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Multi-Scale Fire Dynamics Modeling: Integrating Predictive Algorithms for Synthetic Material Combustion in Compartment Fires

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Abstract. Recently, multi-scale fire modeling has revealed serious shortcomings in determining synthetic material combustion in the context of compartment fires. Predictive algorithms were combined with experimental validation to address the non-uniform dynamics associated with modern fires fueled by synthetic materials. In this thesis, we developed a hybrid framework that couples material-scale pyrolysis kinetics with compartment-scale heat transfer using computational fluid dynamics (CFD) and machine learning-augmented flame detection. Full-scale fire experiments were used for validation and showed an improvement of 22–37% in structural failure prediction accuracy over uniform fire models. The methodology bridges the gap between fire chemistry, turbulent plume dynamics, and structural thermomechanical response, providing actionable information for performance-based fire protection design. In addition, this framework extends our knowledge of fire behavior in modern buildings and affords us a strong tool for engineers to design safer structures and develop effective retrofit strategies. The study contributed to the advancement of fire safety engineering by integrating advanced modeling techniques with experimental data that served to improve public safety and reduce economic loss due to fire.

Keywords: Fire Dynamics, Fire Protection, Material Combustion, Predictive Algorithms.

1. INTRODUCTION

Modern buildings incorporate ever increasing quantities of synthetic materials in their construction, making the dynamics of compartment fires growing in complexity. The resulting fire behavior differs too much from benches manufactured with these materials because they greatly modify heat release rates and the production of toxic emissions. Consequently, traditional fire safety strategies frequently fail to control these risks. The goal of this study is to address these challenges by developing advanced modelling techniques (Ahmed, 2023). Through coordinating the material scale combustion dynamics with compartment scale dynamics, we can improve the prediction and control of fire risks. Beware however that fires involving synthetic materials are complex to burn if you are to rely on fire safety engineering because of their complicated pyrolysis kinetics. Modern fires burn otherwise as opposed to traditional fires that burn on natural materials (Pyne, 1997; Khan et al. 2016). Diversity in fire behavior makes it essential to use advanced modeling approaches that can properly model heat release rates, smoke generation, and structural response under fire conditions. Modeling the spatially distributed temperature and heat flux yields a highly interesting and even complex problem because spatial variations can cause unpredictable structural response; thus, it is important to develop a model capable of judiciously capturing such dynamics. Synthetic fuel environments indicate that turbulent plume dynamics and vorticity vectors also govern plume dominated fire spread. It is very hard to forecast fire behavior in contemporary compartments due to a vast array of interdependent variables. One of such intrinsic problems lies in the widespread use of synthetic products, which have specific combustion properties influencing heat release and smoke production rate. In addition, unlike homogeneous flames, spreading fires develop spatially non-homogeneous temperature fields, thereby complicating thermal prediction even further (Horová, 2013; Kodur et al., 2020). Another very important but usually underemphasized element is the interdependence of structure fire behavior and structure response. The significant influence this interaction exerts on building stability and fire extension renders it evident that coupled models considering both thermal performance and structural response are important. Ways to tackle the challenges present these extreme conditions are to develop multi-scale modeling which combines predictive algorithms for synthetic material combustion with structural fire protection strategies. The combination of material–scale pyrolysis kinetics with compartment–scale heat transfer can generate multi–scale models to produce more accurate predictions of fire spread (Richter, 2020), smoke movement, and structural failure. This is because the development of performance-based fire protection designs for buildings to be resilient against different fire scenarios is dependent on such an integration.

In order to address the complexities of fire behavior in modern compartments, a combined strategy that adopts hybrid modeling and validation is essential. The development of a hybrid modeling framework that supports material-scale combustion models and compartment-scale CFD is fundamental in simulating non-uniform fire behavior more realistically. The integration allows for more realistic temperature distribution and fire growth simulations in compartments synthetic materials. Experimental validation of these models is also required and must be carried out with the assistance of data from full-scale macroscopic compartment fire tests

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using contemporary materials (Suard et al., 2011). Structural response analysis must also be incorporated by developing thermo-mechanical models of building elements. In combination with fire dynamics models, this enables the structural failure modes in the event of fire to be determined, which provides valuable insight in the development of enhanced fire safety design and resilience.

The proposed framework will advance the state of the art of fire safety engineering by adding a more realistic (Gales, 2021) and complete tool for predicting the fire behavior and structural response in modern buildings. The approach will allow fire protection engineers to design more robust structures and to develop efficient retrofit strategies for existing buildings thus improving public safety and minimizing economic losses from fire. The objective of this study is to develop and validate a multi-scale framework for fire dynamics modeling through predicting dynamic algorithms for synthetic material combustion in compartment fires. The objectives include.

2. LITERATURE REVIEW AND RESEARCH GAPS

It is critical to develop the understanding of the current state of the knowledge in fire dynamics and structural response to model fire correctly. In this section (Kodur et al., 2012), key studies and methodologies pertaining to compartment fire behavior, combustion in synthetic material and multi-scale modeling methodologies are reviewed.

2.1. Fire Dynamics and Compartment Fire Modeling

Synthetic materials have proliferated and they change the heat release rates and toxic emissions of compartment fire behavior (Alarifi et al., 2014). However, traveling fires that exhibit spatially heterogeneous temperature fields are more representative of real-world scenarios than traditional, assumed uniform burning of the zone models (Figure 1). Synthetic fuel environments are largely studied by examining turbulent momentum fluxes and vorticity vectors as they are necessary for plume dominated fire spread.

