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Performance Based Design and Machine Learning in Structural Fire Engineering: A Case for Masonry

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PERFORMANCE BASED DESIGN AND MACHINE LEARNING IN STRUCTURAL FIRE ENGINEERING: A CASE FOR MASONRY

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ABSTRACT

The volatile and extreme nature of fire makes structural fire engineering unique in that the load actions dictating design are intense but not geographically or seasonally bound. Simply, fire can break out anywhere, at any time, and for any number of reasons. Despite the apparent need, fire design of structures still relies on expensive fire tests, complex finite element simulations, and outdated procedures with little room for innovation. This thesis will make a case for adopting the principles of performance-based design and machine learning in structural fire engineering to simplify the process and promote the consideration of fire in all structural engineering applications.

This thesis begins with an overview of relevant topics, providing context and a frame of reference for the coming chapters. The first section of this thesis argues for the adoption of performance-based design for the structural fire design of buildings, as obtained through a comprehensive and much needed literature review. The second half of this thesis revolves around the application of performance-based design and simple machine learning in our field. An Excel file accompanies this thesis as an easy-to-use tool to encourage the consideration of fire criteria in masonry projects, focusing not on how heat affects the material-level properties but rather on how those effects accumulate to affect the final design requirements. An outline for the development of a coding-free machine learning model capable of predicting failure of unreinforced masonry structural elements exposed to elevated temperatures including its abilities and limitations, is

presented. The thesis concludes with a summary of the above information and the potential for related project scopes in the future.

DEDICATION

To my family, for their continual support of my every pursuit.

ACKNOWLEDGEMENTS

I would like to thank my graduate advisor, Dr. M. Z. Naser for his continued support in all facets of life throughout the last couple of years as I have navigated through the graduate program. I would also like to thank my committee members Dr. Brandon Ross and Dr. Laura Redmond for their involvement both in and out of the classroom, with a special thanks regarding the creation of this thesis.

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1. INTRODUCTION

Fire engineering is distinct from other types of structural engineering in that the conditions controlling design criterion (i.e. fires) are not limited geographically or seasonally to any degree. The same cannot be said for wind or seismic loading, which are much more prevalent in structural engineering codes and standards.

The volatile nature of fire and its dependency upon the conditions of its surroundings to determine key characteristics of it makes fire a very difficult medium to predict and quantify. To further complicate the matter, fire design of structures still heavily relies on expensive fire tests, complex finite element (FE) simulations, and outdated procedures that restrict the progress of innovation [1]. The direct application of experimental fire tests requires recreating standard structural tests under elevated temperatures, which in turn requires sophisticated equipment [2]. This limits access to it both because it is expensive and because it is specialized, so there are not a lot of other applications to justify the cost outside of a purely research environment.

The finite element models used to predict the behavior of fire-exposed structures can get complex, as they require a lot of theoretical knowledge of the inner-workings of the software used to ensure it is an accurate representation of the physical system. While this limitation can be reasonably simple to overcome, while affordable, these could also limit the market. In terms of outdated procedures, the United States currently relies on the more traditional, conservative prescriptive approach to fire resistance design and analysis [3]. This approach relies on the results from standardized testing, without any need of actual analysis from the engineer, which are known to, without a doubt, preserve the integrity of the structural design. The standard approach for many other countries is the performance-based design approach. This approach allows the engineer some flexibility in design as long as adequate safety can be demonstrated. While progress is being made to shift fire engineering design standards in the United States from a prescriptive to performance-based approach, it's slow going and mainly utilized for very specific cases rather than uniformity across the board.

In a way, designing structures to withstand the adversity of fire remains a lengthy and complex endeavor – yet one that is essential for the safety of the public and individuals. *The overarching goal of this project is to create a foundation for next-gen structural fire engineering tools that is not only streamlined but autonomous in nature.* To this end, our study will utilize principles of performance-based design and machine learning to generate the knowledge needed to bypass existing complexities in current fire design procedures while maintaining an accurate and validated process for fire resistance building design [4].

