelerate the process, it is not a "real-time" approach. Then, the model training part is neither a "real-time" part as it takes 1390 seconds to train a GB model with 500 fire scenarios in the dataset. However, it is still acceptable as these parts can be done before the fire. For the third part, when the model is well trained for prediction, it only takes less than 1 second to get the result. This is the "real-time" prediction. During building fire emergencies, when the temperature data collected from the temperature sensors preinstalled in the building structure varies in real-time, the prediction of structural fire response will be updated in real-time accordingly by using the well-trained ML model.

3.4.5 Robustness and sensitivity analysis

The robustness of the ML models is discussed in terms of the quality of the input data from temperature sensors in the testing set. The ML model takes the real-time temperature data from the sensor as model input, and it is possible that the sensor may induce some errors when collecting the data. Therefore, the robustness of the model is evaluated by manually inducing some noises in the temperature data to see how the ML model performs in terms of its predictive accuracy. Gaussian noise with a mean value of 0 and a standard deviation of σ is added to the temperature data. σ is determined by the assigned signal-to-noise ratio (SNR). As shown in Fig. 3-16 and Fig. 3-17, MSE decreases and R^2 increases when SNR increases for all models, while the SVM shows the lowest MSE when SNR is less than 20, indicating that SVM is the most robust among four models against noise in temperature data, followed by GB and RF. Still, MSE is less than 0.02 and R^2 is greater than 0.85 when SNR is greater than or equal to

15, showing that all models are capable to perform well in terms of predictive accuracy if the error of data from the temperature sensor is smaller than 6.67%.

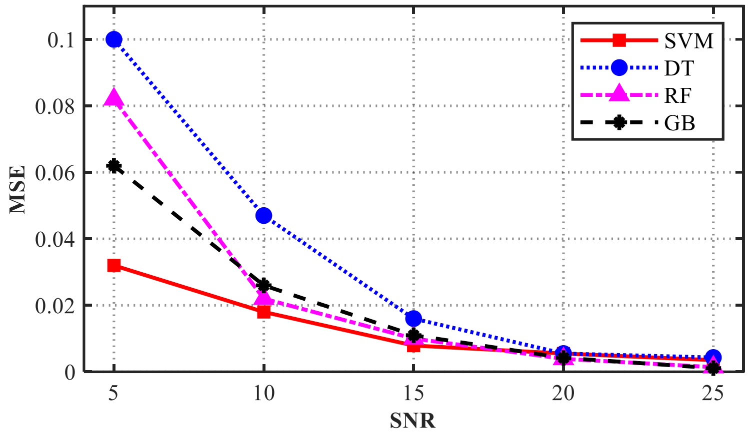


Fig. 3-16 MSE of ML models under different SNRs

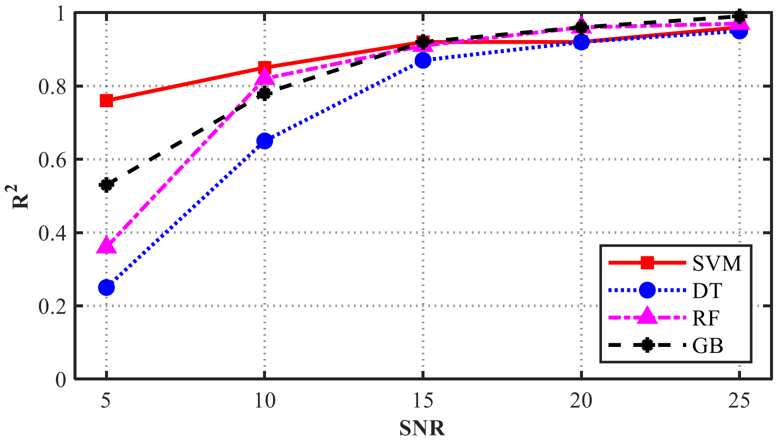


Fig. 3-17 R^2 of ML models under different SNRs

The sampling interval is the time duration between which temperature data are recorded from the sensor. A shorter sampling interval means collect the temperature data more frequently, which enriches the dataset with more lines of data for model training and might help improve the predictive performance. However, a larger sample size is supposed to lower the computational efficiency in model training. The impact of sampling interval on model performance is discussed as follows. Fig. 3-18 and Fig. 3-19 show the MSE and R^2 of all ML models with different sampling intervals ranging from 0.1min to 2min. Similar trends of MSE curves are found for all ML models that MSE increases slightly and steadily with the increase of sampling intervals from 0.1min to 1min and when sampling interval reaches up to 2min, MSE increases sharply. Likewise, R^2 decreases gently when the sampling interval is less than 1min for all ML models. Among the four ML models, GB shows optimal predictive performance among all models when the sampling interval is less than or equal to 1min, while RF performs slightly better when the sampling interval reaches 2min. As indicated from the results, the suggested sampling interval should not exceed 1min in terms of predictive performance.

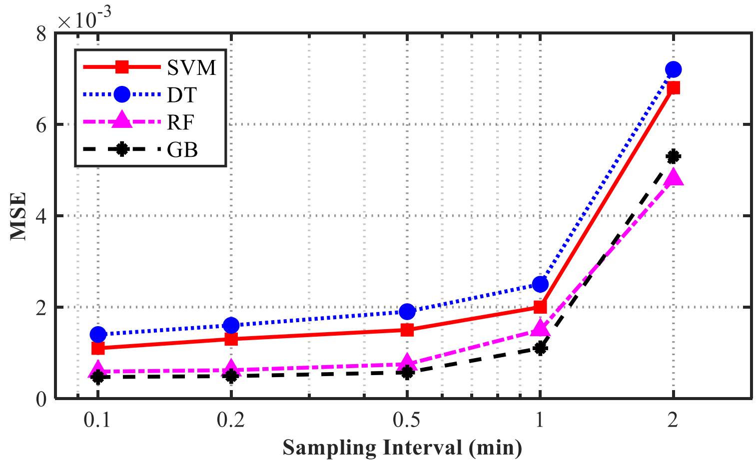


Fig. 3-18 MSE of ML models with different sampling intervals

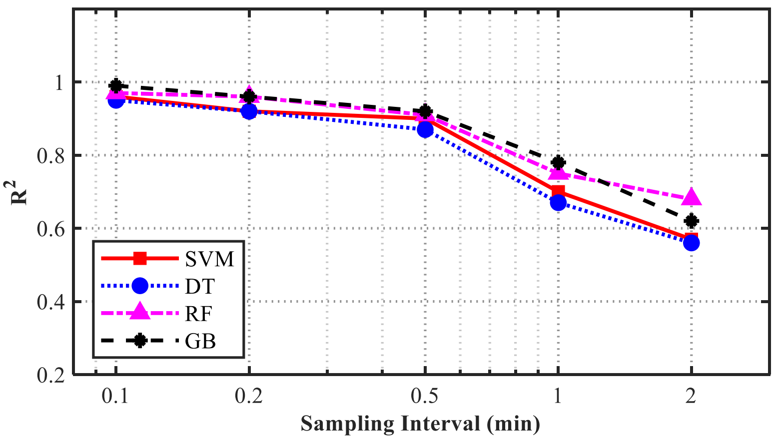


Fig. 3-19 R^2 of ML models with different sampling intervals

The primary source of input data for model predictions is temperature data collected from simulated fire scenarios. To ensure accuracy, this data is rigorously verified through a comparison with established fire behavior models (e.g., EC parametric curves). Furthermore, the models are subjected to robustness testing under various conditions, including the introduction of artificial noise and data variations. This testing helps in assessing the model's ability to handle data imperfections and maintain predictive accuracy. These measures collectively enhance the reliability of model predictions.

3.4.6 The impact of slab on fire performance of the steel frame

Steel structure with slabs is more common in the real world and previous studies have indicated that slabs have a positive impact on the fire-resistance performance of steel members, as well as the resistance to the progressive collapse of the structure since slabs contribute significantly to the integrity of building structures. To facilitate the understanding of the impact of slabs on the fire performance of the tested steel frame, a simulation of the frame with reinforced concrete (RC) slabs over the beams was conducted. Based on our previous work (Ye et al., 2019), the depth of the RC slab was designed as 100mm, with longitudinal reinforcement designed as Φ10@120mm with steel grad of HPB400. More details about the geometrical configurations and material properties of the slab and can be found in (Ye et al., 2019). In the FEM model, the slab is connected to steel beams using Tie constraint in ABAQUS by assuming that there is no relative motion between the slab and the beams. The result of the frame with slab subjected to the same fire scenario as shown in Fig. 3-11 is presented in Fig. 3-20 and Fig. 3-21. It is shown that beam deflections of the frame with RC slab are much smaller than the frame without RC slab, which indicates a beneficial influence of RC slab in structural fire performance. For instance, when the temperature reaches 600°C, the displacement of beam D is -0.11m for the frame without RC slab (as shown in Fig. 3-12) and only 0.03m for the frame with RC slab (as shown in Fig. 3-21).

Fig. 3-20 Deflection pattern of the steel frame with RC slab

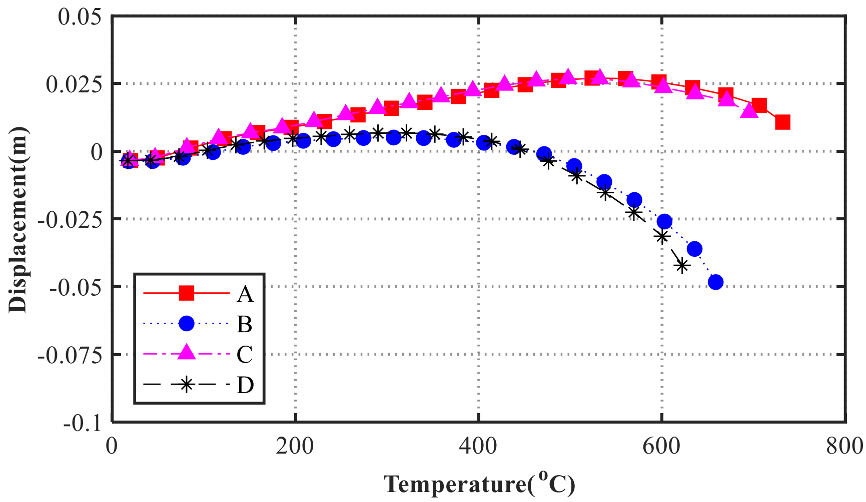


Fig. 3-21 Temperature vs. displacement of the beams of the frame with RC slab

The predictive performance of the FEM-based ML model trained from the databases of the steel frames with and without slabs, respectively, with 200 fire scenarios in the training dataset and 20 fire scenarios in the testing dataset using RF and GB is shown in Fig. 3-22. Even though the deflection pattern of the frame with RC slab in Fig. 3-20 is different from that without slab in Fig. 3-11, the MSE and R^2 of the predictions resulting from their corresponding database are similar, which indicates the applicability of the proposed FEM-based ML framework in predicting structural fire responses both with and without slabs.

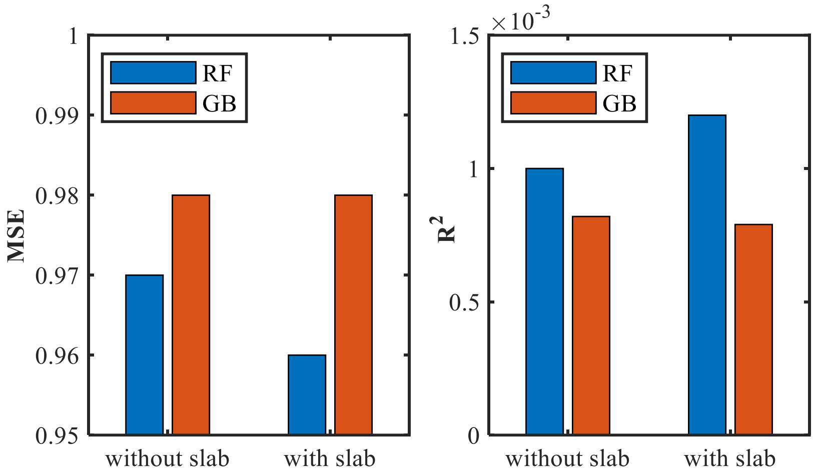


Fig. 3-22 Predictive performance of the FEM-based ML models

3.4.7 Discussions on limitations and prospects

The numerical results indicate the capacity of FEM-based ML models in real-timely predicting the displacements at specific locations of the structure under new fire scenarios. Specifically, the adopted FEM modeling approach is validated by comparing the numerical results with the experimental results of a steel frame in the literature. From the results of FEM-based ML models, in terms of both predictive accuracy and computational efficiency, RF and GB are of high potential to be applied to real-time structural response prediction during fire emergencies. All models are found robust against the noise in temperature data when SNR is greater than 15, and sampling interval is suggested not to exceed 1min. Moreover, the results of the numerical examples indicate the applicability of the proposed FEM-based ML model in both the frames with and without RC slabs.

As an exploratory study, the limitations of the current work are discussed as follows, which could be the directions of the future work concerning the real-time prediction of structural responses to fire. EC parametric fire curve is adopted to simulate the fire in the FEM model, which could be less realistic. A possible improvement is to integrate Computational Fluid Dynamics (CFD) results from Fire Dynamic Simulator (FDS) into the FEM models to better simulate the temperature field of the structure in a fire. As a starting point, the preliminary results presented in this report only select the real-time vertical displacement of a particular beam as the dependent variable in the ML model. A significant improvement is to predict the displacement in the near coming future (e.g., 30 seconds in advance) with the input of the temperature field history (temperature development in the last minute). Moreover, The FEM-based ML framework proposed in this chapter is a building-specific one, which means the FEM model and the ML model are developed and trained for a particular building structure. The virtual numerical example presented in the current paper only contains one structural layout with non-changeable building dimensions, which is not extracted from a real building. More numerical cases with more diverse and realistic structural layouts and dimensions will be included in future works to explore the applicability of the proposed FEM-based ML models. Furthermore, more attempts will be made to explore the feasibility of constructing a general ML model for a group of buildings with similar features.

3.5 Chapter Summary

An FEM-based ML framework has been developed in this chapter for real-time prediction of structural responses to fire based on temperature data of structural members. A numerical database of a steel frame structure subject to hundreds of fire scenarios was established. Structural responses to the fire were simulated in ABAQUS using the FEM method. The temperatures and the displacements at specific locations of steel members during the fire processes were recorded in the database. Then, ML models were trained based on the numerical database with temperature data as input and displacement data as output.

1. The FEM-based ML framework developed in this chapter enables the real-time prediction of structural fire response using ML models based on the FEM database, which complements the shortage of time-consuming in traditional FEM when applying in fire emergency context.
2. The developed ML model is evaluated in terms of predictive accuracy, computational efficiency, robustness, and sensitivity. The results indicate the feasibility of adopting the developed model in the real-time prediction of structural fire response.
3. This study integrates FEM and ML techniques for boosting computational efficiency in predicting structural responses to fire during building fire emergencies.

The findings of this chapter indicate the feasibility of using the proposed FEM-based ML framework in the real-time prediction of structural response to fire. Practically, it is expected to be applied in firefighting scenarios for providing firefighters with reliable predictions of structural safety conditions in a real-time manner.

CHAPTER 4 TOWARDS FIRE DYNAMICS: INTEGRATING CFD AND FEM WITH DATA-DRIVEN STRUCTURAL FIRE DEFORMATION PREDICTION [2]

4.1 Introduction

Fire-involved structural failures or collapses are frequently reported as a component of building fire disasters all over the world (e.g., the Notre Dame Cathedral in France (Ferreira, 2019), the Plasco Building in Iran (Behnam, 2019), and the World Trade Center Building in the US (Bažant and Verdure, 2007)). People will be trapped inside a building if a fire causes building members to fail or even the entire building to collapse, resulting in devastating losses in human life and property (Kodur et al., 2019). Timely and reliable monitoring, prediction, and warning of structural fire safety conditions for building fire emergencies are of great significance (Duron et al., 2005b, Madrzykowski and Kent, 2011a), especially for firefighters when they conduct fire rescue operations

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[2] Chapter 4 is based on a published study and being reproduced with the permission of Elsevier. Ye, Z., & Hsu, S. C. (2022). Predicting real-time deformation of structure in fire using machine learning with CFD and FEM. Automation in Construction, 143, 104574. https://doi.org/10.1016/j.autcon.2022.104574

as they are subject to unfamiliar, dynamic, and dangerous environments (Jiang et al., 2020a).

In structural fire engineering, numerical approaches like Computational Fluid Dynamics (CFD) for fire simulation and Finite Element Methods (FEM) for structural analysis are popularly adopted for both academic and engineering purposes (Bernardi et al., 2020, Janardhan et al., 2022, Khan et al., 2021a, Chen et al., 2018, de Boer et al., 2019, Feenstra et al., 2018, Malendowski and Glema, 2017). These numerical methods can provide reliable computational results characterizing fire development and structural response to fires at a high level of resolution with a proper modeling approach and calibration, verification, and validation processes. However, they are generally computationally intensive and time-consuming, and thus fail to be directly adopted for obtaining real-time solutions in the context of building fire emergencies (Bresler, 1985, Ren et al., 2007). Recently, a few studies have been conducted to explore the feasibility of a real-time solution in structural fire response prediction (Ye et al., 2022) and/or structural fire safety monitoring and warning based on temperature field data (Jiang et al., 2020a, Jiang et al., 2020b). Due to the complexity of the possible thermal-mechanical, mechanical-thermal, and even thermal-mechanical-thermal coupling effects in structural fire response analysis, an accurate and efficient solution to this problem has not yet been fully investigated until now.