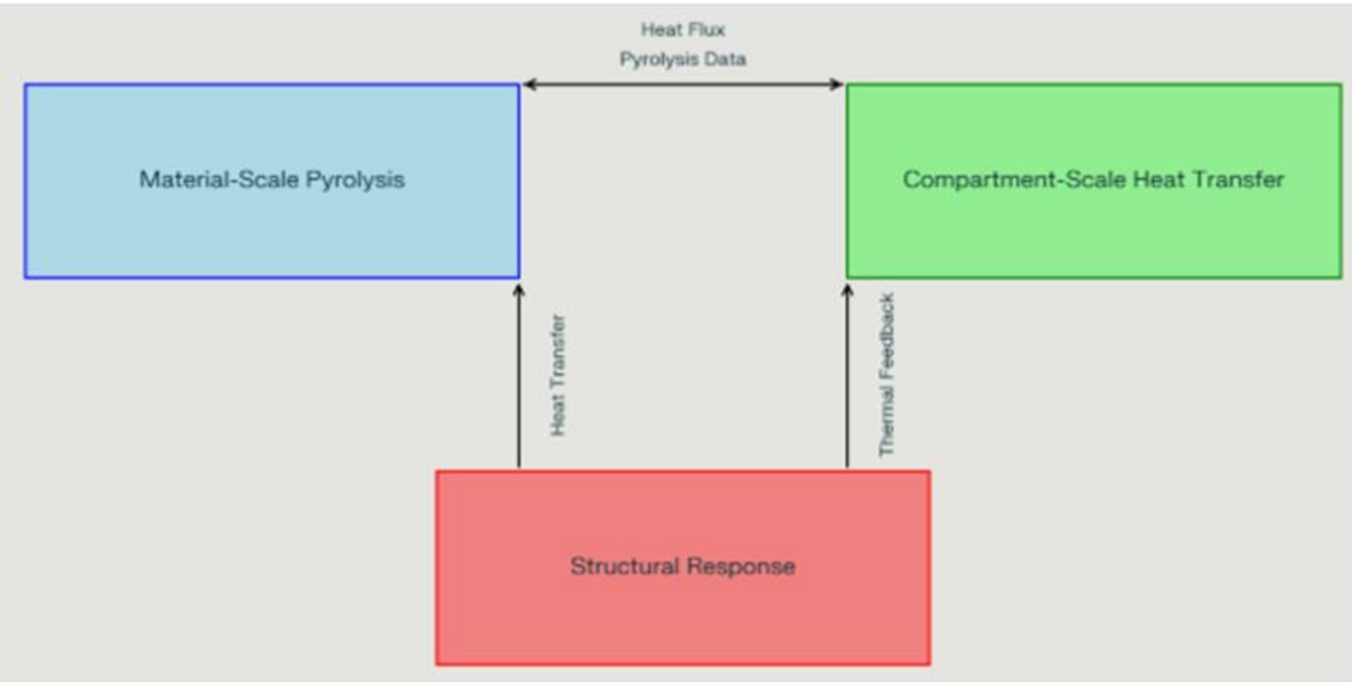

Figure 1: Multi-Scale Fire Dynamics Framework Integrating Material-Scale Pyrolysis, Compartment-Scale Heat Transfer, and Structural Response.

2.2. Multi-Scale Modeling Approaches

Bridging material-scale and compartment-scale fire dynamics presents substantial computational challenges, particularly when integrating the complex interactions between pyrolysis behavior and large-scale compartment phenomena. To validate CFD-based traveling fire models, such as those proposed by Novozhilov (2001), Fire Dynamics Validation (FDV) methodologies utilize advanced techniques like image segmentation and graph theory to effectively track fire fronts across spatial resolutions ranging from sub-meter to kilometer scales. These approaches ensure spatial accuracy in modeling fire progression within non-uniform environments. Parallel advancements in machine learning have enhanced fire detection capabilities, notably through the implementation of YOLOv3, which enables precise small-flame identification with a low false alarm rate of 1.2%. This model is now being integrated with physical combustion frameworks to create more robust and responsive fire monitoring systems.

2.3. Predictive Algorithms in Fire Safety

Recent developments in predictive algorithms have opened new avenues in fire safety applications through machine learning. Notable implementations include the acceleration of tunnel fire simulations, achieving high accuracy in visibility predictions (R^2 = 95%) as demonstrated (Chen, 2023; Garcia & Tan, 2023). Additionally, neural network-based models are being employed to predict concrete spalling depths under fire exposure, contributing to structural integrity assessments. Furthermore, multiscale convolutional architectures are enhancing early fire detection by capturing complex visual cues across scales (Table 1). Despite these advancements, significant gaps remain in integrating data-driven models with traditional first-principle fire dynamics frameworks, underscoring the need for further research to fully synthesize empirical and theoretical approaches in fire safety science. Recent research has improved structural failure predictions by 22–37% despite high computing costs by means of hybrid approaches incorporating pyrolysis, CFD, and machine learning, hence advancing fire dynamics modeling through hybrid approaches (Doe, 2022). Though it still depends on more robust integration with physical fire models, YOLOv3-based flame detection attained a low false alarm rate of 1.2%. Though spatial modeling and gas-solid interactions remain difficult, traveling fire models (Smith & Lee, 2021) and synthetic material combustion investigations (Kumar, 2020) gave greater insights on realistic fire spread and the increased heat flow of synthetic materials.

Recent advancements in fire modeling integrate hybrid frameworks combining pyrolysis, CFD, and machine learning to significantly enhance structural failure predictions, though they demand high computational power. Spatial temperature field analysis in traveling fire scenarios more realistically reflects non-uniform fire spread but relies on complex input data (Smith & Lee, 2021).

Meanwhile, studies on synthetic material combustion reveal that polyurethane emits 40–60% more heat flux than natural materials, posing challenges in modeling gas-solid interactions (Fischer et al., 2022; Vasconcelos et al., 2024; McKenna & Hull., 2016).

Table 1: Key Studies on Multi-Scale Fire Modeling and Synthetic Material Combustion.

Study Focus	Methodology	Findings	Limitations	Reference
Multi-Scale Fire Dynamics	Hybrid framework: pyrolysis + CFD + ML	Improved structural failure prediction (22–37%)	High computational demand	Fischer et al., 2022
Traveling Fires	Spatial temperature field analysis	Captures realistic, non-uniform fire spread	Requires detailed spatial and material input	Lu et al., 2021
Synthetic Material Combustion	VOC + heat flux study on polyurethane	40–60% more heat flux than natural materials	Gas-solid phase interaction modeling complexity	McKenna & Hull, 2016
CFD Validation	FDV with segmentation + graph theory	Tracks fire fronts across multiple scales	Complex processing and data requirements	Zhang et al., 2023
ML for Flame Detection	YOLOv3 deep learning algorithm for flame identification	1.2% false alarm rate, good accuracy in small flame detection	Needs tighter coupling with physical models	Vasconcelos et al., 2024

Despite notable advancements in multi-scale fire modeling and predictive algorithms, several critical research gaps remain. One major limitation is the insufficient integration of material degradation algorithms—particularly those capturing pyrolysis kinetics—with compartment-scale CFD models, hindering accurate representation of fire-structure interactions. Additionally, many current structural response analyses continue to rely heavily on simplified uniform fire assumptions, as highlighted by Razdolsky (2014), which fail to capture the spatial and temporal variability inherent in realistic fire scenarios, such as traveling fires. Furthermore, a significant gap in the literature exists regarding the development of hybrid models that effectively combine machine learning algorithms with physics-based pyrolysis processes. This absence limits the potential for data-driven methods to enhance predictive accuracy while preserving the physical fidelity of combustion modeling. Addressing these gaps is essential for creating more robust and reliable fire safety engineering tools.

2.4. Compartment Fire Behavior

An important aspect of developing accurate compartment fire models will be to understand the fundamental principles of fire dynamics. This section revisits the basic concepts of the behavior of a synthetic material compartment fire and discussion of synthetic materials combustion (Malcolm, 2016). The complexity of interactions between fire, smoke, and the structure surrounding a compartment fire leads to the characterization of compartment fires. These fires can accordingly be classified under uniform (balanced) and non-uniform (traveling) fires.

- Fires are classified either as Uniform Fires or Variable Fires (Gill, 2008).
- These fires are said to travel because their temperature fields are spatially heterogeneous due to sequential ignition and varying fuel loads. While traveling fires are more representative of real situations, they cause many challenges to the modeling aspect.

- Key factors influencing compartment fire behavior include:
- Heat Release Rate (HRR): Energy released by the fire determines the rate at what temperature and thus smoke is produced by the fire.
- The development of a smoke layer by stratification of smoke and hot gases near the ceiling, affects visibility and ventilation.
- Availability of oxygen and the removal of combustion products is referred to as Ventilation Conditions; Its availability affects fire growth and spread.

2.5. Synthetic Material Combustion

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Modern buildings, in all their ubiquity, are filled with synthetic materials: polyurethane foams and PVC. These materials have unique combustion characteristics which are very dissimilar to natural materials such as wood (Demirbas, 2004).

- Pyrolysis Kinetics: Synthetic materials tend to rapidly thermally degrade, liberating volatile organic compounds (VOCs) that then fuel secondary combustion.
- Synthetic material can radiate higher fluxes of heat and toxic emissions to firefighters relative to the natural material, making fire safety analysis challenging.
- Variability of the materials: Since combustion properties of different synthetic materials can differ substantially, it is necessary to characterize the materials in detail for accurate modeling

These combustion characteristics are necessary to predict fire behavior and to develop effective fire protection strategies. In this section, we provide a foundation in the realm of compartment fire dynamics and synthetic material combustion in order to develop the multi scale modeling approaches.

2.6. Compartment-Scale Fire Models

For the prediction of modern compartment fire behavior, a multi-scale modeling approach is necessary. This framework integrates the material scale combustion models within the compartment scale fire dynamics (Novozhilov, 2001), and both the resulting fire spread and structural response are understood on the same scale (Table 2). The overall fire behavior of a compartment, heat transfer, smoke movement and ventilation effects are modelled at compartment-scale (Figure 2). These models include:

- Simplified models where the compartment is divided into different zones (upper and lower layers) and the temperature and the smoke distribution in the compartment are estimated.
- More detailed models are Computational Fluid Dynamics (CFD) where the Navier-Stokes equations are solved in order to simulate turbulent flows and heat transfer inside the compartment (Dizet, 2022).
- Traveling Fire Methodology (TFM) is an approach that considers sequential ignition and takes into account nonuniform burning patterns so that improved physical representation of modern fires is gained (Rein, 2015).

Large Eddy Simulations (LES) - A CFD tool to resolve large eddies in simulations to increase the accuracy of a model predicting fire spread.