Given the accuracy and efficiency it can offer when applied in a variety of settings, machine learning (ML) has become more widely used in structural engineering fields (Kim et al., 2020, Thirumalaiselvi et al., 2018, Nguyen et al., 2019, Asghari et al., 2020). In structural fire engineering, previous studies adopted ML in estimating the occurrence of flashover points in a compartment (Dexters et al., 2020), predicting evolving temperature distribution during a fire (Wu et al., 2021), and identifying the ignition location and fire intensity inside a tunnel (Wu et al., 2020). A finite element (FE)-based ML framework was also recently developed for predicting structural response to fire based on a database of standard fire curves and FEM models (Ye et al., 2022). ML is shown to complement traditional theoretical or numerical approaches to structural analysis for achieving higher predictive accuracy and/or computational efficiencies (Xue, 2010, Hodges et al., 2019, Fu, 2020, Naser, 2019).

Computational methods like CFD, FEM, and ML have each been found to be individually effective tools in solving structural fire engineering problems, while recent studies have also explored the synergies of these methods by investigating their possible combinations, such as CFD and ML (Wu et al., 2021), FEM and ML(Ye et al., 2022), and CFD and FEM (Janardhan et al., 2022). Nonetheless, there has been a lack of an integrated and unified solution for real-time prediction of structural fire responses in the context of building fire emergencies. For instance, Ye et al. (2021) developed an FEM-based ML model for structural fire response prediction, but parametric fire curves were adopted to represent the fire scenarios, which may not be realistic for fire development simulation, and therefore could lead to less reliable results in depicting structural response (Ye et al., 2022). Given that CFD is an effective tool for simulating temperature distribution and development in fire scenarios, Wu et al. (2020) developed a CFD-based ML model for predicting the temperature field distribution of a tunnel during a fire (Wu et al., 2021, Wu et al., 2020). However, structural safety analysis is not included in their model framework. Previous studies could be built upon by integrating CFD results from Fire Dynamic Simulator (FDS) into FEM models in ABAQUS to better simulate the temperature field of a structure in a fire as well to obtain more realistic structural fire responses. This structural fire response data could then be fed into a CFD/FEM-based ML framework in order to generate more accurate and efficient predictions of structural responses in fire emergencies using a numerical database.

CFD plays a crucial role in accurately simulating the behavior of fire, including aspects like temperature distribution, smoke movement, and heat transfer within the building. This level of detail is essential for a nuanced understanding of how fire interacts with the building. By combining CFD with FEM, the predictive model gains a more holistic view of both the fire behavior and the structural response. This integration is key to improving the accuracy and reliability of the predictions, especially in complex fire scenarios. With these considerations in mind, this chapter proposes a CFD/FEM-based ML framework that integrates CFD, FEM, and ML methods. Using an 8m×8m×0.6m steel roof structure, a demo model is constructed to establish a numerical database consisting of 1200 virtual fire scenarios with 1.2 million pieces of data. The CFD and FEM models are validated with experimental data from the literature. The proposed framework could be helpful in real-time structural fire safety monitoring and alarm configuration by providing timely and reliable predictions of structural safety conditions.

4.2 Methodology

4.2.1 Workflow of the proposed framework

An ML framework is developed in this chapter by integrating CFD and FEM simulations. The workflow of the proposed CFD/FEM-based ML framework is shown in Fig. 4-1 and has three main components: 1) development of the CFD and FEM model for data generation, 2) development of the CFD/FEM-based ML model, and 3) real-time prediction using the CFD/FEM-based ML model.

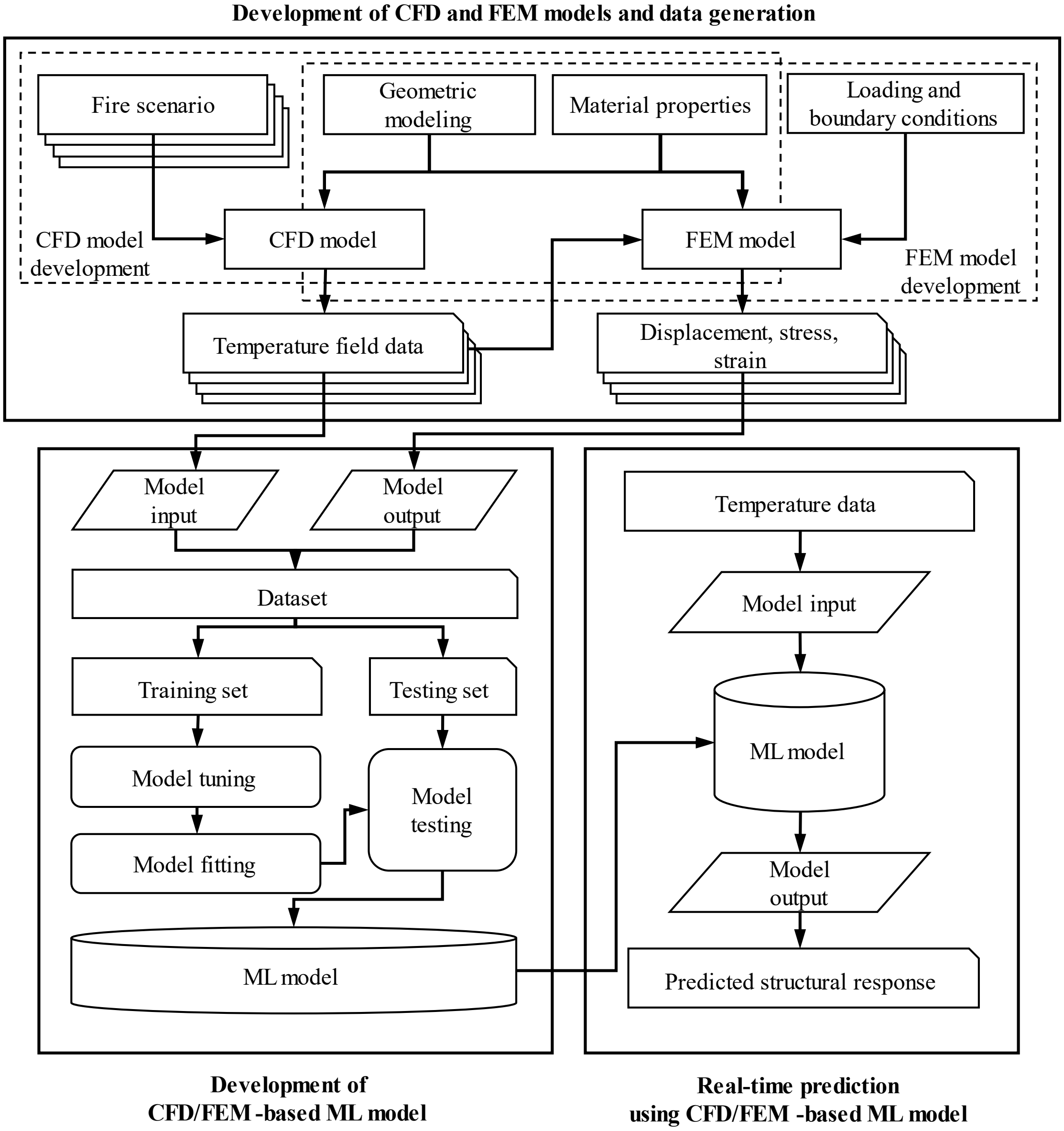


Fig. 4-1 Workflow of the proposed CFD/FEM-based ML framework

Firstly, the CFD model was developed for the targeted building structure to simulate the spatiotemporal distributions of air temperature under fire conditions given the parameters of a fire scenario such as ignition position, heat release rate, and ventilation conditions. Then, the corresponding FEM model was developed for the same building structure for structural analysis by importing the temperature field data from the CFD model to obtain the structural response to fire, e.g., displacement, stress, and strain fields. By repeating the simulation for various fire scenarios with diverse fire parameters, a numerical dataset with hundreds of thousands of temperature data points and structural response data at different locations in each time step is established.

This numerical dataset was adopted in ML model training and testing for the prediction of the structural response under new fire scenarios. As a demonstrative example of the proposed CFD/FEM-based ML framework, four commonly used ML algorithms—support vector machine (SVM), decision tree (DT), random forest (RF), and gradient boosting (GB)—were adopted in this chapter to illustrate the feasibility and validity of the proposed framework for real-time prediction of structural fire responses based on the temperature field data. The temperature data generated by CFD simulations is used to train the ML model. This training involves correlating temperature profiles with subsequent structural responses, as predicted by FEM. This comprehensive dataset allows the ML model to learn the complex relationships between fire dynamics and structural behavior under various scenarios.

After the development, training, and tuning of the ML model, the model can be easily applied to generate real-time predictions of structural fire responses with the input of temperature field data from the preinstalled sensors in a building structure. In actual fire incidents, real-time temperature data on site provides the necessary input for the ML models to make immediate predictions about structural safety, guiding firefighters and rescue operations.

In addition, for exploring the extensibility of the proposed framework to predicting immediately subsequent structural responses with historical temperature data, a long-short term memory (LSTM) recurrent neural network model is developed and discussed in section 4.4.5 as a complement to the main framework.

4.2.2 Theoretical background

1. CFD for fire simulation

CFD fire simulation solves a set of partial differential equations (PDEs) describing the fluid flow and heat transfer from the development of fire, which are more specifically momentum equations (Navier-Stokes equations) (Constantin and Foias, 1989) and the energy equation (the First Law of Thermodynamics) (Cemič, 2005). Momentum equations can be written as:

$$\begin{cases} \nabla \cdot u = 0 \\ \rho\left(\dfrac{\partial u}{\partial t} + u \cdot \nabla u\right) = -\nabla p + \mu \nabla^2 u + f \end{cases} \tag{4-1}$$

where u represents the velocity vector of the fluid, ∇ denotes the gradient operator, ρ is the density of the fluid, t represents time, p denotes the pressure, μ is the dynamic viscosity, and f represents any external forces acting on the fluid. The energy equation for compressible flow in terms of total temperature can be written as:

$$\rho C_p\left(\frac{\partial T}{\partial t} + V_i \frac{\partial T}{\partial X_i}\right) = \frac{\partial}{\partial X_i}\left[k \frac{\partial T}{\partial X_i}\right] + q_V + \mu V_i \left[\frac{\partial^2 V_i}{\partial X_j \partial X_j} + \frac{\partial}{\partial X_i}\frac{\partial V_j}{\partial X_j}\right] + \frac{1}{2C_p}\frac{\partial}{\partial X_j}\left[k \frac{\partial}{\partial X_j}(V_j V_j)\right] + \Phi \tag{4-2}$$

where T is temperature; C_p is the specific heat at constant pressure, k is thermal conductivity, q_V is the volumetric heat source, and Φ is the dissipation function. Note that Einstein tensor notation is used in Eq. (2), and i and j refer to the global coordinate direction, (i.e., *x*-, *y*-, and *z*-directions). Specifically, X_1, X_2, and X_3 denote *x*, *y*, and *z* in Eq. (1), respectively, and V_1, V_2, and V_3 denote *u*, *v*, and *w* in Eq. (1), respectively. By solving the governing equations with sufficient parameter information and boundary condition, the spatiotemporal distribution of the thermodynamic properties of the field can be obtained. However, the non-linearities and the coupling between these equations make these PDEs difficult to be solved analytically. Numerical solutions are available in most CFD software and platforms, such as FDS for fire simulations. This study will use PyroSim (a user-friendly interface for FDS) (ThunderHead Engineering, 2011) to simulate the temperature development of the space within a building structure in a fire. More detailed descriptions of the mathematical models adopted in FDS can be found in (McGrattan et al., 2005).

2. FEM for structural analysis

FEM is a method that provides numerical solutions for differential or integral equations governing problems in nature, allowing users to understand the spatiotemporal evolution of one or more variables representing the behavior of a physical system. In structural analysis, FEM quantitatively calculates the displacements, strains, and/or stresses in a structure under a set of static, dynamic, thermal, or other formats of loads. This study adopted ABAQUS (Systèmes, 2014) to develop the structural fire analysis model to analyze the structural response to fire under the standard protocol of FEM. Details of the procedures of FEM model development for structural fire analysis can be found in (Ye et al., 2022).

4.3 Model Development

4.3.1 CFD and FEM model development

As fire-induced collapses are commonly seen and reported in steel structures, this chapter develops a demo model corresponding to the proposed CFD/FEM-based ML framework to illustrate the workflow step-by-step. Considering that steel truss structures are widely adopted, especially as the roof components of large-span structures, a full-scale steel roof truss structure that was subjected to a real fire test, producing detailed experimental data as reported in the literature (Jiang et al., 2020b), is selected as the case example in this chapter.

1. Geometric and material specifications of the virtual structure for the fire test

Fig. 4-2 shows the geometric specifications of the steel roof structure for the fire test, with a diameter of 8m and a total height of 600mm (Jiang et al., 2020b). The cross-section for the top chord is a rectangular hollow section with a width of 40mm and a thickness of 2mm (i.e., □40×2). For the bottom chord, the cross-section is □40×1.5. The vertical bracing trusses are 590 mm in height with a cross-section of □30×1.5. The purlin cross-section is a "C-shape" section with the specification of C160×60×20×2, and the purlin hanger cross-section is an "L-shape" section with the specification of L30×3. The steel material is Q235 under the Chinese grade standard, of which the yield strength is 235MPa, and the ultimate strength is 375MPa. Buckets of iron sand with a total weight of 2206.65kg are placed on top of the structure to apply vertical load. The specimen was simply supported by brick walls as shown in Fig. 4-3. More details regarding the manufacturing features of the structure can be found in (Jiang et al., 2020b).

2. Temperature and displacement measuring points of the tested case

Temperature data on the surrounding air environment and displacement data on the structural components of particular measuring points are shown in Fig. 4-3 and recorded in the experimental program in (Jiang et al., 2020b), where G1-G13 refers to the gas temperature measuring points and D1-D9 refers to the structural displacement measuring points. Both the temperature and displacement measuring gages were placed in the plane of axis 3 and 6, as identified in the upper right part of Fig. 2. WRNK-191K type thermocouples, which have a diameter of 3 mm and a maximum working temperature of 1200 °C, were adopted for gas temperature measuring. Linear variable differential transformers (LVDTs) with the model type of EY-200 were adopted for measuring the vertical displacements at D1-D9, whose maximum range is 200 mm. For validation and comparison purposes, the numerical results for these measuring points will also be extracted from the developed CFD and FEM models. Note that apart from these highlighted measuring points, CFD and FEM models are capable of presenting temperature field data and structural response data for any point or element in the model.

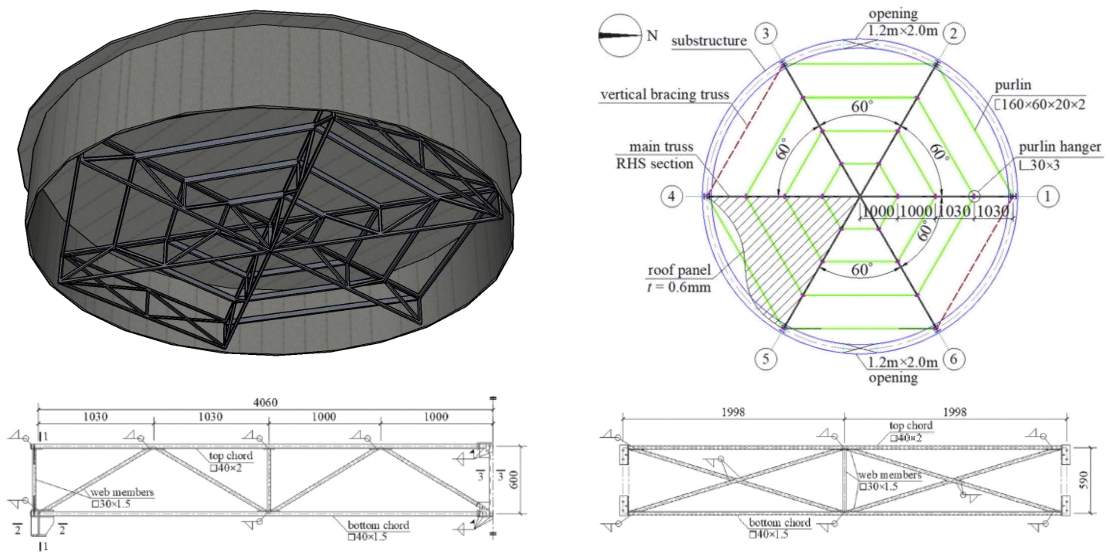


Fig. 4-2 Geometric specifications of the tested structure

3. Development of the CFD fire simulation model in PyroSim

After importing or establishing the geometric model of the tested steel structure in Pyrosim (ThunderHead Engineering, 2011), fire scenarios were assigned to facilitate the CFD computation of the model. It is critical that three key parameters, i.e. fire position, heat release rate, and ventilation conditions, are defined in the model. For instance, Fig. 4-4 shows a screenshot of a fire scenario with an ignition position at the center of the model with an area of 1m×1m at a height of 0.8m, a heat release rate of 70MW, and a ventilation speed of 0m/s for all openings. According to the experimental results in (Jiang et al., 2020b), some LVDTs reached the maximum range after burning for around 860s, and then the tested structure lost the majority of its stiffness and bearing capacity. For the sake of simplicity, the duration of the fire is set to be 1000s, which may be sufficient for capturing the critical structural failure behavior of the tested roof. Temperature field data on selected points are recorded once per second during the virtual fire. After performing the fire simulations using the CFD model, the resultant spatiotemporal distribution of temperature data is imported into the FEM model as temperature loads for structural analysis. Specifically, the temperature field data in the roof structure area during the fire simulation period is extracted as Plot3D files for all time steps, and then interpolated and transferred into a .csv file using Python for each fire scenario in the format of (temp, t, x, y, z,), where x, y, z denotes the spatial coordinates, t denotes the time step, and temp denotes the temperature value at the point (x, y, z) at time t.