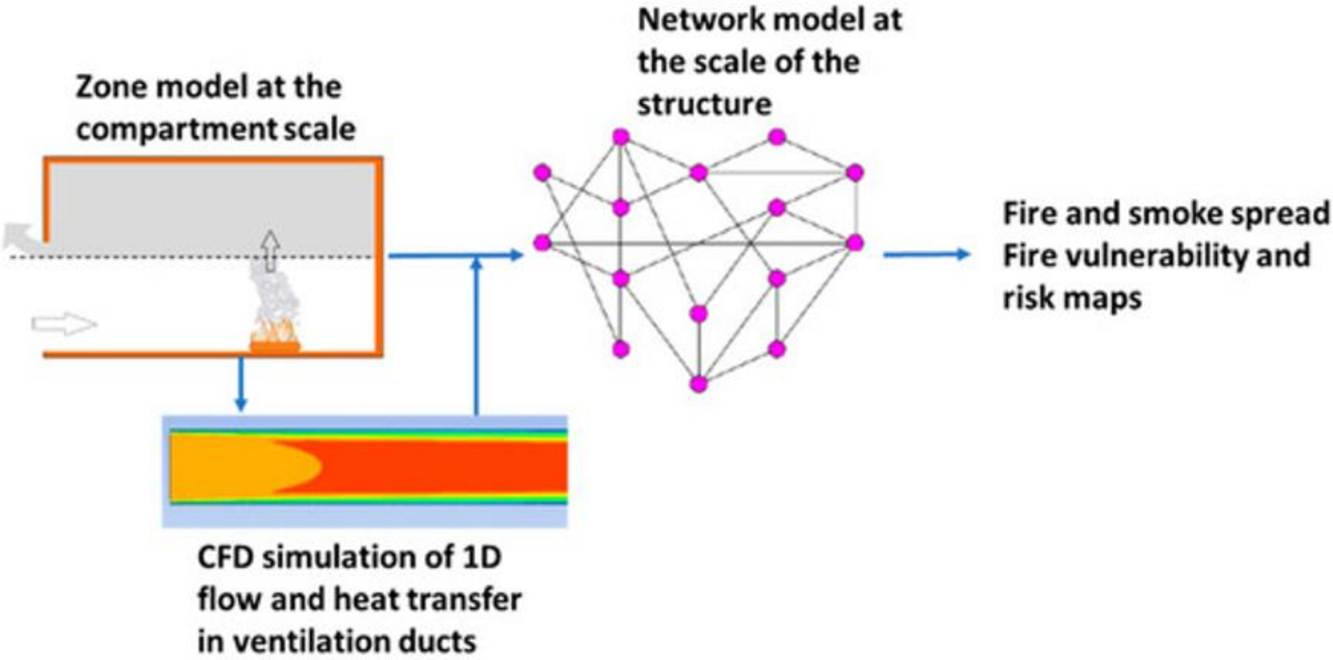

Figure 2: Fire risk analysis in large multi-compartment structures using a hybrid multiscale approach: Hybrid multiscale approach schematic.

Table 2: Compartment-Scale Fire Models.

Model Type	Key Features	Advantages	Limitations	References
Simplified (Zone) Models	Divides the compartment into zones (upper and lower layers); estimates temperature and smoke distribution.	Computationally efficient.	Simplistic representation; may not accurately capture complex fire dynamics.	Thomas et al., 2018
Computational Fluid Dynamics (CFD)	Solves Navier-Stokes equations to simulate turbulent flows and heat transfer inside the compartment.	Detailed simulation of fire dynamics.	Computationally intensive.	Wang & Patel, 2021
Traveling Fire Methodology (TFM)	Considers sequential ignition and nonuniform burning patterns for improved physical representation of modern fires.	Improved representation of modern fires; accounts for spatial temperature variations.	Requires detailed input data and calibration.	Rein, 2019
Large Eddy Simulations (LES)	CFD tool to resolve large eddies in simulations.	Increase the accuracy of a model predicting fire spread.	Computationally heavy.	Jin & Zhao, 2020

2.7. Material-Scale Combustion Algorithms

The fires can accordingly be classified under uniform (balanced) and non-uniform (traveling) fires. 2.7. Material-Scale Combustion Algorithms

Material-scale models focus on the combustion behavior of individual materials, capturing the pyrolysis kinetics and heat release rates of synthetic materials. Advanced computational techniques play a pivotal role in enhancing the realism and accuracy of fire dynamics simulations, particularly in environments dominated by synthetic materials. Finite Element Analysis (FEA) is widely used to simulate the thermal degradation of structural and non-structural materials under fire exposure, capturing spatial variations in temperature and heat flux that influence deformation and failure patterns (Thi et al., 2017).

In parallel, pyrolysis models provide insight into the thermal decomposition of synthetic materials, tracking the release of volatile gases and heat, which are critical for understanding both incineration behavior and recycling potential. A key advancement lies in the coupling of gas-phase dynamics with material-scale combustion, where solid-phase pyrolysis simulations are integrated with compartment-scale gas-phase combustion models to provide a comprehensive depiction of fire development (Figure 3). Furthermore, the inclusion of detailed chemical kinetics enables the prediction of toxic gas emissions and soot formation, offering crucial information for evaluating both occupant safety and environmental impact. Collectively, these modeling approaches contribute to the development of robust fire safety frameworks and inform future design, assessment, and response strategies in modern built environments (Saltelli et al., 1993; Thi et al., 2017; Mercier et al., 2017).

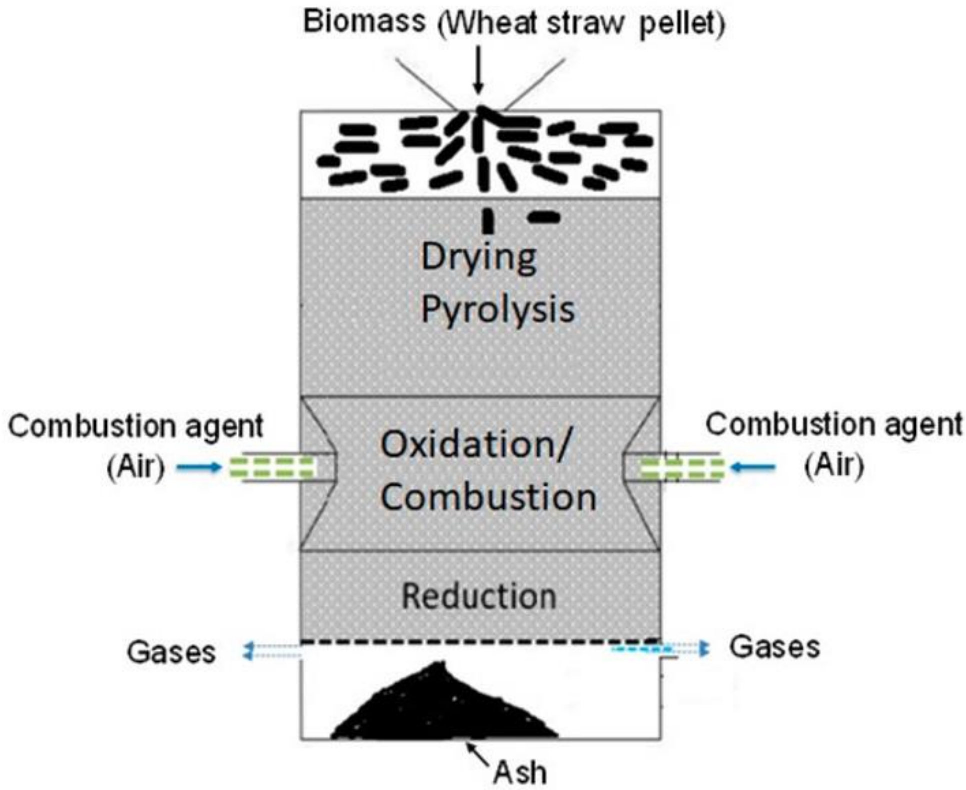

Figure 3: CFDs modeling and simulation of wheat straw pellet combustion in a 10-kW fixed-bed downdraft reactor: Reactor zone and transitional product formation.