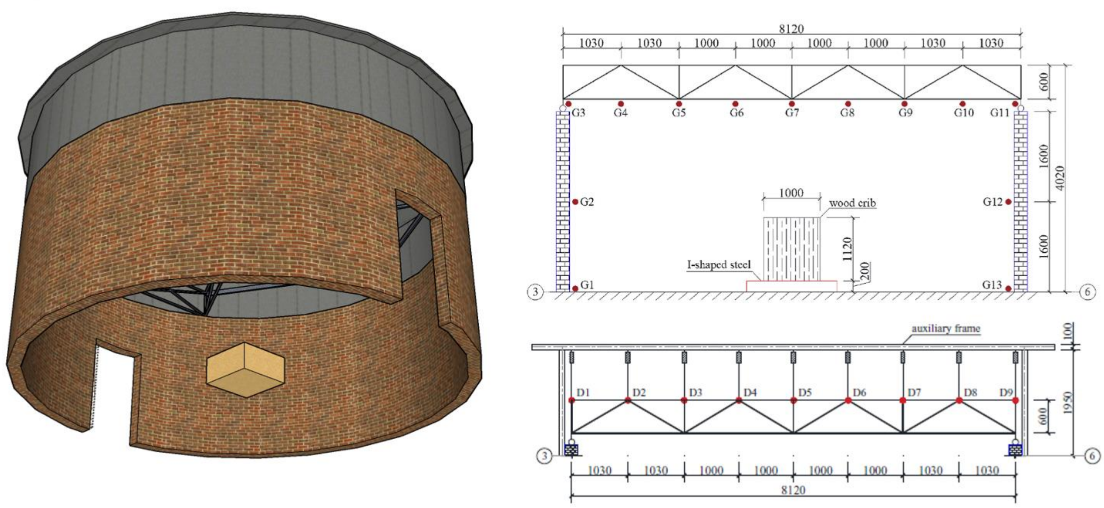


Fig. 4-3 Temperature and displacement measuring points

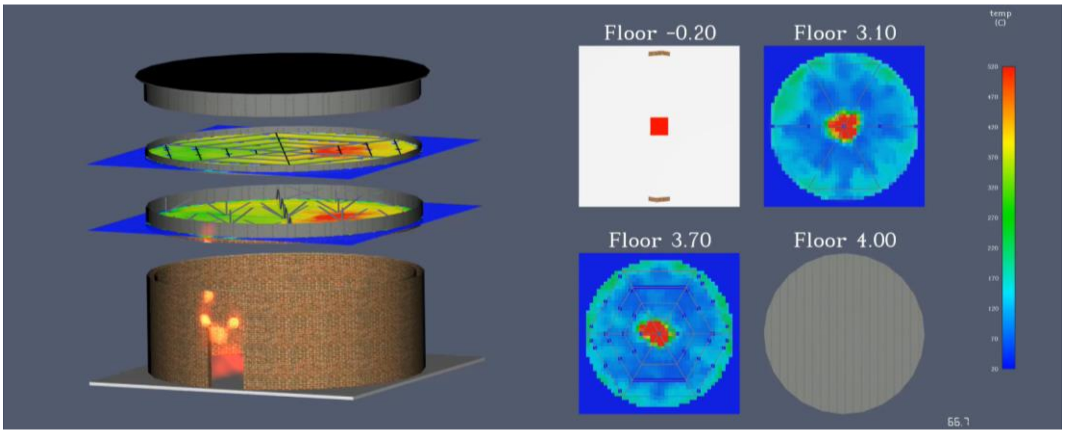


Fig. 4-4 Sample output of the CFD model under one of the fire scenarios

4. Development of the FEM structural analysis model in ABAQUS

The structural analysis model is established in ABAQUS (Systèmes, 2014), which only includes the steel structural members without the supporting brick walls and protective steel plates. More detailed geometric and material information is provided in Section 3.1. A simplified trilinear model with isotropic hardening is applied to simulate the material property under room temperature with the elastic modulus $E_s = 2.1\times10^5$ MPa, yield strength f_y = 235MPa, and ultimate strength f_u = 375MPa according to experimental results from (Jiang et al., 2020b). The reduction coefficients of strength and Young's modulus of steel at elevated temperatures suggested by Eurocode (EC) 3 (European Committee for Standardisation, 2005b) are adopted and shown in Fig. 4-5. The thermal expansion rate of steel is taken to be zero between temperatures ranging from 750 °C to 860 °C, and 1.4×10-5°C^{-1} at other temperatures. To keep the boundary and loading conditions consistent with the experimental settings in (Jiang et al., 2020b), the structure is simply pinned at the supporting points of each bottom chord as shown in Fig. 4-6. A vertical concentrated load of 2206.65kg×9.8N/kg = 21.63kN is applied at the middle of the structure (i.e., D5 in Fig. 4-3).

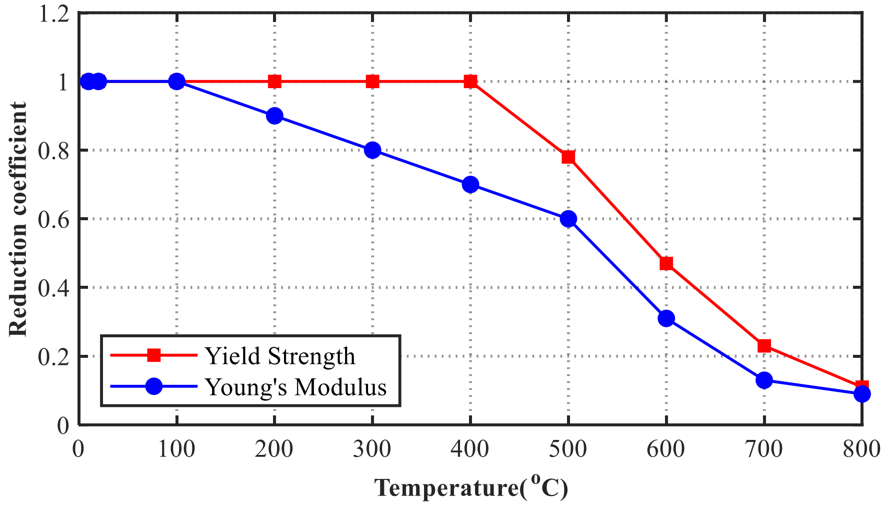


Fig. 4-5 Degradation of steel mechanical properties at elevated temperatures

Vertical load is first applied to the test frame and then is held constant, with the temperatures of the heated structural components subsequently increased according to the .csv temperature field files transferred from the CFD models. The temperature is imported to ABAQUS using the UTEMP user subroutine to specify the prescribed temperature field in the format of "DIMENSION TEMP(NSECPT), TIME(2), COORDS(3)" for each fire scenario. In this context, it is assumed that the temperature in the structural members is the same as the gas temperature recorded in the CFD model. By importing the temperature field data from the CFD model, a sequential thermal-mechanical analysis is conducted in ABAQUS to obtain the structural response to the imported fire scenario. Beam element B31 is adopted as the element type for the analysis. The trial results of mesh dependency analysis indicate that a mesh size of 0.2m fails to accurately simulate the failure mode of the steel roof, while the result for a mesh size of 0.05m starts to converge with that of 0.01m. In this context, 0.05m is chosen as the basic mesh size in consideration of both simulation accuracy and efficiency. "Nlgeom" is turned on in ABAQUS to consider geometric nonlinearities. The results of the FEM model for the particular fire scenario consistent with Fig. 4-4 is shown in

Fig. 4-6. For the sake of simplicity, the displacement data at displacement measuring points in the experimental program (i.e., D1-D9 in Fig. 4-3) will be extracted for further use in ML model training.

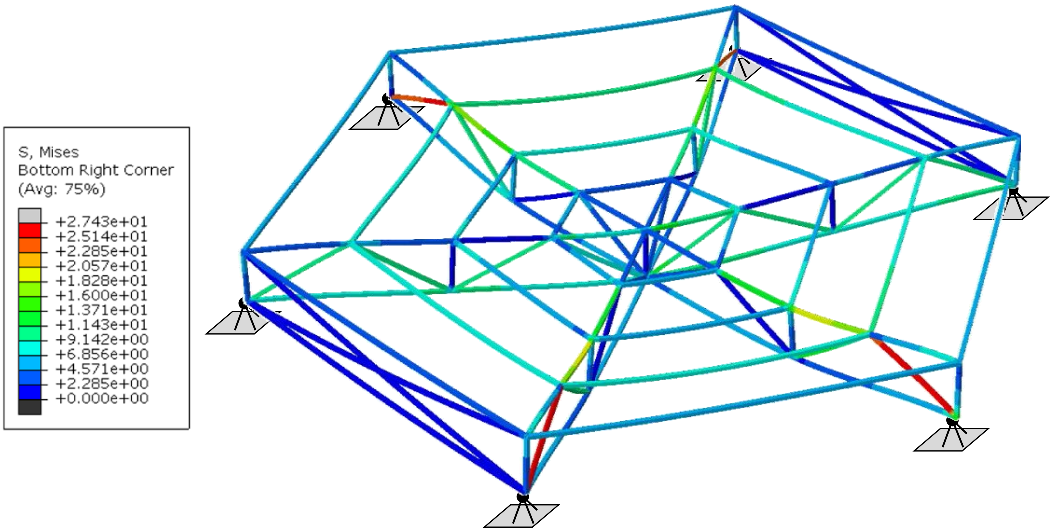


Fig. 4-6 A sample of the FEM model under fire conditions

4.3.2 CFD and FEM model validation

1. CFD fire simulation model

The CFD models developed using PyroSim are designed to simulate the spatiotemporal development of particular fire scenarios. To validate the effectiveness of the developed CFD model in representing the development tendencies of fire scenarios, the experimental data from Jiang et al. (Jiang et al., 2020b) were extracted as a validation reference for the numerical results under the same fire scenario, i.e., the destructive fire scenario as described in (Jiang et al., 2020b). Specifically, six wooden cribs with a unit size of 1.0m×1.0m×1.12m and a total weight of 975kg were installed as fuels, and a 0.7m×0.7m 2L diesel oil pool was used for ignition at the center of the specimen. The doors and windows on the wall were kept open to emulate natural ventilation conditions. Fig. 4-7 plots the temperature-time curves obtained from the CFD models and experimental results at selected gas temperature measuring points. Note that in CFD models, 5 different ventilation speeds ranging from 0m/s to 2m/s (e.g., 0, 0.5, 1, 1.5, 2 m/s) were adopted for 5 independent fire scenarios, and the results as shown in Fig. 4-7 are the envelope bands of the 5 scenarios.

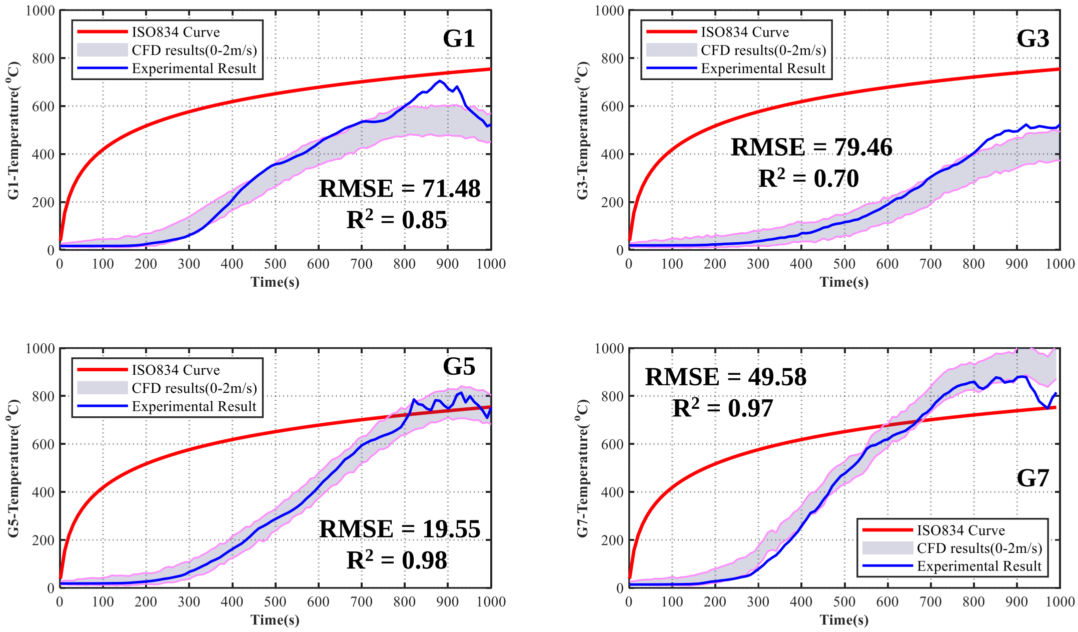


Fig. 4-7 Temperature-time curves of the experimental and CFD model results

The Root Mean Square Error (RMSE) is a frequently used measure of the differences between the predicted values of a model and the observed values, while the Coefficient of Determination (R^2) is commonly used to indicate how much variation in the targeted predicted variable is explained by the independent predictor variables in a regression model. By comparing the experimental data with the mean value of CFD results, RMSE and R^2 are calculated for the four measuring points as shown in Fig. 4-7. A maximum RMSE of 79.46 and a minimum R^2 of 0.7 indicate the effectiveness of the developed CFD model in representing temperature development trends in the temporal and spatial domains under the designated fire scenario. On the other hand, a noticeable gap can be observed between the experimental results and ISO834 curves, indicating that within the tested fire scenario, the ISO834 curve does not fully represent the heating process, and numerical simulation could work as a complementary approach to capturing the spatiotemporal patterns of temperature development in building fires.

2. FEM structural analysis model

Based on the gas temperatures obtained from the CFD model, FEM structural analyses are conducted using ABAQUS to simulate the structural response under fire. By developing the ABAQUS model with the same experimental settings as Jiang et al. (Jiang et al., 2020b) and importing the temperature field data from the validated CFD model, sequential thermal-mechanical analysis was conducted for the 5 fire scenarios for validation of FEM models. Fig. 4-8 shows the comparisons between the numerical and experimental results at selected displacement measuring points, after temperature-time curves were extracted from the FEM models.

As shown in Fig. 4-8, the FEM results are capable of representing the overall deformation patterns of the tested steel roof structure. For instance, a clear arching deformation with a positive value is observed between 500s to 700s after fire ignition, which is possibly due to the decreased Young’s modulus under elevated temperatures and the unsymmetric thermal expansion of the top and bottom chords. Then the displacement dramatically decreases downwards after approximately 650-750s in both the experimental and FEM results. This sharp decrease might be explained by both the dressed Young’s modulus and the yield strength of steel materials that lead to the deterioration in the stiffness and load-bearing capacity of the roof structure. Quantitatively, the maximum RMSE is less than 40mm and the minimum R^2 is above 0.7 between the experimental data and the mean value of the FEM models for the 5 fire scenarios with different ventilation speeds, which indicates the validity of the developed FEM models in simulating the structural fire response under given fire scenarios obtained from CFD models.

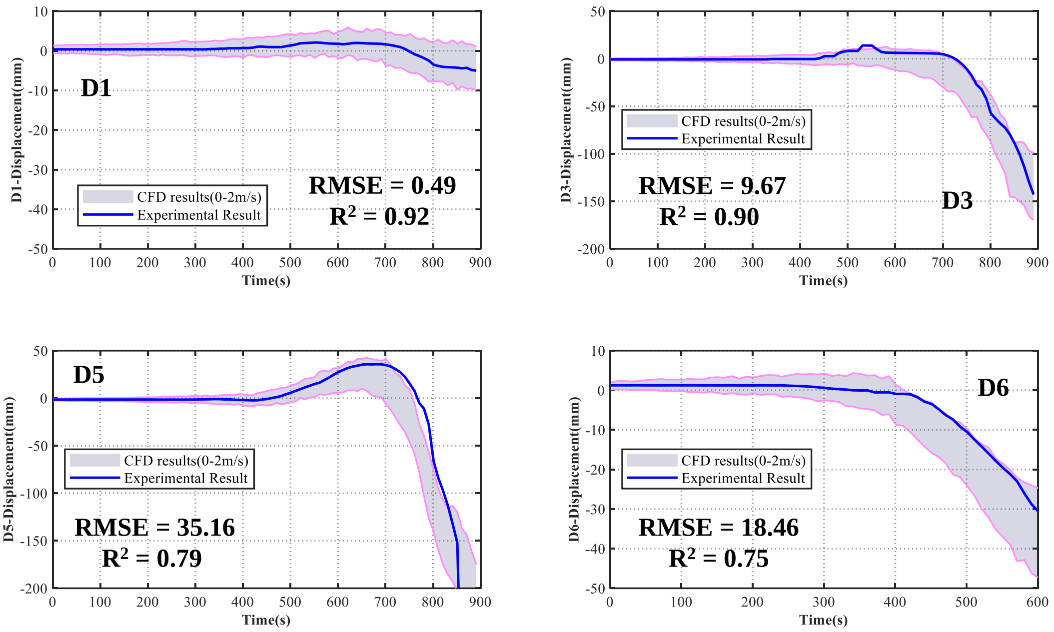


Fig. 4-8 Displacement-time curves of the experimental and CFD model results

4.3.3 ML model development

1. ML Data Generation from CFD and FEM models for various fire scenarios

After the development of the CFD models for fire simulation in PyroSim and FEM models in ABAQUS, temperature field data from the CFD models and structural response data from the FEM models were extracted to construct a datasheet for ML model training. For the tested steel roof structure, temperature data from the 13 measuring points (i.e., G1-G13 in Fig. 4-3) and vertical displacement data from the 9 measuring points (i.e., D1-D9 in Fig. 4-3) were extracted for each fire scenario, as shown in Table 4-1. For a fire scenario lasting for 1000s, the size of the datasheet will be 1000 lines with 23 columns (1 time column, 13 temperature columns, and 9 displacement columns) if the data is recorded once every second.

Table 4-1 A sample of datasheet extracted from CFD and FEM model

No.	Time (s)	Temperature from CFD model				Displacement from FEM model			
		G1 (°C)	G2 (°C)	…	G13 (°C)	D1 (mm)	D2 (mm)	…	D9 (mm)
1	1	24	28	…	20	0.0	0.0	…	0.0
2	2	34	51	…	24	0.0	-0.1	…	0.0
3	3	48	98	…	23	-0.2	-4.9	…	-0.3
…	…	…	…	…	…	…	…	…	…
1000	1000	425	763	…	486	-8.7	-576.6	…	-6.8

Bulk models are generated using python by revising fire parameters in ".fds" files for FDS models in PyroSim for CFD simulation and by creating multiple models using ".py" files for FEM analysis in ABAQUS. In this chapter, 1200 fire scenarios are considered in total, with different combinations of the three fire parameters, as shown in Table 4-2. For instance, H70V15X1Y2 refers to a fire scenario where the heat release rate is 70MW, the ventilation speed is 1.5m/s, and the position of the ignition point is 1m away from the center of the x-axis and 2m away from the center of the y-axis. Therefore, the total number of fire scenarios equals the product of the number of values set for each parameter, i.e., 15×5×4×4=1200).

Table 4-2 Value space for different fire scenarios

Fire Parameter	Number of values	Value Space
Heat Release Rate (MW)	15	{30,35,40,45,50,55,60,65, 70,75,80,85,90,95,100}
Ventilation speed (m/s)	5	{0, 0.5, 1, 1.5, 2}
X-Position (m)	4	{0, 1, 2, 3}
Y-Position (m)	4	{0, 1, 2, 3}

2. ML model training and tuning with the numerical dataset

The numerical database with 1.2 million lines of data generated from the CFD and FEM models for 1200 fire scenarios is used for ML model training and tuning. Among the commonly-used ML algorithms in structural engineering, SVM (Noble, 2006) is especially powerful in modeling the non-linear relationship of the independent and dependent variables with numerous kernel functions, and DT (Lewis, 2000) has understandable tree-like decision logic and high efficiency in model training. RF (Breiman, 2001) and GB (Friedman, 2001b) are two popular ensemble algorithms in both regression and classification problems. Given that previous research has shown the potential of SVM, DT, RF, and GB models in structural fire response prediction (Ye et al., 2022), these four models are also employed in this chapter to test the feasibility of the proposed CFD/FEM-based ML framework. Python is employed with "sklearn" for developing the four ML models (Pedregosa et al., 2011). In each model, the 13 points of temperature data (i.e., G1-G13) are taken as model input and the mid-span vertical displacement data of D5 are taken as the predictive model output for the sake of simplicity in this example. Among the 1200 fire scenarios in total, 200 fire scenarios were randomly selected to be excluded from the training dataset in order to serve as the testing dataset, while the other 1000 fire scenarios form the training dataset.

Hyperparameter tuning is critical for ML models to achieve predictive accuracy. The penalty constant C and the kernel parameter γ for the RBF kernel are the two hyperparameters for SVM (Noble, 2006). Three parameters are considered for DT including 1) the maximum depth of the tree d_{max}; 2) the minimum number of samples on a tree node s_{node}, and 3) the minimum number of samples on a tree leaf s_{leaf} (Lewis, 2000). Apart from the three parameters as included in the DT model, three more parameters, which are: 1) the number of trees n_{tree}, 2) the number of samples n_{sample}

to draw from the dataset to each tree using bootstrap sampling, and 3) the number of features m_{try} to consider at each split, are included for RF (Breiman, 2001). GB, as another ensemble model for DT, considers three more parameters than DT, including 1) the number of boosting stages n_{tree}, 2) learning rate η , and 3) the number of features m_{try} to consider at each split (Friedman, 2001b). Detailed justifications for the hyperparameters of each ML model can be found in (Ye et al., 2022).

Table 4-3 Search space for parameter tuning of ML models

Model	Parameter	Search space
SVM	C	{0.01, 0.1, 1, 10, 100, 1000, 10000}
	γ	{0.001, 0.01, 0.1, 1, 10, 100}
DT	d_{max}	{3,5,7,9, None}
	s_{node}	{2, 4, 6, 8, 10}
	s_{leaf}	{1, 2 ,3 ,4 ,5}
RF	n_{tree}	{50,100,150,200,250}
	n_{sample}	{20%, 40%, 60%, 80%, 100%}
	m_{try}	{Sqrt, Log2, All}
	d_{max}	{3,5,7,9, None}
	s_{node}	{2, 4, 6, 8, 10}
	s_{leaf}	{1, 2 ,3 ,4 ,5}
GB	n_{tree}	{500,1000,1500,2000,2500}
	η	{0.005, 0.01, 0.02, 0.05, 0.1, 0.2}
	m_{try}	{Sqrt, Log2, All}
	d_{max}	{3,5,7,9, None}
	s_{node}	{2, 4, 6, 8, 10}
	s_{leaf}	{1, 2 ,3 ,4 ,5}

Table 4-3 presents the search space for all hyperparameters, while Table 4-4 summarizes the optimal combination of hyperparameters for each model under different numbers of fire scenarios included in the training dataset through the Grid

Search method with 5-fold cross-validation. In grid search, each set of possible combinations of the parameters is tested and the one with the highest accuracy is selected as the final value. For instance, in model tuning for RF, a total of 5×5×3×5×5×5 = 9375 possible combinations of the six parameters as listed in Table 4-3 were considered, and 9375×5= 46,875 models were trained under 5-fold cross-validation.

Table 4-4 Optimal values after parameter tuning of ML models

Model	Number of fire scenarios in the training dataset			
	100	200	500	1,000
Support Vector Machine (SVM)	C = 10 γ = 0.1	C = 10 γ = 0.1	C = 10 γ = 0.1	C = 10 γ = 0.1
Decision Tree (DT)	d_{max} = None $s_{node} = 2$ $s_{leaf} = 1$	d_{max} = None $s_{node} = 2$ $s_{leaf} = 1$	d_{max} = 7 $s_{node} = 2$ $s_{leaf} = 1$	d_{max} = 9 $s_{node} = 2$ $s_{leaf} = 1$
Random Forest (RF)	n_{tree} = 100 n_{sample} = 80% m_{try} = sqrt d_{max} = 7 s_{node} = 2 s_{leaf} = 1	n_{tree} = 100 n_{sample} = 80% m_{try} = sqrt d_{max} = 9 s_{node} = 2 s_{leaf} = 1	n_{tree} = 200 n_{sample} = 80% m_{try} = sqrt d_{max} = 7 s_{node} = 2 s_{leaf} = 1	n_{tree} = 100 n_{sample} = 80% m_{try} = sqrt d_{max} = 7 s_{node} = 2 s_{leaf} = 1
Gradient Boosting (GB)	n_{tree} = 2000 $\eta = 0.02$ m_{try} = sqrt d_{max} = 7 $s_{node} = 2$ $s_{leaf} = 1$	n_{tree} = 2000 $\eta = 0.02$ m_{try} = sqrt d_{max} = 9 $s_{node} = 2$ $s_{leaf} = 1$	n_{tree} = 2000 $\eta = 0.01$ m_{try} = sqrt d_{max} = 9 $s_{node} = 2$ $s_{leaf} = 1$	n_{tree} = 2000 $\eta = 0.01$ m_{try} = sqrt d_{max} = 7 $s_{node} = 2$ $s_{leaf} = 1$

4.4 Case Results and Discussions

4.4.1 Predictive performance of CFD/FEM-based ML models

Given the well-tuned model parameters as shown in Section 4.2, ML models are trained with different numbers of fire scenarios in the training dataset (i.e., 100, 200, 500, 1000), and testing data are randomly selected from the other unused 200 fire scenarios with a test-train ratio of 20:80. For instance, if 200 fire scenarios (i.e., 2000×1000 lines of data) are included in the training dataset, 50 fire scenarios will be randomly selected from the unused fire scenarios to form a datasheet with 50×1000 lines as the testing dataset.

RMSE and R^2 are selected as the predictive accuracy performance measures of the ML models for structural displacement prediction. Table 4-5 summarizes the RMSE and R^2 results for predicting the structural deformation of D5 in the testing dataset of the four ML models trained under different numbers of fire scenarios, according to which the tendency lines are drawn in Fig. 4-9. It can be observed that the RMSE is lower than 5mm for all models, and the minimum R^2 is higher than 0.8, demonstrating that the CFD/FEM-based ML model is capable of predicting the vertical displacement at a specific location (i.e., D5) using the numerical dataset obtained from the CFD and FEM models. All models show similar patterns: as the number of fire scenarios included in the training set increases, the RMSE decreases and R^2 increases. SVM was found to perform better than DT, while RF and GB outperform both SVM and DT in terms of both RMSE and R^2. The RMSE starts to converge when the number of fire scenarios reaches 200 for RF and GB, and reaches 500 for SVM. For DT, it seems that more fire scenarios could eventually achieve a lower RMSE level.

Table 4-5 RMSE and R^2 of ML models under different numbers of fire scenarios

Model performance		Number of fire scenarios in the training dataset (N)			
		100	200	500	1000
SVM	RMSE	2.34	1.81	1.43	1.34
	R^2	0.87	0.89	0.91	0.93
DT	RMSE	3.07	2.66	2.07	1.70
	R^2	0.81	0.86	0.88	0.89
RF	RMSE	1.49	0.91	0.78	0.64
	R^2	0.94	0.97	0.98	0.99
GB	RMSE	1.19	0.85	0.55	0.51
	R^2	0.95	0.98	0.99	0.99

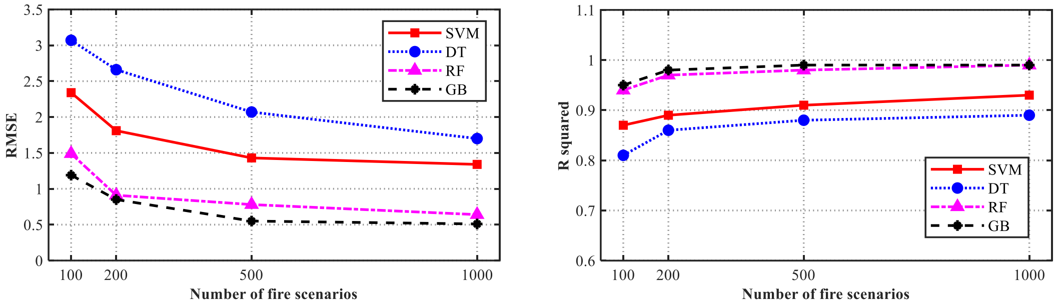


Fig. 4-9 RMSE and R^2 of ML models under different numbers of fire scenarios

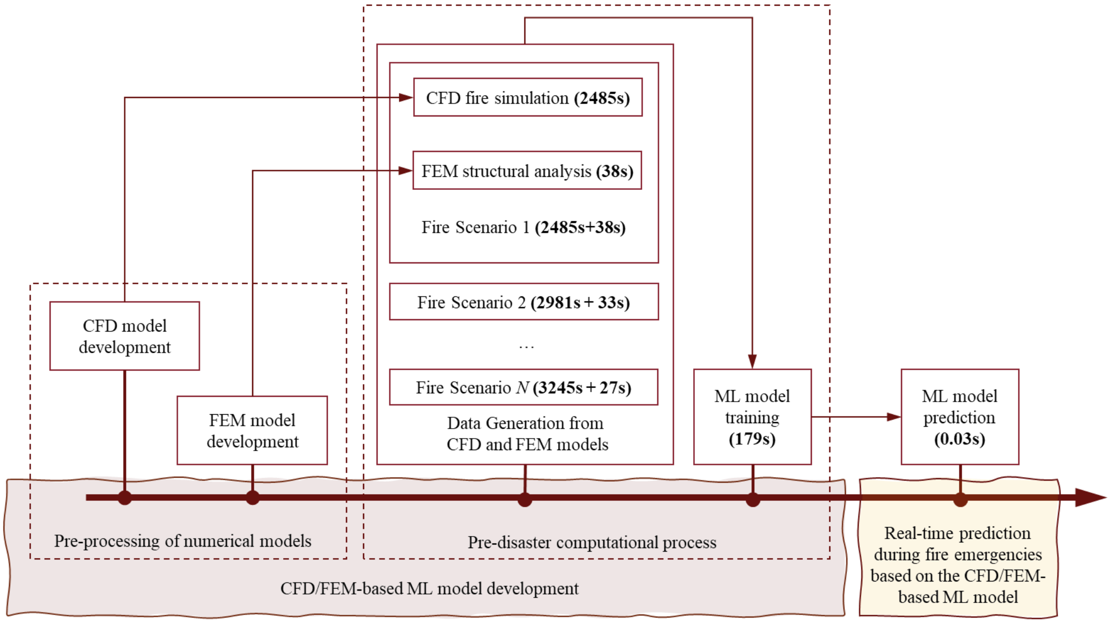
4.4.2 Computational efficiency of CFD/FEM-based ML models

Apart from predictive accuracy, computational efficiency is another great concern, as this chapter aims to facilitate the real-time prediction of structural fire response in the context of building fire emergencies. The workflow of the CFD/FEM-based ML framework can be divided into two phases: 1) model development based on the numerical data generated from the CFD and FEM models and 2) real-time prediction during fire emergencies based on the developed model. Fig. 4-10 shows the workflow, along with the corresponding computational costs of each process using the case of the tested steel roof truss. The computational processes were conducted on a PC with an Intel® i7-8700™ CPU (6 cores, 3.2 GHz) and 32GB of RAM.

As shown in Fig. 4-10, for the tested steel roof structure, which has 84 steel members and a global size of 8m×8m×0.6m, when subjected to a fire scenario lasting for 1000s, it takes approximately 2000s-3600s wall-clock time to get the CFD results in FDS, and 20s-50s wall-clock time to get the FEM results in ABAQUS, which comprises the most time-consuming portion of the workflow. In both CFD and FEM simulation processes, the RAM (32GB) was nearly fully occupied. Note that one of the possible ways to boost the speed of the CFD and FEM model computation is parallel computing, i.e. simultaneously processing different fire scenarios on different computers. Nonetheless, this is far from a "real-time" approach. For ML model training, the computational cost varies for different models under different sizes of the training dataset, as shown in Table 4-6. For instance, it takes 179s to train an RF model with a 500-fire-scenario training dataset. From Table 4-6, SVM is found to be the most time-consuming among all the four models, and the cost increases dramatically as the number of fire scenarios increases. In contrast, DT is the most computationally efficient. RF, GB, and the ensemble version of DT take longer times than DT, but are still substantially faster than SVM, especially when the number of fire scenarios is large. Data generation from CFD and FEM models and ML model training can be jointly identified as the pre-disaster computational process, as shown in Fig. 4-10. Even though the process is time-consuming and not a "real-time" approach, it can be conducted in advance before the model is put to use. The "real-time" prediction, in this context, lies in the final block in Fig. 4-10, i.e., the prediction of structural response during fire emergencies with a well-trained ML model. Accordingly, it takes only 0.03s to get a prediction result for a single point at a particular moment, a which is a nearly instantaneous time interval that qualifies as a "real-time" prediction.

Table 4-6 Comparison of ML model training run times (in seconds)

Model	Number of fire scenarios in the training dataset (N)			
	100	200	500	1,000
SVM	273	1,182	5,014	18,476
DT	0.7	3.8	7.5	9.1
RF	18.2	82	179	285
GB	14.8	76	142	335



* Numbers in parentheses refer to the computational costs of their corresponding processes. For instance, 2485s means that the CFD fire simulation for Fire Scenario 1 takes 2485 seconds in total.

Fig. 4-10 Computational cost of the CFD/FEM-based ML framework

4.4.3 Impact of signal-to-noise ratios on model performance

To better evaluate the model performance of the CFD/FEM-based ML framework, the robustness of the predictive accuracy of the ML model against noise from the temperature data was tested and analyzed as follows. As designed in the framework, the well-trained ML model is expected to collect real-time temperature data from preinstalled sensors on the building structure as model input for the prediction. Errors or noise in the temperature data may be induced by the sensors to prevent the model from accurately perceiving the temperature field of the physical environment. Therefore, the proposed ML model should function well under a certain level of noise in the temperature data. Gaussian noise is introduced to the temperature data in the testing set to compare the predictive performance of the ML models under different levels of noise. For the sake of simplicity, the mean value of the Gaussian noise is assigned as 0 and the standard deviation σ is determined by the signal-to-noise ratio (SNR) ranging from 5 to 25.

Table 4-7 and Fig. 4-11 present the RMSE and R^2 values of the predictive results from the four ML models under different levels of SNRs when the number of fire scenarios in the training dataset is 500. An obvious decrease in RMSE and increase in R^2 are observed for all four models when SNR increases from 5 to 15. When the SNR is larger than or equal to 15, the RMSE starts to converge and the R^2 is around 0.8 for all models. The converging RMSE indicates that all models perform well when SNR is greater than or equal to 15, meaning that the ML models are capable of functioning well under a maximum noise level of 6.67%. Specifically, SVM shows better predictive performance than DT, RF, and GB under the SNR of 5 or 10, indicating that SVM is more robust than the other models. Nonetheless, RF and GB perform similarly and are better than DT in terms of both RMSE and R^2. The results suggest that SVM, RF, and GB are robust against noise with an SNR greater than or equal to 10, that is, by using SVM, RF, or GB, the tolerance for noise is 10% (i.e., SNR = 10) while still obtaining an R^2 of approximately 0.8.