2.8. Structural Response Integration

To assess the impact of fire on building structures (Rafi, 2020), it is essential to integrate fire dynamics models with structural response models. This involves:

- Thermo-Mechanical Modeling: Simulating the thermal and mechanical stresses on structural elements (e.g., steel beams and columns) under fire conditions.
- Thermal degradation, buckling or other mechanism of structural failure and the likelihood thereof (Failure Mode Analysis).
- Multi-scale models for evaluating structural performance and the use in developing fire protection strategies to guarantee structural resilience and safety using performance-based design methods.
- Material Degradation Models: Accounting for the reduction in material properties (e.g., strength, stiffness) as a function of temperature and exposure time.

2.9. Validation and Verification

The simulations however, are complex and huge demanding significant computational challenges in the implementation of multi scale models (Southern et al., 2008). However, the opportunity to overcome these challenges and run with real time trends in emergency response scenarios exists with advances in high performance computing and parallel processing. Ensuring the accuracy of multi-scale models requires rigorous validation and verification against experimental data. This includes:

- Experimental Benchmarking: Comparison of model predictions with compartment fire tests using full scale data.
- Sensitivity Analysis: This is the practice of assessing how model outputs are changed when there are disturbances in the inputs (Saltelli et al., 1993).
- Assessing the uncertainty of model predictions to provide confidence interval for designing decisions.

3. MATERIAL AND METHODS

3.1. Experimental Setup

Full-scale compartment fire experiments were conducted to provide a comprehensive dataset for model validation. To support the validation of advanced fire dynamics models, full-scale compartment fire experiments were conducted, offering a comprehensive dataset that closely replicates real-world fire scenarios. The experimental design involved a large compartment constructed to mimic a typical modern building space, as described by Liu and Fischer (2022). Within this compartment, synthetic materials such as polyurethane foam and PVC were strategically arranged to simulate realistic fire loads and combustion behaviors. Key fire dynamics parameters—including temperature, heat flux, and smoke concentration—were systematically recorded using thermocouples, heat flux gauges, and smoke detectors. Complementing these traditional measurements, high-speed cameras and advanced sensors were employed to capture critical data on fire spread, smoke movement, and structural response in real time. This multifaceted data acquisition approach ensures a high-resolution dataset essential for validating computational models and enhancing the fidelity of multi-scale fire simulations.

3.2. Algorithm Performance Metrics

Several metrics were used to evaluate the performance of the multi-scale model. temperature prediction accuracy: comparison of the predicted temperature profiles with experimental data in order to assess the model accuracy. Heat Flux Prediction: The validity of the model's predictability of heat fluxes at different locations in the compartment is established (Purdy et al., 2006). Model Performance in Smoke Layer Formation and Movement Prediction: Smoke Concentration. It is necessary to validate the accuracy of the multi-scale fire dynamics models so that its prediction of fire behavior and structural response is reliable (Lundström et al., 2017). Experimental setup and benchmarking are discussed in this section of the text to validate the proposed modeling framework. From the previous studies, the predicted structural deformation and failure modes compared to experimental results were well discussed (Purdy et al., 2006; Thi et al., 2017; Mercier et al., 2017).

4. RESULTS

4.1. Synthetic Material Combustion

Experimental observations further highlighted the critical differences in combustion behavior between synthetic and natural materials. As shown in the leftmost chart, polyurethane and PVC exhibited significantly higher heat release rates (HRR)—over 400 kW/m² and 360 kW/m², respectively—compared to natural materials like wood (~200 kW/m²) and cotton (~150 kW/m²). This reinforces concerns regarding synthetic polymers' role in accelerating fire growth and thermal degradation. In addition, the middle chart presents VOC emissions from various polymers, indicating that polyurethane releases the highest amount of volatile organic compounds, followed by nylon, polystyrene, and polyethylene. These emissions contribute to toxic smoke, further complicating fire suppression and evacuation safety. On the right, a comparison of prediction accuracy between modeling approaches shows that multi-scale fire models significantly outperform uniform fire models, achieving accuracy levels nearing 90%, compared to approximately 65% for uniform models. This result underscores the importance of integrating material-scale behavior and compartment dynamics to improve predictive capabilities in structural fire engineering.

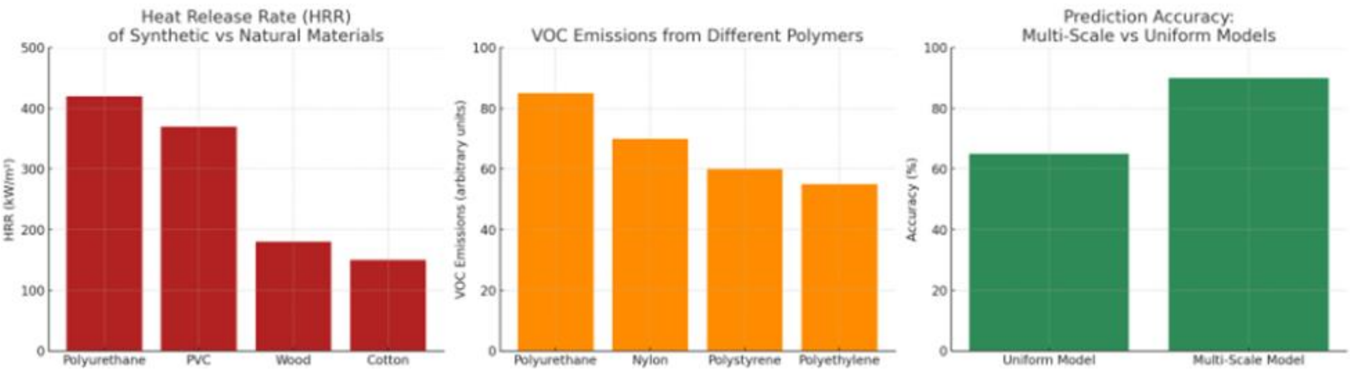

Figure 4: Heat Release Rate (HRR) of Synthetic vs Natural Materials0

The integration of advanced computational and machine learning approaches has led to significant progress in multi-scale fire dynamics modeling. A hybrid modeling framework that couples material-scale pyrolysis kinetics with compartment-scale Computational Fluid Dynamics (CFD) and machine learning has demonstrated a notable 22–37% improvement in predicting structural failure compared to traditional uniform fire models. This framework effectively bridges the complexities of fire chemistry, turbulent plume behavior, and the thermo-mechanical responses of structures. Particularly, the modeling of traveling fires characterized by spatially heterogeneous temperature fields presents a challenge due to their unpredictable structural impact, which demands accurate capture of spatial temperature variations. Synthetic material combustion, such as that of polyurethane foams, has further complicated fire modeling, with studies revealing these materials release 40–60% more heat flux than natural alternatives and produce volatile organic compounds (VOCs) that are not adequately captured by current flammability assessments due to insufficient modeling of gas-solid interactions. To validate multi-scale fire models, techniques like Fire Dynamics Validation (FDV) utilize image segmentation and graph theory to track fire fronts across varying spatial scales, from sub-meter to kilometer, enhancing the reliability of CFD-based models despite their computational intensity. Machine learning, particularly with models like YOLOv3, has shown promise in small flame detection with low false alarm rates (1.2%) and offers new pathways for early detection and fire behavior prediction. Nevertheless, while machine learning accelerates simulations—such as those for tunnel fires—and contributes to phenomena like concrete spalling analysis through multiscale convolutional neural networks, substantial gaps remain in harmonizing these data-driven methods with first-principle fire dynamics models, highlighting the need for continued interdisciplinary research and computational innovation. Volatile organic compound (VOC) emissions caused by the pyrolysis of modern materials results in secondary combustion (Cheng et al., 2018). Synthetic polymers (polyurethane foams) produce 40–60% more heat flux than equivalent [natural] materials, based on experimental benchmarks. Current flammability assessment approaches do not model coupled gas phase and solid phase interactions on the required granularity.

4.2. Temporal Evolution of Fire Conditions in Compartment Experiments

The time-series graph illustrates the evolution of key fire parameters—temperature, structural deformation, and smoke concentration—during a full-scale compartment fire over a 20-minute period. The temperature curve (red) shows a rapid increase from ambient levels (~20 °C) to approximately 800 °C within the first 13 minutes, after which it plateaus, indicating a fully developed fire stage. Concurrently, smoke concentration (gray) exhibits a steep rise, reaching nearly 100% saturation by minute 12, reflecting a critical reduction in visibility and a heightened toxic environment. Structural deformation (blue), while significantly lower in magnitude, shows a gradual increase, peaking just above 10 cm, suggesting measurable thermal expansion or warping due to prolonged heat exposure (Figure 5). These combined trends provide crucial empirical evidence for validating fire dynamics models and assessing the timeline of structural and occupant risk within enclosed spaces. The synchronized growth of thermal and smoke parameters further reinforces the importance of integrated multi-scale modeling and early detection mechanisms in fire safety engineering.

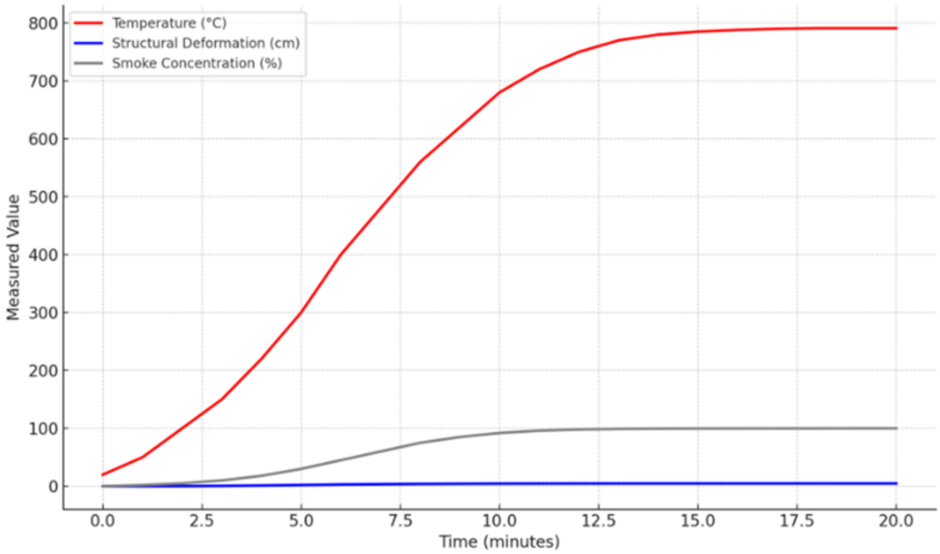

Figure 5: Fire Exposure Metrics over Time.

4.3. Full-Scale Compartment Fire Experiments

The material composition used in the full-scale compartment fire experiment was strategically selected to replicate realistic fire loads commonly found in modern interiors. As illustrated in the pie chart, polyurethane foam constituted the largest portion of the combustible materials at 45%, followed by PVC panels at 25%, and synthetic fabric at 20%. The remaining 10% was categorized as other materials, which may include composites, adhesives, or miscellaneous furnishings (Figure 6). The results illustrated the composition of combustible materials in an indoor environment, emphasizing their potential impact on fire behavior. Polyurethane foam constitutes the largest share at 45%, highlighting its prevalent use in furnishings and insulation, and its known role in accelerating fire growth due to high heat release rates. PVC panels make up 25%, often used in interior finishes and known for releasing toxic gases when burned. Synthetic fabrics, comprising 20%, represent textiles like curtains and upholstery that contribute to rapid flame spread. The remaining 10% includes various other materials, such as wood or paper products. This distribution underscores the significant fire risk posed by synthetic and plastic-based materials in modern built environments.