Table 4-7 RMSE and R^2 of ML models under different SNRs

Model performance (N=500)		Signal Noise Ratio (SNR)				
		5	10	15	20	25
SVM	RMSE	58.87	30.61	14.69	8.69	6.08
	R^2	0.76	0.85	0.87	0.88	0.90
DT	RMSE	160.46	92.09	33.89	10.00	8.94
	R^2	0.25	0.65	0.79	0.84	0.88
RF	RMSE	100.46	28.11	18.33	6.95	2.71
	R^2	0.36	0.82	0.83	0.89	0.96
GB	RMSE	84.41	50.44	16.77	6.17	1.87
	R^2	0.53	0.78	0.84	0.91	0.97

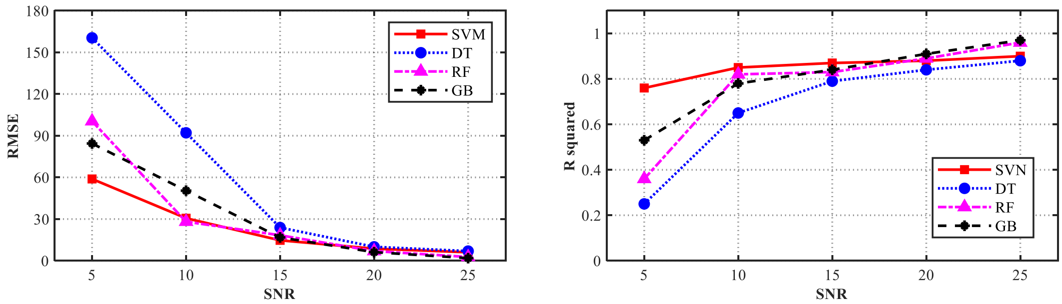


Fig. 4-11 RMSE and R^2 of ML models under different SNRs

4.4.4 Impact of sampling intervals on model performance

Another critical consideration when evaluating the performance of the ML model is the data requirement. The more data an ML model requires, the stricter its application conditions are. In this chapter, an indicator for measuring the data requirements of an ML model can be the sampling interval, i.e., the time duration between which the temperature data are collected from the sensor. More frequent data collection entails a shorter sampling interval, corresponding to a longer dataset with more lines of data for each fire scenario for ML model training. Although a shorter sampling interval could enrich a dataset with more data to improve the sample diversity of the training dataset and the refreshment frequency of the predictive results in the testing dataset, such a shorter interval will definitely lower the computational efficiency in training the ML model. The trade-off between sampling interval and computational efficiency should be considered. The impact of sampling intervals on the predictive performance of the ML models is compared in Table 4-8 and Fig. 4-12, with sampling intervals ranging from 1s to 30s and the number of fire scenarios included in the training set fixed at 500.

Table 4-8 RMSE and R^2 of ML models under different sampling intervals

Model performance (N=500)		Sampling Interval (s)					
		1	2	5	10	20	30
SVM	RMSE	1.43	5.99	15.92	20.26	22.05	34.53
	R^2	0.91	0.89	0.85	0.82	0.80	0.70
DT	RMSE	2.07	6.75	18.84	24.05	48.68	124.05
	R^2	0.88	0.87	0.85	0.79	0.63	0.23
RF	RMSE	0.78	1.58	4.11	14.63	35.29	83.99
	R^2	0.98	0.96	0.93	0.88	0.78	0.33
GB	RMSE	0.55	1.49	7.66	13.96	47.58	93.57
	R^2	0.99	0.96	0.93	0.89	0.74	0.49

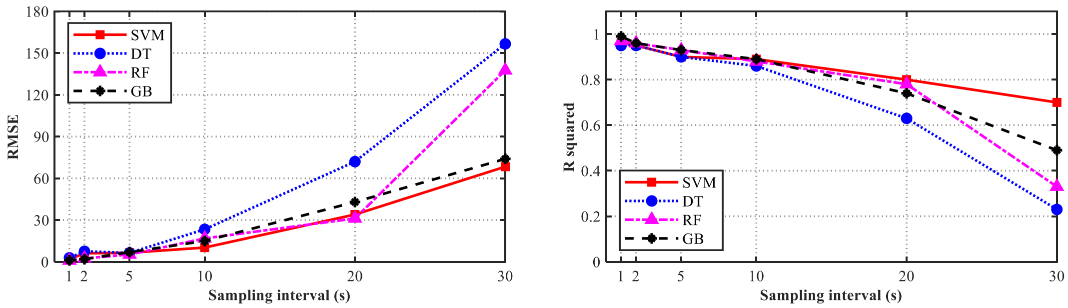


Fig. 4-12 RMSE and R^2 of ML models under different sampling intervals

As shown in Fig. 4-12, the RMSE is less than 30mm and R^2 is greater than 0.8 when the sampling intervals are less than or equal to 10s. When sampling intervals increase to more than 10s, the RMSE and R^2 deteriorate sharply. Among the four models, SVM, RF, and GB perform similarly in terms of both RMSE and R^2 when the sampling intervals are less than or equal to 20s, while SVM is the most robust one against longer sampling intervals, followed by GB when the sampling interval reaches 30s. In other words, when the data is not sufficiently rich or diverse in terms of sampling frequency, SVM and GB have the potential to show better predictive accuracy than DT and RF. From the overall results, as shown in Table 4-8, the suggested sampling interval for this particular steel roof structure case is 5s, under which the RMSE is less than 10mm for RF and GB and the R^2 is greater than 0.85 for all models.

4.4.5 Applicability of the framework in more complex predictive tasks

In assessing the applicability of the proposed CFD/FEM-based ML framework in predicting structural response in the immediate future (e.g., within 10 seconds) with the use of historical temperature field data as model input, the time-dependent nature of the temperature and deformation data needs to be considered. Neural networks have recently become more popular in time-dependent structural response modeling (Freitag et al., 2011). The long short-term memory (LSTM) network, an improved form of the recurrent neural network, has been found to be effective in resolving long time series problems (Hochreiter and Schmidhuber, 1997). Given the strong non-linear fitting capability of an LSTM network in predicting time-varying structural responses with the input of historical data (Zhang et al., 2019), in our study an LSTM model was trained to demonstrate the applicability of the framework to more complex predictive tasks involving time-dependent patterns in the dataset. The LSTM model was developed using Keras in Python (Gulli and Pal, 2017).

The LSTM model aims to predict the displacement of D5 in the next 10s with the input of historical temperature field data from the last 30s. Taking sampling intervals of 5s, the input for the LSTM model is a matrix with the size (6,13). Each line corresponds to the temperature field of a historical moment in the past 30 seconds at a 5s interval, and each column corresponds to the temperature data of particular measuring points (i.e., G1 to G13). The output of the model is still the displacement of D5, but in the next 10s. In this context, each fire scenario contributes 196 pieces of data to the dataset. For the sake of simplicity, 200 fire scenarios are included in the dataset and there are in total 39200 pieces of data in the dataset. 10% of the data (i.e., 3920 pieces of data) are randomly selected and hold out as the validation set to evaluate the predictive performance of the LSTM model. The basic structure of the LSTM is listed in Table 4-9. After tuning the LSTM model, the hyperparameters are: the optimizer selected to be “Adam”, a loss function assigned as “MSE”, the maximum epoch set to 1000, and a batch size of 128.

The development of loss values with the increase of epoch is depicted in Fig. 4-13. The MSE between the predictive results from the ML model and the calculation results from the FEM model decrease sharply when the epoch approaches 100. When the epoch reaches 200, the MSE starts to converge. Greater oscillation in validation loss can be observed, while the training loss looks more stable. On the other hand, the validation loss is generally smaller than the training loss in this case. One possible explanation is that if the validation set is more representative of the scenarios that the model handles well, it might show lower loss values than training loss. Nonetheless, the maximum MSE for the validation set when the epoch is greater than or equal to 200 is below 0.05, which indicates the feasibility of applying the LSTM model in the proposed CFD/FEM-based ML framework for predicting structural deformation in the immediately successive moment (e.g., in 10s) with historical temperature field data.

Table 4-9 Structure of the LSTM model

Layer(type)	Output Shape	Number of parameters
Lstm_6 (LSTM)	(None, 13)	1404
Dense_6 (Dense)	(None, 1)	14

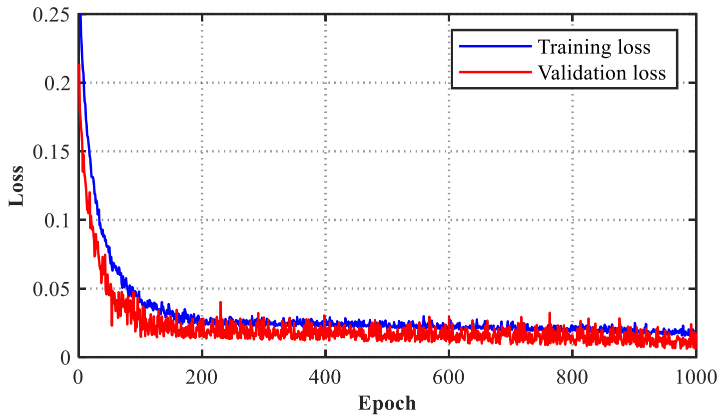


Fig. 4-13 Training loss and validation loss in the LSTM model

4.4.6 Discussions on limitations and prospects

As an exploratory attempt to integrate CFD, FEM, and ML methods for real-time structural fire response prediction, this chapter could be further improved in future work in terms of the complexity and computational time of CFD and FEM models, the predictive accuracy of the ML models, and the scope of applicability of the CFD/FEM-based ML framework.

The complexity of the CFD and FEM models developed for the tested steel roof structure is customized and tuned with particular consideration of accuracy in the simulation as well as computational time for each fire scenario. However, other structures with more complex geometric features would require far more time to generate CFD and FEM simulations if the numerical models are not built and tuned according to an appropriate level of complexity. Further analysis could be conducted to determine the optimal resolution or complexity of the numerical model to improve the computational efficiency of the models for obtaining results with an acceptable degree of accuracy. Another factor affecting the computational costs of the CFD and FEM models is the number and the diversity of fire scenarios. A more diverse range of fire scenarios would enhance the comprehensiveness of the training dataset so that the model is more likely to capture the inherent patterns between the temperature and deformation data. However, more computational tasks must be performed if more diverse fire scenarios are modeled. The trade-off between computational cost and simulation resolution always exists and a reasonable justification is critical.

On the other hand, considering that the SVM, DT, RF, and GB models developed in this chapter only focus on the prediction of the instant mid-span deformation (i.e., D5) based on the input of the corresponding instant temperature data (i.e., G1-G13), which ignores the time-dependent nature of the structural fire response problem, an LSTM model is included in the discussion part to demonstrate the extensibility of the proposed framework. Nevertheless, the predictive performance of the ML models could be further improved by adopting more advanced ML models that include more features potentially affecting the structural response (e.g., material deterioration due to building aging, the real-time varying loading condition of the building, and initial imperfections in the structure) and to take into account the implicit time-dependent nature of the structural fire response, e.g., the impact of the loading and heating history of the building on structural deformation or collapse.

Moreover, future research could be performed to include more complex building structures with more possible failure modes (e.g., local buckling and/or progressive collapse) into the database to demonstrate the workflow of the proposed framework more realistically. Other potential influential factors like material degradation can also be considered when predicting structural responses. Nonetheless, with a steel roof structure selected and tested as the case study, the framework can be applied similarly to other building structures with the necessary structural information inputted.

4.5 Chapter Summary

To facilitate the real-time prediction of structural response under complex fire scenarios in building fire emergencies, this paper developed a CFD/FEM-based ML framework for predicting structural displacement taking temperature field data as model input. Numerical models of a virtual steel roof structure were developed as a demonstrative case to construct a numerical database with 1200 virtual fire scenarios. The CFD and FEM models of the tested structure are validated with experimental data from the literature. Using the constructed numerical database, ML models including SVM, DT, RF, and GB models have been trained for predicting mid-span vertical deformation with real-time temperature field data as model input. The four RL models are compared in terms of predictive accuracy, computational efficiency, and robustness against SNR and sampling intervals. Moreover, an LSTM model has also been trained to predict structural deformation in the next 10s with historical temperature field data from the last 30s of a fire disaster. Based on our case results and analysis, three key conclusions can be drawn:

1. The CFD and FEM model developed using FDS and ABAQUS are capable of simulating the fire development and structural behavior under fire for the case of a tested steel roof structure as demonstrated through comparison of the simulated results with the experimental results for the tested fire scenarios.
2. RF and GB models are found to outperform SVM and DT models regarding predictive accuracy in predicting the real-time vertical displacement of the tested

structure with R^2 up to 0.97 and RMSE less than 1mm when the number of fire scenarios in the training dataset is greater than or equal to 200, establishing the feasibility of the proposed CFD/FEM-based ML framework for real-time, fire-induced structural vertical deformation prediction.

3. The CFD/FEM-based framework developed in this paper enables the real-time prediction of structural deformation under fire within 0.03s after the ML model is well-trained, which complements the “time-consuming” drawbacks of CFD and FEM models in obtaining structural fire responses.
4. The performance of the developed LSTM model provides evidence for the ability of the developed framework to perform more advanced predictive tasks such as predicting structural displacement in the immediate future. The results show that the validation loss starts to converge to 0.01 when the epoch reaches 200, indicating the feasibility of the framework for more advanced ML models like LSTM.

The CFD/FEM-based ML framework developed in this paper could act as an essential core component in a real-time structural fire safety monitoring and warning system, which may help provide timely and reliable predictions of structural safety conditions during fire scenarios. With predictions about imminent structural changes, firefighters can make informed decisions about safe navigation routes within the building. This predictive capability also assists in planning and executing rescue operations more effectively, by identifying the safest routes for both firefighters and trapped occupants. Still, this paper could be further improved in future work regarding the complexity and computational time of CFD and FEM models, the predictive accuracy of the ML models, and the scope of applicability of the CFD/FEM-based ML framework. Further analysis could be conducted to determine the optimal resolution or complexity of the numerical model to improve the computational efficiency of the models for obtaining results with an acceptable degree of accuracy. The predictive performance of the ML models could be further improved by adopting more advanced ML models that include more features potentially affecting the structural response. Moreover, more complex building structures could be included in the database to demonstrate the workflow of the proposed framework more realistically.

CHAPTER 5 ADAPTIVE INDOOR FIRE RESCUE PATH PLANNING UNDER TIME-VARYING STRUCTURAL SAFETY CONDITIONS

5.1 Introduction

Firefighting is one of the most perilous professions globally, with a high incidence of occupational injuries and fatalities. According to the U.S. Fire Administration, there were approximately 60,450 reported firefighter injuries in 2021 (Campbell and Hall, 2022), with many of these occurring during fire ground operations. Notably, these figures only account for reported cases in the United States, and the global figures are undoubtedly much higher. The statistics underscore the inherent occupational risks in firefighting and the vital importance of implementing measures to enhance firefighter safety and effectiveness.

Firefighters operating in building fire scenarios face extreme external conditions, including high temperatures, smoke, and exposure to toxic gases (Horn et al., 2019, Romet and Frim, 1987, Khan et al., 2022). These conditions can severely impair their situational awareness, compromising their ability to make effective and safe decisions and increasing the risk of injuries and fatalities (Fabio et al., 2002, Britton et al., 2013, Li et al., 2014). The operational environment during a building fire is often dynamic and unpredictable, with time-varying structural safety conditions that add a layer of complexity to the decision-making process (Ye et al., 2022, Ye and Hsu, 2022, Jiang et al., 2020a, Jiang et al., 2020b). Moreover, the structural components of a building in a fire scenario can reach exceedingly high temperatures, sometimes over 1,000ºC, posing a significant risk to the structural integrity of the building and the safety of firefighters (Kodur, 2014, Li et al., 2003).

The unpredictable and high-risk nature of building fires necessitates the use of path optimization algorithms to guide firefighters' movements within the building (Chou et al., 2019). By determining the most efficient and safe routes, these algorithms can help to minimize firefighters' exposure to dangerous conditions. Traditional path planning algorithms, such as Dijkstra's algorithm (Johnson, 1973), Bellman-Ford (Goldberg and Radzik, 1993), and A* algorithms (Liu and Gong, 2011), have been widely used in various applications due to their proven efficiency in static environments (Chou et al., 2019, AbuSalim et al., 2020, Gao et al., 2021, Hamieh et al., 2020). However, their performance in dynamic, unpredictable environments such as building fires is often suboptimal due to the inherent assumptions of static environmental conditions.

One of the significant causes of firefighter fatalities during fire rescue operations is the partial or complete structural failure or collapse of buildings (Reuters, 2021, Campbell and Hall, 2022). This reality underscores the importance of considering dynamic structural safety in fire evacuation and rescue path planning. Although there are some studies on evacuation or escape paths in the case of a building fire spreading, they mainly focus on fire rendering and dynamic planning, and only a few studies have been conducted on dynamic path optimization in a building fire scenario considering the time-varying development of the fire. Most previous studies assumed that the building remained structurally well as they mainly focus on the evacuation process instead of the firefighting process (Ding et al., 2016, Wang et al., 2021, Yakhou et al., 2023). This gap in current path-planning approaches limits their effectiveness and applicability in real-world fire rescue operations, leading to an urgent need for path-planning models that dynamically incorporate structural fire safety conditions.