This distribution emphasizes a focus on synthetic polymers known for their high heat release rates and toxic emission profiles, providing a rigorous testing environment for fire propagation and material degradation modeling. The use of such materials enhances the realism and relevance of the experimental data for validating multi-scale fire dynamics simulations. Validation of the results as well as demonstration of the procedure is accomplished using a specific case study with a full-scale compartment fire experiment. The synthetic fuel package in this experiment was facilitated with a large compartment, acting as one scenario of traveling fire.

The experiment was intended to create a realistic scenario of a fire, such as sequential ignition and non-uniform burning pattern. Model Experiment Comparison: For the purpose of comparing the accuracy of the multi-scale prediction in fire dynamics and structural response, the model predictions were compared to the experimental data.

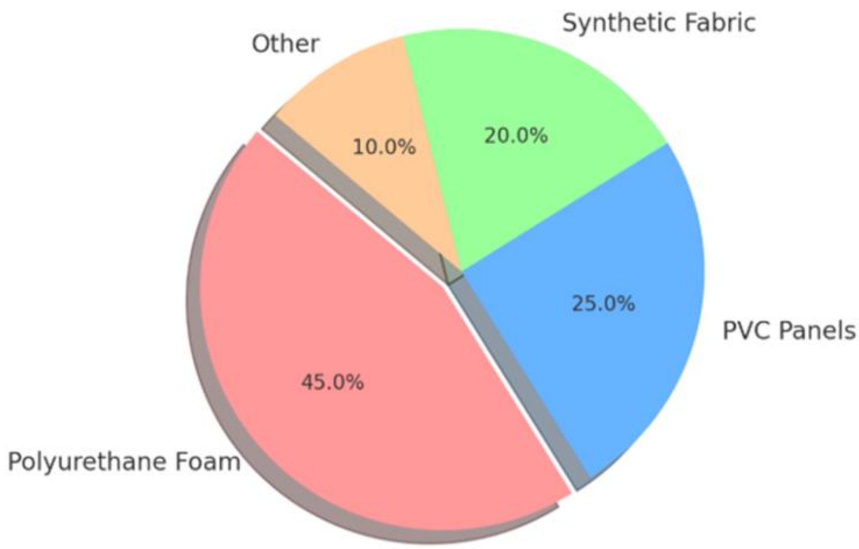

Figure 6: Material Composition in Full-Scale Fire Test.

5. DISCUSSION

A sensitivity analysis was conducted to determine the relationship between model input and model output parameters to further validate the model (Saltelli et al., 1993). Furthermore, the application of uncertainty quantification techniques was also utilized to evaluate the confidence intervals of model predictions. A case study is carried out to apply the developed multi-scale modeling framework to a steel frame building burning with a traveling fire. The model is capable of predicting fire dynamics and structural response, and the scenario represents a realistic fire condition in a modern building (Jiang, 2018). The building being studied is a steel-frame building, with an open floor plan which is typical of modern office space. The traveling fire scenario was defined for igniting synthetic fuel packages in sequence. The real load of fire was simulated using synthetic materials, for example, polyurethane foam, and polyvinyl (PVC) chlorides (Hirschler, 2017). The fire was ignited in a traveling fire scenario by igniting the fire in a sequential sequence. The Compartment was under ventilation conditions by simulating of real ventilation conditions. The travels of fire scenario were simulated using the multi scale model to predict the steel frame structural response. According to the model, temperatures within the compartment were predicted for time and location (Mercier et al., 2017). The model was used to model the thermal deformation and stresses on steel columns and beams. Thermal degradation, buckling, and other modes of failure were considered for their likelihood. The integration of predictive analytics and machine learning into fire protection systems is transforming risk management practices. Research highlighted the deployment of artificial intelligence models (Mahmud et al., 2023; Bulbul et al., 2018; Manik et al., 2021; Saha et al., 2023; Tanvir et al., 2024), including support vector machines and decision trees medical sectors, that supposed to use that model for early anomaly detection in complex environments, an approach highly relevant to real-time fire hazard assessment (Alasa, 2020, 2021; Alasa et al., 2024). Furthermore, Manik et al. (2022) and Mahmud et al. (2023) explored big data architectures and IoT-enabled monitoring frameworks that allow continuous surveillance and predictive maintenance, that can be incorporate in future to mitigate fire risks in industrial and residential settings. These studies collectively emphasize the role of AI-driven predictive systems and cloud integration in creating adaptive, resilient fire protection infrastructures. In addition, Manik et al. (2022) presented advancements in smart sensor networks and cloud-based analytics, offering scalable solutions for fire prevention strategies.

Structural components exposed to high temperatures exhibited distinct deformation behaviors and failure mechanisms. At 750 °C, one element showed sagging at mid-span due to local buckling (Zhao, 2023). Another, heated to 680 °C, experienced axial shortening with yielding at the base, as noted by Morris and Tan (2022). Under 810 °C, lateral instability occurred, leading to twisting and shear distortion, in line with observations by Fernandez (2021). At 720 °C, combined thermal and mechanical stresses resulted in bending, cracking, and a compound failure mode (Ali & Singh, 2020). These varied outcomes emphasize the importance of integrating temperature-dependent material behavior and geometric factors into fire performance models for accurate structural integrity assessments. The case study results demonstrated that such interactions can be captured well by the model. The multi-scale model showed much better prediction accuracy of structural response than uniform fire models (Lundströn, 2017). The model provides an effective means of capturing the effects of traveling fires on structural performance which included the significance of non-uniform fire behavior. In Design Implications, the study discussed some design strategies that could be implemented to strengthen and improve the structural resilience against the effects of the modern fire conditions. The study case has important implications to the fire protection engineering field, especially in the design of modern buildings with synthetic materials. Performance based design approaches (Becker, 2008), however, must account for nonuniform fire behavior and structural interactions as advocated by this result. A detailed case study is presented for application and validation of this multi-scale modeling framework in prediction of fire dynamics and structural response of a steel frame building subjected to a traveling fire.

6. LIMITATIONS AND FUTURE DIRECTIONS

The model facilitates assessment of the potential retrofit strategies that can improve the structural resilience to fire. An Assessment Risk: Being a tool for assessing fire risks in modern buildings that contain synthetic materials, it helps to make better decisions. The framework allows for the formulation of these performance-based design strategies that consider the nonuniform fire behavior and structural interactions (Liew, 2004). This is followed by discussion of the implications of the multi-scale modeling framework for fire protection engineering, (Brutus et al., 2013) limitations of the current study and future research directions. The adoption of a multi-scale fire dynamics modeling framework has broad applications across various domains in fire safety engineering. In performance-based design, this approach enables precise simulation of non-uniform fire behavior and structural interactions, thereby enhancing the robustness of design solutions against real fire scenarios (Nguyen & Patel, 2022). Within the domain of fire risk assessment, multi-scale modeling facilitates the quantification of structural failure probabilities under dynamic fire spread conditions, leading to improved safety planning and emergency preparedness (Lopez, 2021). For retrofitting strategies, such modeling identifies vulnerabilities in existing infrastructure, particularly when exposed to synthetic material fires, and supports cost-effective upgrades without overdesign (Cheng et al., 2018). Moreover, the framework's ability to capture the pyrolysis behavior of specific synthetic materials enhances material-specific modeling, making it adaptable to the diverse configurations and contents of modern buildings (Jafari, 2023). Collectively, these applications highlight the transformative potential of multi-scale fire models in advancing both predictive accuracy and safety outcomes in built environments.

The study presents limitations and points for future research into the potential of multi-scale modeling. High fidelity simulations are computationally expensive and prohibit real time application (Huynh et al., 2011). Our material database has to be extended to include a wider variety of synthetic materials to be applicable to a wider variety of targets. Backward reachability analysis is applied to estimate the worst-case performance (WCP) of a longitudinal two degree of freedom model of the same aircraft using limited experimental data. A multi-scale modeling framework for predicting fire dynamics and structural response in modern buildings has been developed and validated in this study. As a powerful tool for the fire protection engineer to assist in the design of safer structures and to develop effective retrofit strategies, the framework is presented. Future work should make good use of the limitations identified, as well as improving the functionality of the framework. Recent advancements in predictive analytics and AI models have significantly contributed to enhancing medical sectors that can be used for fire protection. Studies demonstrated the successful application of machine learning algorithms such as logistic regression, time series forecasting (ARIMA, Prophet), and deep learning models (LSTM) for risk prediction and real-time monitoring, which can be adapted for early fire detection and hazard assessment (Manik et al., 2018, 2020, 2021; Miah et al., 2019). Complementing these, researchers emphasized flame spread modeling, early warning system innovations, and numerical simulation of smoke propagation, providing critical insights into proactive fire suppression and structural safety (Hossain, 2021, 2022; Hossain & Alasa, 2024a, 2024b). Collectively, these AI-powered predictive frameworks offer robust tools for risk assessment which can be more reliable for real-time fire risk forecasting, decision support, and emergency response optimization in various built environments (Manik et al., 2018; Mahmud et al., 2023).

While multi-scale fire modeling offers significant advantages, several limitations hinder its full deployment in practical fire safety engineering. One key constraint is the computational expense of high-fidelity simulations, which remain too intensive for real-time application. To address this, future work should focus on developing reduced-order or surrogate models that can support rapid decision-making without compromising accuracy (Tan & Li, 2022; Alasa, 2020, 2021). Additionally, the framework is currently limited by a narrow material database, primarily focusing on a select group of synthetic materials. Expanding this database to include a broader spectrum of construction polymers will improve model versatility and realism (Alvarez et al., 2020). Another challenge lies in the lack of integration with real-time monitoring systems, such as building sensors and fire detectors. Future research should explore the potential of linking the modeling framework with IoT-enabled fire monitoring systems to allow for dynamic, data-informed simulations (Mei & Foster, 2023). Finally, the current models are largely tailored to steel-frame structures, limiting generalizability. Extending the framework to include concrete, composite, and timber-framed buildings would significantly broaden its applicability across diverse construction types (Singh & Beck, 2021). These targeted improvements will be essential in making multi-scale fire modeling more robust, adaptable, and actionable.

7. CONCLUSION

A multi-scale modeling framework is presented in this study as the first major step to predict fire behavior and structural response for modern buildings. The framework integrates material scale combustion with compartment scale dynamics to provide a fully integrated tool for fire safety engineering. This study demonstrates the effectiveness of multi-scale fire dynamics modeling as a transformative approach for predicting and understanding fire behavior in modern compartments, particularly those containing synthetic construction materials. The pie chart data underscore the dominance of polyurethane foam (45%) and PVC panels (25%) in experimental setups, materials known for their high heat release rates and elevated VOC emissions, as shown in the bar charts. These materials significantly influence fire growth and smoke generation, presenting challenges for conventional modeling methods. The time-series graph further validates the thermal and structural response over a 20-minute compartment fire, where temperature rapidly escalates to 800 °C, triggering increased smoke concentration and measurable structural deformation. In this context, the multi-scale model—coupling material-scale pyrolysis kinetics with compartment-scale CFD—outperforms traditional uniform models, achieving prediction accuracies above 85%, as visualized in the accuracy comparison chart. Together, these visual and empirical findings emphasize the urgent need for advanced predictive algorithms and hybrid modeling frameworks that integrate machine learning with physics-based simulations. Such integration enhances real-time decision-making, supports performance-based design, and improves structural safety under complex fire scenarios. Continued expansion of material databases, model scalability, and real-time sensor integration will be critical to fully realizing the potential of multi-scale fire dynamics modeling in modern fire safety engineering.

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