In recent years, the advent of Internet-of-Things (IoT) and artificial intelligence (AI) technologies has sparked considerable interest in the concept of smart firefighting (Wu et al., 2022, Eltom et al., 2018, Kandavel et al., 2022). These technologies enable real-time monitoring of fire scenes and predictive analytics, providing firefighters with critical and up-to-date information to guide their response (Wong and Lee, 2023). For instance, IoT sensors can monitor temperatures and structural integrity in different parts of a burning building (Chou et al., 2019, Sha et al., 2006, Eltom et al., 2018), while AI algorithms can use this data to predict future fire behavior and structural failure risks (Ye et al., 2022, Ye and Hsu, 2022, Wu et al., 2022).

Despite these technological advances, there is a clear gap in the development of adaptive path planning models that consider dynamic building fire environments and time-varying structural safety conditions. To address this gap, this chapter proposes an adaptive path planning model that can recommend efficient and safe rescue paths under dynamic building fire environments. The proposed model integrates a real-time temperature-based structural fire response prediction model with a dynamic grid-based search algorithm, allowing it to adapt to changing fire conditions while minimizing overall cost in terms of time, distance, and risk. The findings from this chapter have the potential to significantly enhance the safety and efficiency of fire rescue operations, making a valuable contribution to the field of smart firefighting.

5.2 Methodology

5.2.1 Workflow of the proposed methodology

The proposed adaptive path planning model is designed to provide efficient and secure rescue routes for firefighters in the context of dynamic building fire environments, with the workflow as shown in Fig. 5-1. The framework begins with the deployment of a real-time structural fire safety analysis and diagnostic model, which is utilized to predict the potential failure risk of varied structural components in a fire emergency. It assimilates real-time data with building layout data, including temperature readings and displacement measures, thereby facilitating a comprehensive assessment and prediction of the prevailing structural condition. Secondly, the data derived from the preceding analysis is utilized to persistently update a dynamic risk map of the building. This grid-based map represents the varying risk levels throughout different areas of the building, highlighting regions with imminent structural failure risk as high-risk areas. Thirdly, the culminating component of the framework encompasses the development and application of an adaptive path-planning algorithm. This algorithm employs the data extracted from the dynamic risk map and takes into account the firefighter’s current location along with the pre-determined destination (for example, the location of trapped occupants or the nearest exit). Finally, it generates a rescue path that optimally reduces exposure to high-risk areas while augmenting the efficiency of movement. The rescue information could be delivered to firefighting agents through electronic devices like smart phones or AR glasses/helmets. In this context, the proposed workflow delivers a comprehensive and robust solution to rescue path planning in dynamic building fire environments by integrating real-time structural safety assessments, dynamic risk mapping, and adaptive path planning.

In the context of dynamic building fire environments, the concept of optimality involves balancing multiple factors, including safety, efficiency (in terms of time and distance), and the ever-changing nature of fire scenarios. The model aims to recommend paths that optimize these criteria under current and anticipated conditions. Given the unpredictable and evolving nature of fires, the model's goal is to provide paths that are as close to optimal as possible at the time of the decision. These paths are optimal in the sense that they are the optimal choices available based on the current understanding and predictions of the fire's progression and structural integrity. The model continuously updates its path recommendations in response to real-time data, ensuring that the paths remain as close to optimal as possible as the situation changes. While absolute optimality is challenging in such unpredictable scenarios, the model prioritizes firefighter safety and operational efficiency, striving to recommend the most advantageous paths under the given circumstances.

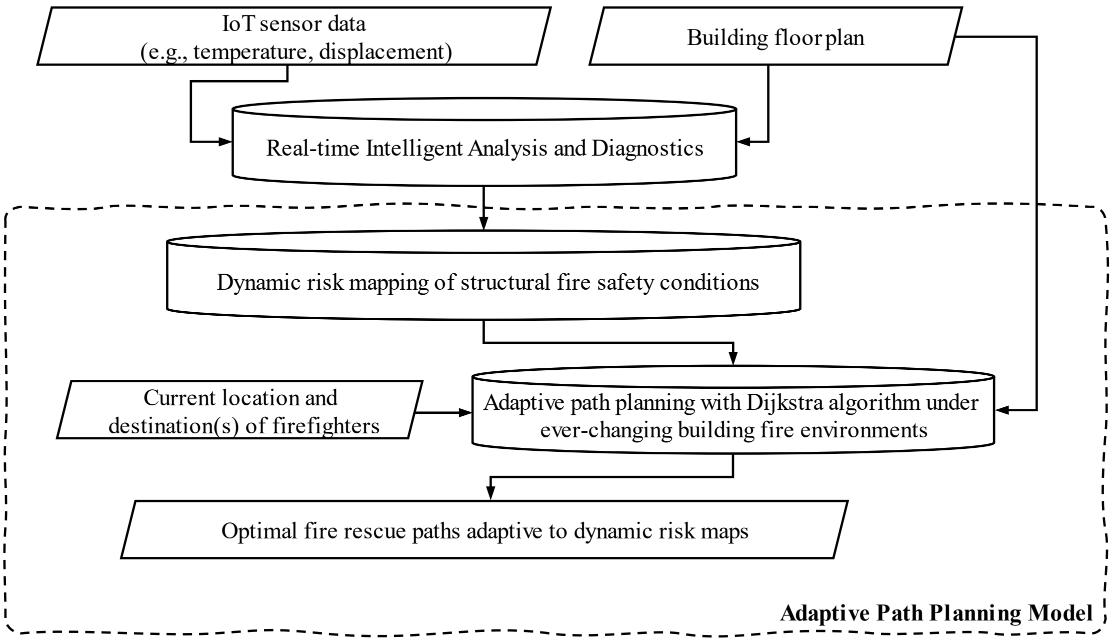


Fig. 5-1 Workflow of the adaptive fire rescue path planning framework

5.2.2 *Theoretical background*

1. Structural fire safety analyses and diagnostics

Structural fire safety analyses and diagnostics are generally conducted using a two-fold method encompassing CFD for fire simulations and FEM for structural fire analysis. CFD provides a framework for simulating fire development by solving a set of partial differential equations (PDEs) that describe fluid flow and heat transfer. These include the momentum equations (Navier-Stokes equations) (Constantin and Foias, 1989) and the energy equation (the First Law of Thermodynamics) (Cemič, 2005). The momentum equations capture the dynamics of fluid (fire and smoke in this case) flow, which can be expressed as:

$$\begin{cases} \nabla \cdot u = 0 \\ \rho\left(\dfrac{\partial u}{\partial t} + u \cdot \nabla u\right) = -\nabla p + \mu \nabla^2 u + f \end{cases} \tag{5-1}$$

where u represents the velocity vector of the fluid, ∇ denotes the gradient operator, ρ is the density of the fluid, t represents time, p denotes the pressure, μ is the dynamic viscosity, and f represents any external forces acting on the fluid. The energy equation can be written as:

$$\rho\left(\frac{\partial e}{\partial t} + u \cdot \nabla e\right) = -p\nabla \cdot u + \nabla \cdot (k\nabla T) + Q \tag{5-2}$$

where e denotes the internal energy per unit mass, k is the thermal conductivity, T denotes the temperature, and Q represents any heat sources or sinks within the system. Given their non-linear and coupled nature, these PDEs are typically difficult to solve analytically but could be solved numerically using software like Fire Dynamic Simulators (FDS).

For structural analysis, FEM facilitates the generation of solutions to differential or integral equations that govern the behaviors of a physical system, enabling users to comprehend the spatiotemporal evolution of the targeted variables. Specifically, in structural analysis, FEM quantitatively calculates the displacements, strains, and/or stresses in a structure subjected to various forms of loads, including static, dynamic, or thermal. Detailed procedures regarding the development of FEM models for structural fire analysis can be found in (Ye et al., 2022). Note that real-time structural fire safety prediction models like the FEM-based ML model by Ye et al. (Ye et al., 2022) and the CFD/FEM-based ML model by Ye and Hsu (Ye and Hsu, 2022) can also be adopted in the proposed framework to facilitate real-time structural fire safety analyses and diagnostics.

2. Dynamic Risk Mapping

To evaluate and visualize real-time structural safety conditions, a dynamic risk mapping approach is employed. This approach hinges on a comprehensive failure criterion, which encapsulates the risk of failure for each structural component. A significant parameter in the failure criterion is the limit-state function, $g(X)$, defined as the difference between the allowable value and the current value of a selected parameter such as stress, strain, or critical temperature. For instance, the limit-state function for the stress ratio could be expressed as:

$$g(X) = \sigma_{allowable} - \sigma \tag{5-3}$$

where σ represents the current stress in the component, and $\sigma_{allowable}$ is the allowable or yield stress of the material. Similar limit-state functions can be defined for strain and critical temperature ratios:

$$g(X) = \varepsilon_{allowable} - \varepsilon \tag{5-4}$$

$$g(X) = T_{critical} - T \tag{5-5}$$

where ε is the current strain in the component, $\varepsilon_{allowable}$ is the maximum allowable strain before failure, T is the current temperature, and $T_{critical}$ is the critical temperature at which the material properties alter drastically or the component fails.

Once these limit-state functions are defined, they are used to compute the reliability index, β, a measure of the safety level of a system (Haldar and Mahadevan, 2000, Melchers and Beck, 2018). The reliability index is typically used in reliability engineering to quantify the risk associated with a system. The reliability index is calculated as the ratio of the expected value (mean) of the limit-state function to the standard deviation of the limit-state function:

$$\beta = E[g(X)]/\sigma_g \tag{5-6}$$

where $E[g(X)]$ is the expected value of the limit-state function, and σ_g is the standard deviation of the limit-state function. Both $E[g(X)]$ and σ_g can be calculated based on the properties of the material and the current state of the component. The failure probability, P_f, can be then calculated from the reliability index using the standard normal cumulative distribution function, Φ:

$$P_f = \Phi(-\beta) \tag{5-7}$$

The structural safety risk of each component is quantified using the estimated failure probability P_f, which is translated into a risk value on a predetermined scale, e.g., 0 (low risk) to 1 (high risk). This means that a higher failure probability signifies a higher risk, offering an intuitive measure for firefighters and other rescue personnel to understand the risk associated with each grid. This approach enables a real-time, probabilistic assessment of structural safety risk under dynamic fire conditions, enhancing the effectiveness of fire rescue path planning.

3. Adaptive Path Planning

Given the dynamic nature of building fire environments, an indoor fire rescue path can be planned to minimize the travel time and avoid areas that pose higher safety risk to firefighters. The moving speed of the firefighters is estimated according to the fire, smoke, and structural safety conditions of each area (Cłapa et al., 2015).

The model for adaptive path planning operates within an 8-directional grid-based network. Each grid cell in the network corresponds to a vertex, and the edges connect each vertex to its adjacent vertices. In this context, "adjacent" includes not only the four cardinal directions (North, South, East, and West) but also the four intercardinal directions (Northeast, Northwest, Southeast, and Southwest). This 8-direction connectivity increases the model’s flexibility in creating path options.

The adaptive path planning algorithm takes the dynamic risk map and firefighters’ current location as inputs. The cost function associated with the transition from grid i to the adjacent grid j in the network is defined as:

$$C_{ij} = \alpha D_{ij} + \beta T_{ij} + \gamma R_j \tag{5-8}$$

where D_{ij} is the distance traveled, T_{ij} is the time spent, R_j is the risk value at the adjacent grid j derived from the dynamic risk map, and α, β, and γ are weight factors that balance the importance of distance, time, and risk in the cost function.

The search algorithm is a modification of Dijkstra's algorithm, a renowned shortest-path-finding method. The regular version of the algorithm finds the shortest path by minimizing the cumulative cost from the starting point to each vertex in the network. In the adapted version used in the current study, the algorithm dynamically updates the path by recalculating the cost function as the risk map evolves in real time. Thus, the path is not only the shortest but also the safest, given the real-time risk values.

During the search process, the algorithm dynamically generates a sequence of path segments connecting the firefighter's current location to the destination. The generated path aims to avoid high-risk areas, where structural component failure or collapse is more likely, to ensure the safety of firefighters during fire rescue operations. This approach showcases the advantage of adaptive path planning, which leverages real-time risk information to dynamically adjust the rescue path, leading to safer and more efficient fire rescue operations.

5.3 Model Development

This section outlines the process of developing the proposed adaptive fire rescue path planning model. A case study of a single-story office building with multiple corridors is deployed to illustrate the model's workflow in a dynamic building fire environment (Xu et al., 2022).

The model assumes continuous, reliable data from temperature and structural integrity sensors, accurately reflecting building conditions. Fire behavior is expected to follow established patterns, with predictable fire spread and intensity based on historical data. A stable communication network for data transmission and emergency response is assumed, alongside consistent behavior of building materials under fire conditions as per known standards. The model presupposes standard firefighting protocols and effective responses from occupants and firefighters to model-generated recommendations. It does not account for external factors like weather or unforeseen environmental impacts and assumes the building's layout and structural integrity are well-documented and unchanged. The computational demands of the model are considered manageable within current technological capabilities, and it is assumed that rescue operations will align with the model's guidance. These assumptions form the basis for the model's development, aiming to enhance the effectiveness and safety of firefighting operations in dynamic fire scenarios.

Model inputs include real-time data from temperature sensors, providing a continuous feed of temperature variations and hotspots within the building during a fire. Structural safety data, which may come from various structural safety monitoring or prediction systems, inform the model about the current safety state of s structural elements. This is complemented by detailed information about the building's layout, including floor plans, material specifications, and architectural designs. Additionally, input data may also encompass the current location and the destination points of firefighting agents for path planning.

The model outputs are designed to assist in dynamic and effective firefighting strategies. The primary output is the real-time predictive structural responses, indicating potential deformations, stress points, and failure risks of various building components under fire conditions. This is closely integrated with dynamic risk maps, which visually represent the varying levels of risk throughout different parts of the building, updating in real-time as the fire progresses. Another crucial output is the adaptive rescue paths. These recommendations provide the safest and most efficient routes for rescue operations.

These outputs are helpful in enhancing the safety and effectiveness of emergency responses in fire incidents.

5.3.1 *Grid-based building layout*

The office building in question is dimensioned at 30m x 30m, embodying a labyrinthine layout with numerous pathways and potential obstacles. This configuration realistically mirrors the challenges that firefighters may encounter during actual operations. The layout of the office building, as depicted in Fig. 5-2, distinguishes between viable and non-viable areas within the structure. The black grids represent walls or columns, signifying non-viable areas that are inaccessible for occupants and firefighters. In contrast, the white grids symbolize viable spaces, areas that can be navigated by occupants and firefighters.

To facilitate the grid-based risk mapping and path planning, the building is divided into a grid of 30 x 30 cells, each representing a square meter of the building. This grid size offers a balance between computational efficiency and spatial resolution. The granularity of a one-square-meter grid cell is sufficient to capture significant spatial variations in the fire and structural conditions, while also keeping the computational demand within reasonable limits for real-time operations.

The building's only entrance and exit is located at the upper left corner of the grid. This entrance serves as the initial position for firefighters entering the building and the target destination in fire rescue scenarios. The average speed of a fully equipped firefighter is assumed to be approximately 1 m/s, which is significantly lower than the average human walking speed of 1.4m/s (Bohannon, 1997, Öberg et al., 1993). However, this speed can be significantly affected by factors such as visibility, heat, smoke density, and structural safety conditions. Therefore, the model adopts a variable speed approach, adjusting the firefighters' speed according to the conditions of each grid cell.

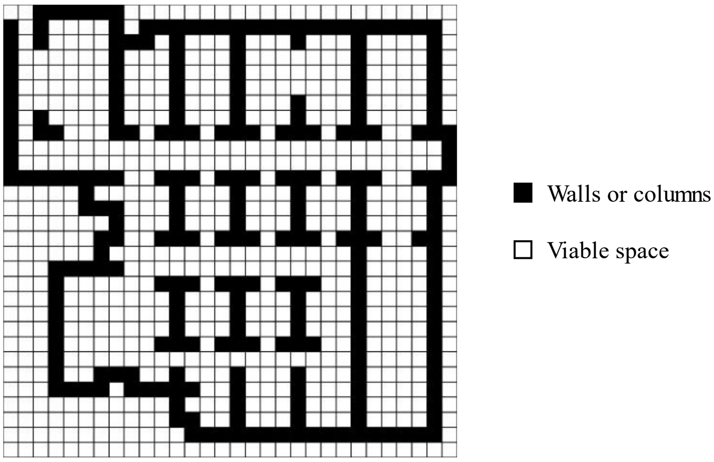


Fig. 5-2 Layout of the office building with multiple corridors

5.3.2 Multiple fire rescue scenarios

To evaluate the performance and robustness of the adaptive path planning model, a diverse set of fire rescue scenarios are established, reflecting the inherently unpredictable nature of actual building fires. These scenarios vary in several critical parameters, thereby demonstrating how the model operates under a wide range of conditions. Fig. 5-3 shows an example of a fire rescue scenario, specifying the starting point and destination of the firefighter, as well as the fire ignition location and fire spreading patterns.

The fire conditions for each scenario are determined according to multiple variables such as the fire's point of origin, its growth rate, and the specific pattern of fire spread. The point of origin is randomly selected for each scenario, representing potential fire ignition points such as electrical outlets or kitchen areas. The growth rate of the fire is manipulated to emulate both slow-developing and fast-spreading fires, thereby testing the model's adaptability to varying fire intensities. The spread pattern of the fire is also altered across scenarios, simulating a diverse range of ventilation conditions, fire suppressant availability, and building materials and their respective combustibility.

For the rescue destination, a set of viable grid locations within the office building is identified. These locations represent potential areas where occupants may be trapped during a fire, such as offices, meeting rooms, or common areas. For each scenario, a rescue destination is randomly selected from this set of viable grids. This random selection process reflects the unpredictable nature of real-world rescue operations, where the exact location of trapped occupants may not be known until the firefighters arrive on the scene.

By representing a wide range of fire conditions and rescue destinations, the scenarios allow for a thorough evaluation of the model's ability to generate optimal rescue paths under dynamic and unpredictable building fire environments.

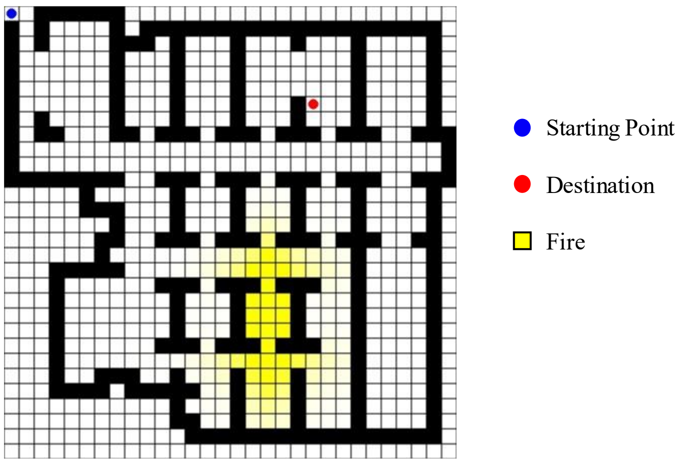


Fig. 5-3 A Fire rescue scenario with starting point, destination, and fire location

5.3.3 Dynamic risk maps

The creation of dynamic risk maps is central to the model's ability to provide real-time navigation in structural fire scenarios. These maps are constructed based on the real-time structural fire response and the associated risk of structural failure. In the general methodological framework, the structural fire response is assessed using the FEM-based structural fire analysis model, which calculates the temperature-dependent material properties and thermally induced deformations of the structural components based on the temperature distribution data from the fire simulations. The failure risk of each structural component is then evaluated by comparing the calculated strains or stresses with failure criteria. However, for this specific case study, a simplified yet effective approach is adopted for assessing the risk, i.e., critical temperature-based risk mapping. This choice is made in the interest of simplifying the risk assessment process while preserving the key features of the proposed framework. This approach focuses on the temperature of structural components, a readily available and effective indicator of structural safety under fire conditions, making it a more computationally efficient choice for real-time applications.

The risk of failure for each structural component is evaluated by comparing the calculated temperature with a critical temperature threshold. This threshold represents the temperature at which a structural component is likely to fail, with values varying depending on the type of material. For instance, a typical threshold for steel is around 550°C, beyond which the steel may experience a significant loss of strength and stiffness. An illustrative example of a dynamic risk map is shown in Fig. 5-4.

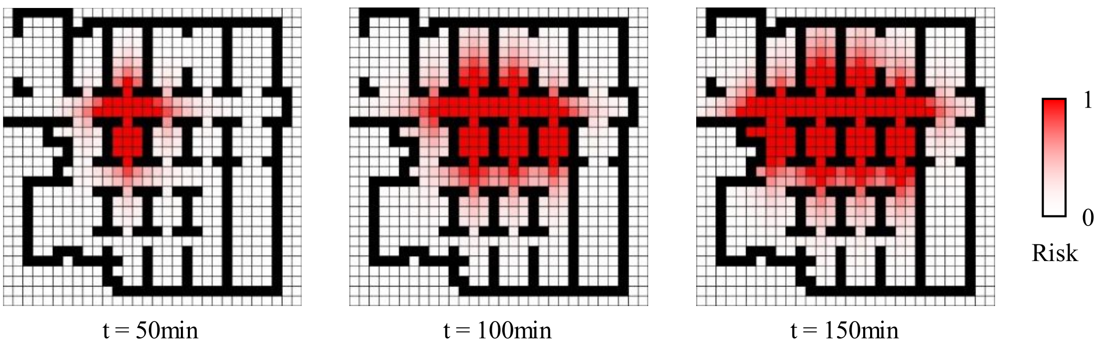


Fig. 5-4 An example of dynamic risk maps under building fire emergency

The risk map is continuously updated as the fire conditions change, providing a real-time assessment of the structural safety conditions of the building during a fire. The dynamic risk map serves as the basis for the adaptive path planning model, informing real-time navigation decisions to ensure the safety of firefighters during fire rescue operations. The adoption of the critical temperature-based risk mapping approach allows for a balance between simplicity and accuracy in real-time fire risk representation.

The effectiveness of adaptive path planning hinges on the availability of real-time or near real-time data. This ensures that the model is working with the most current information about fire progression and structural integrity. Ideally, data should be collected and updated at intervals as short as possible, typically ranging from a few seconds to a minute. This interval is contingent on the capabilities of the building's sensor and data collection infrastructure. Faster intervals provide more up-to-date information, allowing for more responsive adaptation to changing conditions. First responders should receive updates continuously or at very short intervals. This ensures that they have the latest information to guide their decisions and actions. While frequent updates are crucial, it's also important to balance this with the risk of information overload. The communication system should be designed to provide concise, actionable updates that do not overwhelm the first responders. Integrating the model with automated alert systems in firefighting equipment can help in disseminating updates efficiently. These systems can relay path recommendations and risk alerts directly to the responders' equipment.

5.3.4 Adaptive fire rescue paths

The adaptive path planning model, a significant evolution of the traditional Dijkstra algorithm, has been designed to generate the most optimal rescue paths by considering The adaptive path planning model, a significant evolution of the traditional Dijkstra algorithm, has been designed to generate the most optimal rescue paths by considering the dynamic risk map along with the current location and destination of the firefighter. The modifications made to the Dijkstra model primarily revolve around the redefinition of the cost associated with each link, incorporating risk assessments derived from the dynamic risk map.

While the original Dijkstra model calculates the cost based solely on the distance or time associated with each path, the adaptive model introduces an additional layer of complexity by considering the risk value associated with each grid cell in the path. This risk value is derived from the dynamic risk map, reflecting the time-varying structural safety condition of the building during a fire. Therefore, the cost function in the adaptive model encapsulates three factors: time, distance, and risk.

The model employs a grid-based search algorithm that is capable of dynamically responding to the ever-changing fire environment. The algorithm iteratively generates path segments intended to minimize the overall cost. The continuous updating of the risk values on the dynamic risk map allows the algorithm to adaptively respond to the changing fire conditions and adjust the path accordingly. An example of an adaptive fire rescue path suggested by the developed model is shown in Fig. 5-5.

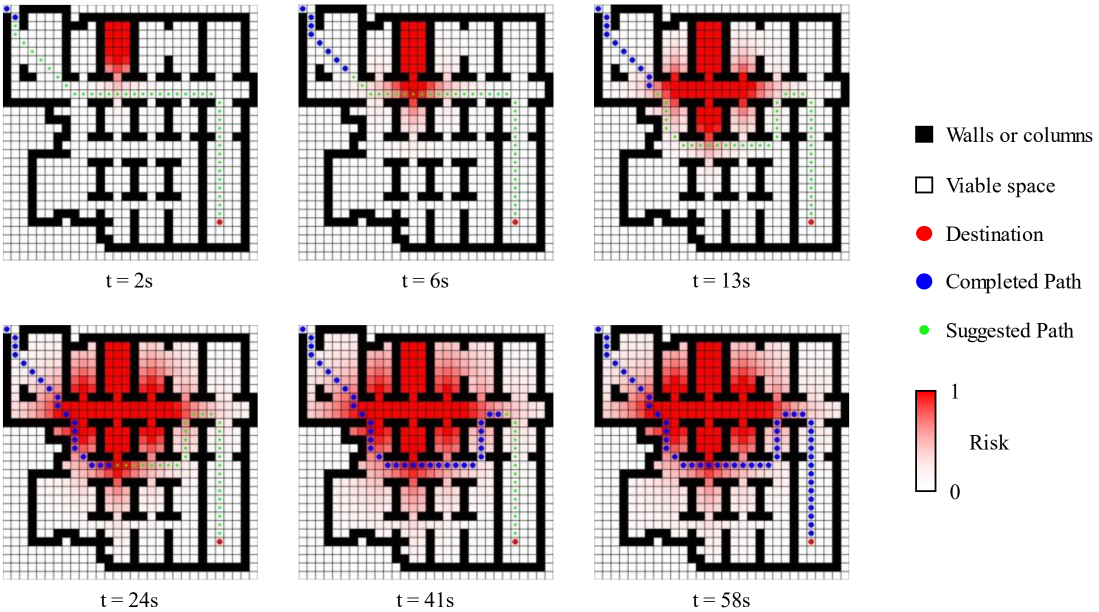


Fig. 5-5 An example of the proposed adaptive fire rescue path

When the firefighter enters the building (t = 2s, 6s), the risk value of the grids on the shortest path toward the destination is small and the model suggests the shortest path as shown in red dots. However, when the fire develops as the fire rescue task continues, the fire risk map changes. When t = 13s, the suggested path is updated to avoid high-risk areas at the cost of a longer travel distance and travel time. Finally, the firefighter is expected to arrive at the destination by 58s with less exposure to high-risk areas. Generally, in the face of high-risk areas, the model guides the firefighters towards alternative routes that, while potentially longer in terms of travel distance, greatly reduce the duration of exposure to hazardous conditions. The performance of this adaptive model is subsequently evaluated by contrasting the adaptive paths with the non-adaptive paths suggested by the traditional Dijkstra algorithm.

5.4 Case Results and Discussions

This section presents the results and analysis of the case study carried out to test the adaptive fire rescue path planning model in comparison to the non-adaptive model. It also explores the impact of the prediction accuracy of the risk map on the model's performance. Finally, the section concludes with a discussion of the limitations of the current model and the prospects for future research and improvement. These investigations serve to demonstrate the model's resilience to uncertainties and its adaptability to varying building structures, emphasizing its potential value in real-world fire rescue operations.

5.4.1 Comparison of the adaptive and non-adaptive model

Fig. 5-6 presents a comprehensive comparison of the paths recommended by the adaptive and non-adaptive models during the 50 tested fire rescue scenarios. While the adaptive model is designed to consider dynamic risk factors, non-adaptive model traditionally operates based on static path costs, typically distance or time, without intrinsic consideration of changing risk factors. The adaptive model, which incorporates real-time risk information into path planning, frequently recommended paths that were strategically designed to circumvent high-risk areas. Despite these paths being slightly longer, with an average of 35.63m, they were effective in significantly reducing the exposure of firefighters to potential structural failure. Specifically, the average exposure was reduced by an average of 1.60s, which represents a notable 45.45% reduction compared to the non-adaptive model. In the context of fire rescue operations, even such marginal time reductions in high-risk exposure durations can be critical, where seconds can differentiate between safe extraction and severe injury, or even loss of life (Khan et al., 2022, Chou et al., 2019). This strategic deviation effectively balances a minor increase in distance (12.94% longer) against substantial safety benefits. The non-adaptive model, which does not account for real-time risk information, tends to recommend shorter paths, with an average distance of 31.55m.

However, these shorter paths often lead firefighters through areas with a high risk of structural failure, resulting in an average exposure time of 3.52s, during which their safety could be severely jeopardized.

This quantitative result reveals a key strength of the adaptive model: it strikes a balanced consideration between path length and safety risk. While the non-adaptive model tends to prioritize shorter distances, it overlooks the potential hazards along these paths. On the other hand, the adaptive model factors in the dynamic risk map and adjusts the path accordingly, even if this results in a slightly longer path. This willingness to accept longer paths for the sake of safety demonstrates the model's emphasis on risk avoidance. The reduction in exposure to high-risk areas has significant implications for fire rescue operations. It not only enhances the safety of firefighters but also increases the likelihood of successful rescue operations, as encountering structural failure during a rescue operation could delay or even halt the operation entirely. Therefore, the adaptive model, with its ability to dynamically adjust the rescue path based on real-time risk information, demonstrates considerable potential in enhancing the effectiveness and efficiency of fire rescue operations.

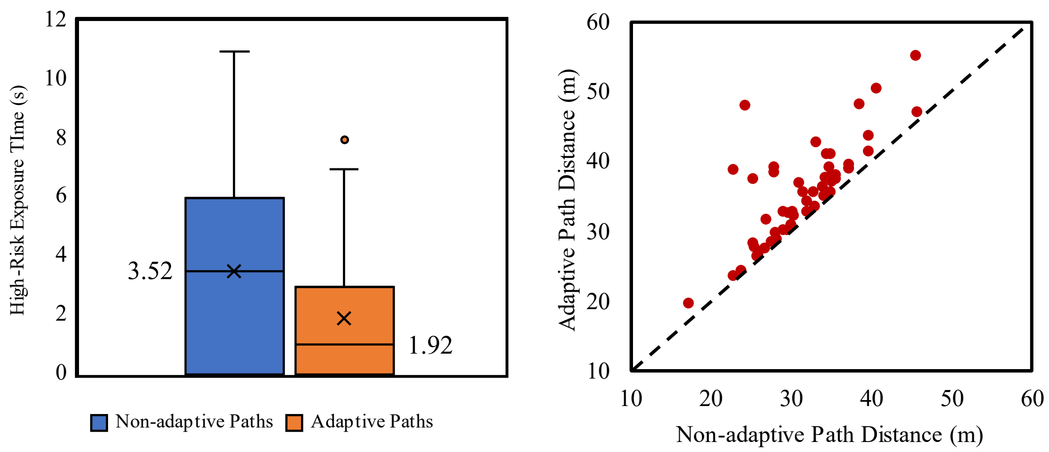


Fig. 5-6 Comparison between adaptive and non-adaptive path planning model

The adaptive path planning model is designed for high-speed execution. The model can process incoming data and update path recommendations within a matter of seconds. This quick turnaround is critical for adapting to rapidly changing conditions in a fire. In tests conducted during the development of the model, the average processing time for generating updated paths was found to be 0.3 second. This speed ensures that firefighters receive near real-time information for navigation and strategy adaptation.

5.4.2 The impact of prediction accuracy of the risk map

In real-world building fire scenarios, data gathered from pre-installed temperature and smoke sensors may not accurately reflect the dynamic conditions due to potential sensor errors, unexpected sensor failures, and other unforeseen complications. It is, therefore, crucial to understand how these uncertainties might affect the performance of the proposed adaptive path planning model. This study introduced varying levels of noise into the risk map (i.e., 0%, 5%, 10%, 15%, 20%, 25%) to simulate these uncertainties and examined the impact on the model's performance with 50 additional simulations of fire rescue scenarios.

As shown in Fig. 5-7, the adaptive model demonstrates robust performance even in the presence of noise. The distance of the suggested path remains similar, while the exposure time to high-risk areas starts to increase slowly as the noise level increased. The detailed comparisons among various noise levels are listed in Table 5-1. The exposure time to high-risk areas is where the adaptive model significantly outperforms the non-adaptive model. As the noise level increases, the exposure time of the adaptive model increases gradually, from 1.56s at 0% noise to 2.22s at 25% noise, which represents a 42.31% increase. Still, even at 25% noise, the exposure time of the adaptive model is 40.48% less than that of the non-adaptive model. On the other hand, the distance of the rescue path suggested by the adaptive model remains relatively stable across different noise levels, fluctuating from 35.24m at 0% noise to 32.28m at 25% noise. This change represents an 8.41% decrease in path distance as the noise level increases from 0% to 25%. The non-adaptive model suggested a relatively shorter path with a consistent distance of 31.07m.

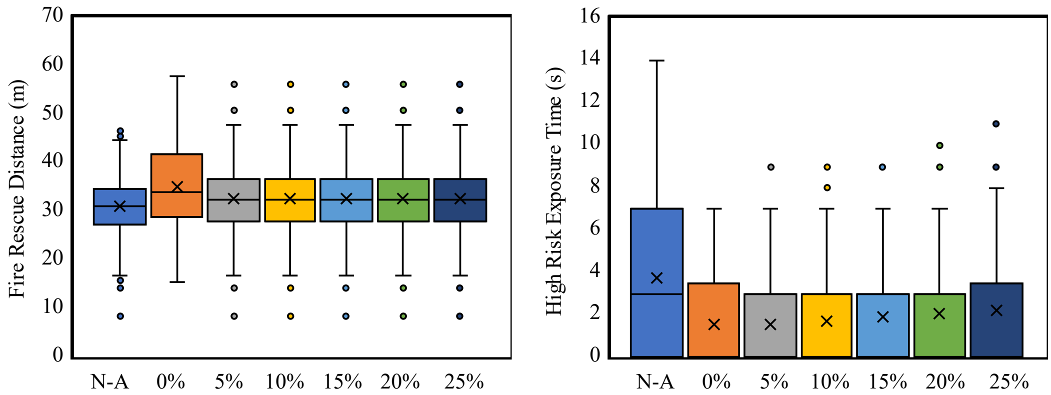


Fig. 5-7 Model performance under different noise levels

This quantitative analysis further demonstrates the adaptive model's robustness to uncertainties in risk prediction. Despite the increase in noise levels, the adaptive model consistently ensures that the firefighters are exposed to high-risk areas for a significantly shorter duration than the non-adaptive model. However, the rise in exposure time with increasing noise levels underscores the importance of minimizing uncertainties in real-world applications to maximize the model's benefits.

From the analysis of Table 5-1, the distance of the rescue path suggested by the adaptive model remains relatively stable across different noise levels, fluctuating from 35.24m at 0% noise to 32.28m at 25% noise. This change represents an 8.41% decrease in path distance as the noise level increases from 0% to 25%. On the other hand, the non-adaptive model suggested a relatively shorter path with a consistent distance of 31.07m.

Table 5-1 Rescue distance and high-risk exposure time

Model	N-A Model	Adaptive model					
Noise Level	/	0%	5%	10%	15%	20%	25%
Distance (m)	31.07	35.24	33.63	33.18	32.78	32.34	32.28
Exposure Time (s)	3.73	1.56	1.56	1.71	1.88	2.05	2.22

5.4.3 Discussions on limitations and prospects

The proposed adaptive path planning model demonstrates significant potential in advancing fire rescue operations in dynamic building environments. It offers the ability to provide real-time risk assessments and tailor rescue paths that balance both efficiency and safety. Despite the promising results, the model can still be improved in the following areas.

The risk mapping in this chapter primarily focuses on real-time structural fire safety, thereby addressing one of the major hazards faced by firefighters during fire rescue operations. However, this focus overlooks other equally crucial factors contributing to risk in fire environments, such as elevated air temperature and the presence of concentrated toxic gases. Prolonged exposure to high temperatures and hazardous gases can result in heatstroke, asphyxiation, or other life-threatening conditions for firefighters. Future research could aim to incorporate these elements into the risk mapping process, providing a more holistic view of the hazards present in the fire environment. This would require the integration of additional real-time data, such as air temperature and gas concentration levels, which could be obtained through advanced sensor technologies or predictive models.

The applicability of the proposed adaptive path planning framework has been tested only in single-story buildings, a common setting but one that does not encompass the full range of possible fire environments. Many fire rescue operations occur in multi-story buildings where the complexity of the environment is significantly increased due to the vertical dimension. Fire propagation and smoke spread can behave differently, and the structural stability of each floor can be interdependent. Future studies should consider extending the model to multi-story buildings, which would undoubtedly increase its utility in real-world fire rescue scenarios. This extension would entail addressing additional challenges, such as modeling the inter-floor fire spread and structural integrity, as well as the movement of firefighters and occupants on stairways or elevators.

Furthermore, the current model assumes that both the current location of the firefighting agent and the destination (such as the location of trapped occupants or an exit) are pre-identified. However, in many real-world scenarios, firefighters may have to conduct a global search without a specific destination in mind. Such a situation would require the model to generate paths that maximize the search coverage while minimizing the risk exposure. This capability is currently not supported by the model, representing an important area for future development. Potential solutions could involve the use of advanced search algorithms or machine learning techniques that can adaptively learn and respond to the dynamic and uncertain nature of fire environments.

While the proposed model represents a significant advancement in the field of fire rescue path planning, the limitations identified herein offer ample opportunities for future research. Addressing these limitations would not only enhance the model’s capability and applicability but would also contribute to the broader goal of improving the safety and effectiveness of fire rescue operations. Despite these challenges, the use of automation and artificial intelligence in fire rescue operations remains a promising area for future exploration, and the lessons learned from the development and application of the current model could provide valuable insights for these future efforts.

5.5 Chapter Summary

This chapter introduces an innovative adaptive path planning model, designed to optimize rescue paths in dynamic building fire environments by minimizing the overall cost in terms of time, distance, and risk. The proposed model utilizes a dynamic risk map that incorporates real-time structural safety conditions and employs a grid-based search algorithm that adapts to these conditions to generate efficient and safe rescue paths. The findings from the case study, involving a 30m x 30m single-story office building and 50 random fire rescue scenarios, can be summarized as follows:

1. The model successfully suggested rescue paths that were adaptive to the dynamic risk map of the environment. Instead of opting for the shortest path, it strategically avoided paths with a high risk of structural component failure or collapse, demonstrating an advanced capability of incorporating real-time risk information into decision-making.
2. The adaptive model demonstrated a significant advantage in reducing the duration in which firefighters would have been exposed to high-risk areas with severe damage or worse. Specifically, the exposure time was decreased by 45.45% compared to paths suggested by the non-adaptive model. This is a critical achievement in ensuring the safety of firefighters during fire rescue operations.
3. Although the adaptive model's paths resulted in an average of 12.94% longer travel time compared to the traditional non-adaptive paths suggested by the Dijkstra algorithm, the safety benefits it provides substantially outweighs this marginal

increase in travel distance. This underscores the model's effectiveness in striking a balance between operational efficiency and safety.

4. Demonstrating its resilience to uncertainties in risk prediction, the adaptive model remained robust even under a noise level of 25% in the risk map. Despite noise in the data, the model consistently suggested rescue paths with substantially lower risk exposure durations than the non-adaptive model.

This research underscores the importance and effectiveness of an adaptive approach to path planning in dynamic fire environments. The findings indicate that the proposed model could significantly enhance the safety and efficiency of fire rescue operations. Future studies could further refine and expand this model to consider more complex building structures and fire scenarios.

CHAPTER 6 CONCLUSIONS AND FUTURE WORKS

6.1 Conclusions

This research has laid the foundation for a novel and effective approach towards real-time structural fire response prediction and adaptive fire rescue path planning in dynamic building fire environments. Leveraging the power of Machine Learning (ML), Finite Element Method (FEM), and Computational Fluid Dynamics (CFD), this research has developed frameworks that not only contribute to the understanding of fire behavior in structures but also provide practical tools for efficient and safe firefighting operations.

In the realm of real-time structural fire response prediction, the findings underscore the utility and efficiency of employing a FEM-based ML framework. Integrating ML models and FEM techniques, this framework addresses the gaps left by the traditional FEM approach, which is often time-consuming and unsuitable for real-time applications. The developed framework demonstrates the potential of ML models to predict real-time structural displacement with high accuracy, robustness, and computational efficiency, even in the presence of noise in temperature data.

To further enhance the structural fire response prediction framework, CFD simulations are incorporated with FEM. This CFD/FEM-based ML approach allowed for a more comprehensive capture of the complex, dynamic interactions between fire-induced temperature fields and structural deformation. It demonstrated a higher level of precision and reliability in predicting real-time and future structural responses to fire, contributing to firefighting teams' decision-making and strategic planning.

On the adaptive fire rescue path planning front, this research introduced a dynamic risk map-based model that suggested optimal rescue paths considering not only the shortest distance but also the evolving structural safety conditions during a fire. The model successfully recommended paths that avoided high-risk areas and minimized firefighters' exposure to these areas, significantly enhancing their safety during fire rescue operations. Despite a slight increase in travel time compared to traditional non-adaptive paths, the model's advantage in terms of safety far outweighs this nominal trade-off. It also exhibited robustness against uncertainties in risk prediction, further testifying to its potential application in real-life fire scenarios.

These research outcomes not only offer theoretical contributions by advancing our understanding of the dynamics of fire propagation and fire-induced structural degradation but also present practical solutions for real-time fire response prediction and adaptive path planning in dynamic fire emergencies. Our findings open new avenues for future research in structural fire safety, smart firefighting, and emergency response planning. Moreover, the developed frameworks serve as a basis for practical tools aimed at enhancing firefighting operations' safety and effectiveness and minimizing risks to firefighters during building fires.

6.2 Contributions

This research makes significant theoretical and practical contributions to the fields of structural fire response prediction, adaptive fire rescue path planning, and dynamic building fire environments. These contributions lie in the intersection of FEM, CFD, and ML techniques.

6.2.1 Theoretical contributions

The first theoretical contribution of this thesis is the development of a novel, data-driven methodology for real-time structural fire response prediction. This methodology leverages the power of FEM, CFD, and ML, combining the strengths of these different techniques to create a more robust and efficient model. The integration of these methods is an innovative step that offers valuable insights and advancements in the theoretical understanding of structural fire safety.

The second theoretical contribution lies in the development of an adaptive fire rescue path planning system. This model considers the dynamics of building fire environments and adapts to changing conditions in real-time. By integrating these dynamic factors into the path planning process, this thesis advances the theoretical knowledge in the field of smart firefighting and emergency response planning.

Additionally, this research carries out a comprehensive literature review and gap analysis in the areas of fire dynamics, structural analysis, and machine learning applications. The identification of areas that require further investigation offers a significant contribution to shaping future research directions in these intersecting fields.

6.2.2 Practical contributions

The practical contributions of this research lie in the development of robust and efficient tools for firefighting teams during building fire emergencies. The data-driven methodology for real-time structural fire response prediction has significant practical applications. It provides a framework for accurately predicting fire dynamics and structural degradation patterns, which can inform strategic decisions during firefighting operations.

Moreover, the adaptive fire rescue path planning model is of paramount practical importance. By considering the dynamic nature of building fire environments and providing real-time adjustments, it significantly enhances the safety and effectiveness of firefighting operations. This model reduces the risks to firefighters during building fires and has the potential to improve emergency response outcomes.

Furthermore, these models serve as a prototype for practical tools to enhance firefighting operations. The integration of FEM, CFD, and machine learning techniques not only makes significant theoretical advancements but also provides practical solutions that could have a profound impact on structural fire safety, smart firefighting, and emergency response planning.

In addition, the CFD and FEM models developed in this study can generate detailed data under various fire scenarios. This data can provide numerical evidence to support or complement existing fire resistance requirements in building codes. The adaptive path planning model, which considers dynamic fire and structural conditions, might inspire new guidelines or recommendations in building design and emergency evacuation protocols, enhancing overall fire safety.

6.3 Future Works

The current research makes substantial theoretical and practical contributions in developing a data-driven methodology for real-time structural fire response prediction and adaptive fire rescue path planning in dynamic building fire environments. Despite these advancements, there are avenues for future research that would further improve the theoretical model and its practical applicability.

6.3.1 Enhanced fire and structural response models

To enhance the authenticity and precision of structural fire response simulations, the future research could aim to refine the current fire simulation techniques by accounting for more complex and spatially varying temperature distributions caused by aspects such as ventilation conditions, the location and size of the fire, and the interaction of the fire with different materials. These improvements could lead to more accurate predictions of structural behavior under fire conditions and enhance the reliability of the safety assessments. Moreover, the performance and predictive accuracy of the FEM-based Machine Learning (ML) models could be bolstered by incorporating advanced ML techniques. The current study only considers temperature as the main independent variable affecting the real-time vertical displacement of a particular beam. However, various other factors could influence structural response under fire conditions. These may include material deterioration due to high temperatures, real-time varying load conditions, initial imperfections in the structure, and the heat history of the structural elements. By developing ML models that account for these additional variables, more accurate predictions of real-time structural responses under fire conditions could be achieved. This would require the collection and processing of a broader range of data but could significantly enhance the reliability and effectiveness of real-time structural fire response prediction tools.

On the other hand, ML models are highly effective in interpolation tasks – making predictions within the range of the training data. The ML models are generally trained on a diverse and extensive dataset generated from various fire scenarios, ensuring a broad and representative range of data for interpolation. This allows the models to accurately predict structural fire responses within the scope of conditions similar to those in the training set. However, extrapolation, or making predictions beyond the range of the training data, is inherently more challenging for ML models. The accuracy of such predictions can be uncertain, as the models are venturing into unexplored territory. In the context of structural fire response prediction, the need for extrapolation is somehow lowered by ensuring the comprehensiveness of the training dataset. More attempts could be made to explore the extrapolation capacity of ML models.

6.3.2 Expanded applicability and realism in fire rescue path planning

Future research could aim to develop a more comprehensive risk mapping process by incorporating additional factors, such as elevated air temperatures and the presence of concentrated toxic gases. Extending the adaptive path planning framework to multi-story buildings is also crucial, as this will enhance the model's utility in real-world fire rescue scenarios. Addressing the complexities of multi-story buildings, such as inter-floor fire spread and structural integrity, as well as the movement of firefighters and occupants through stairways or elevators, is essential. Additionally, the model could be advanced to support scenarios where firefighters need to conduct global searches without a pre-defined destination. A detailed fire incident scenario could be considered to serve as a comprehensive example illustrating the potential application of the models in a real-world context, and will help readers better understand their practical utility in fire incidents.

6.3.3 Advancements in augmented reality for fire emergency support

Building upon the methodologies developed in this study, there is an opportunity to leverage Augmented Reality (AR) technology to enhance situational awareness and support decision-making in fire emergency operations. The development of an AR-based real-time fire emergency operation support system is suggested. Such a system could integrate the structural safety information and rescue path navigation obtained through the methodologies developed in this study and display them through an AR firefighting helmet. This approach utilizes AR's ability to recognize the real-world environment, providing critical information directly in the firefighter's field of view. The development of this prototype would primarily involve instance segmentation to detect and locate structural components and rescue paths, and data visualization techniques to effectively communicate this information in real-time.

By undertaking these avenues for future work, there is an opportunity to build upon the foundational research presented in this study to develop more advanced, efficient, and practical tools and methodologies for firefighting operations in building fire emergencies. The eventual goal would be to significantly enhance the safety and effectiveness of firefighting operations and ultimately contribute to saving lives and protecting property.

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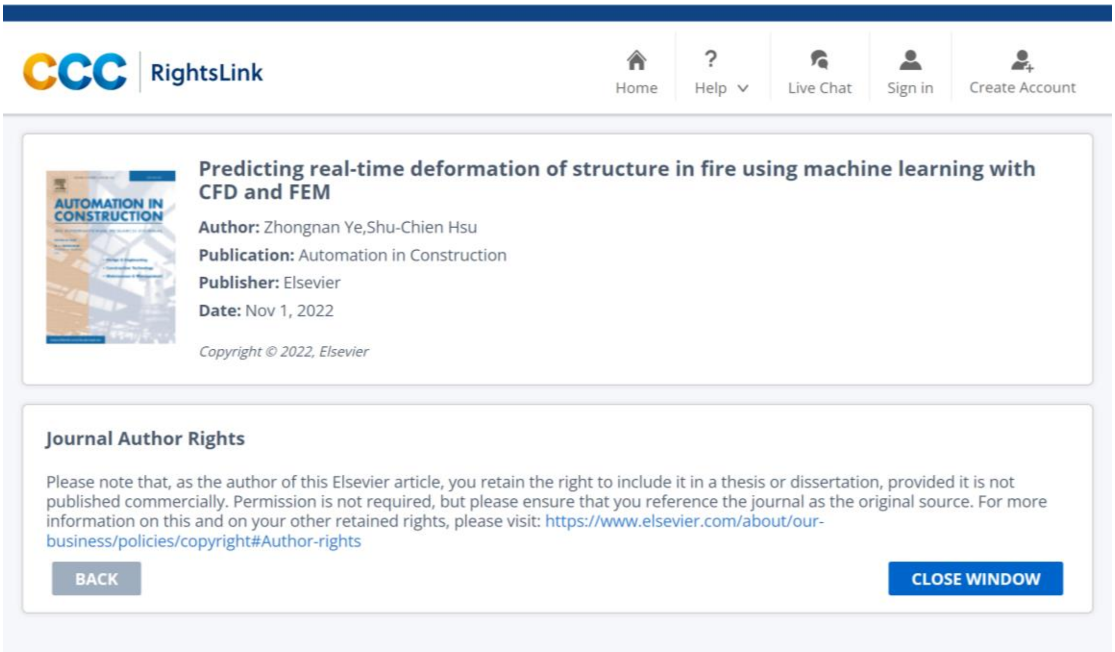

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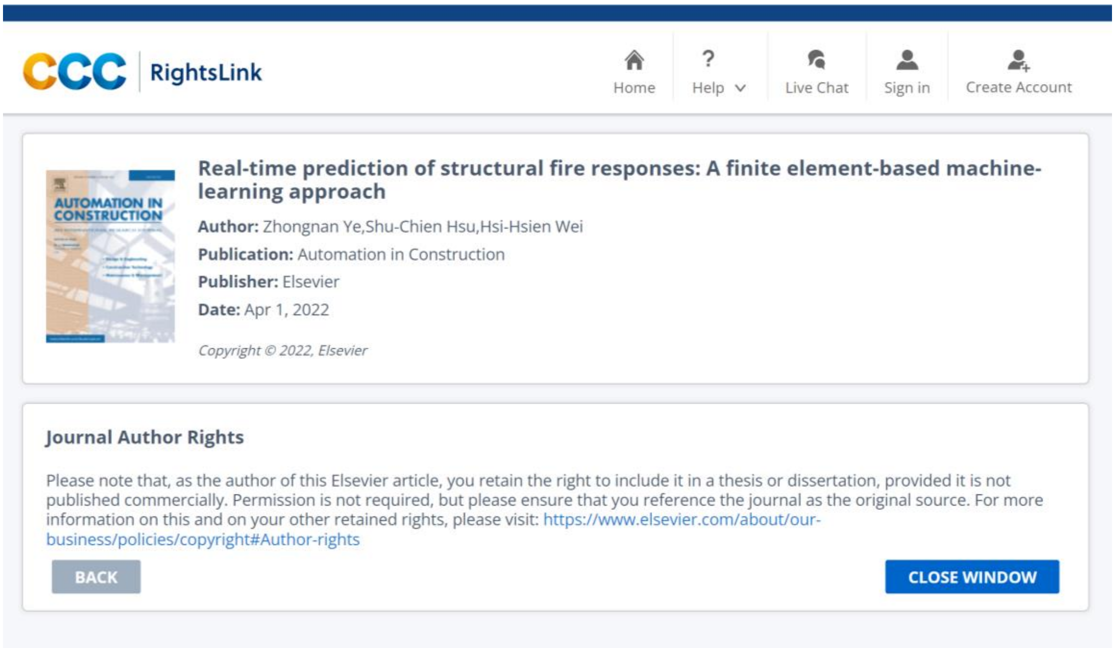

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