From a practical perspective, fire engineering, and fire safety in general, is based on the principle that precaution is better than a cure. Fires can never be prevented entirely; accidents happen but including fire resistance into the design of buildings can save countless lives. Even though its importance has been widely recognized (it is a problem truly as old as time), structural fire engineering remains a lengthy process that only legally requires satisfying the bare minimum. By creating an easy-to-use, streamlined process for fire resistance design, it is the aim that more structural engineers will be encouraged to take fire resistance into consideration for projects of all levels, making for safer buildings across the country, and the world. The impact of this project will set a precedent in integrating novel machine learning technologies into a relatively classical field. Such technologies have already proven to be crucial in overcoming many of the ongoing challenges across other disciplines (i.e. cancer diagnosis in the medical field, Earth-like planet hunting in astronomy, etc.) and will soon prove to be essential in structural engineering [5-6].

1.1 Significance

As stated before, though the importance of fire engineering and fire safety is undeniable, the structural fire engineering design process in the United States remains a lengthy and complicated process based on a conservative and outdated procedures. The use of performance-based design and machine learning (potentially even the combination of both) would innovate the field, as it has with similar disciplines.

According to the National Fire Protection Agency (NFPA), in 2021, local fire departments in the United States responded to calls for approximately 1.35 million fires [7]. These fires lead to 3,800 civilian deaths and 14,700 injuries, not to mention roughly 15.9 billion dollars' worth of property damage. Despite only 36% of those fires being structural fires, they accounted for 79% of civilian deaths and 80% of property damages for the year, a seemingly disproportionate amount. Over time, these statistics have improved, marking a 42% decrease in total deaths from 1980, it shows that there is still quite a way to go before fire can be considered a contained issue.

This thesis mainly revolves around two subjects: performance-based design procedures and the application of machine learning specifically on the design of masonry under fire. The benefits of and need for performance-based design practices will be discussed in depth later, but to summarize, performance-based methods allow for more flexibility in the engineers' design, giving the potential for increased efficiency and minimized costs without sacrificing the safety of the occupants. The second half of this thesis will focus on filling a hole in the current literature about masonry structures under fire. Codes are well-established for masonry in earthquake and hurricane conditions; however, literature for masonry exposed to elevated temperatures is more scare [8-9] . What little is provided in the codes is based on outdated experimental and analytical studies conducted in the 1980s and 1990s [10-11]. These studies were based on standard fires; while the standard fires allow for easy comparison between designs, they're often not a great representation of real fires, which makes any study done based on them superficial at best. Most of the research currently being done on masonry under fire is regarding the material properties side of structural engineering, rather than the design part [12-15]. The Excel file created to go along with this thesis, presented later, is an easy-to-use tool to encourage the consideration of fire criteria in masonry projects, focusing not on how fire affects the masonry at a fundamental level but rather on how those effects add up to affect the final design required. The tool will have certain limitations due to its scope, but it is progress in the right direction, and will provide a precedent for future research to expand upon.

1.2 Objectives of the research

This research involves the creation of machine learning models capable of predicting the failure of unreinforced masonry structural elements when exposed to elevated temperatures, along with the necessary knowledge base to create it. The objectives are as follows:

1) Create an overview of the relevant topics involving the application of performance-based design and machine learning in structural fire engineering design, mainly in regard to masonry elements.
2) Collect a much-needed recent literature review for adjacent fields and document the most applicable findings.
3) Identify machine learning algorithms and procedures with the highest potential for implementation in the fire protection field.
4) Create an easy-to-use tool using Microsoft Excel and machine learning models, in the form of a masonry element design tool for practicing engineers.
5) Promote the use of machine learning in the fire protection field via student- and practitioner-oriented video tutorials, as well as presentations to be delivered at an upcoming SFPE conference.

1.3 Chapter Outlines

Chapter 1 presents an introduction to the research program executed for this thesis. This chapter presents the objectives of the research and outlines the different chapters in this thesis.

Chapter 2 is constructed as an argument for the adoption of performance-based design for buildings exposed to elevated temperatures, otherwise known as structural fire engineering, as a dominant practice in the relevant engineering codes and standards. This is presented through a literature review and written defense. It also covers a brief summarization of the relevant conceptual topics pertaining to but not limited to, structural fire engineering, unreinforced masonry design, and machine learning.

Chapter 3 describes an easy-to-use structural design and analysis tool provided alongside this thesis. This Excel sheet is meant to be an accessible aid to account for elevated temperatures in structural masonry design for practicing engineers to reference whenever applicable in order to encourage consideration of fire criteria in projects of all sizes.

Chapter 4 details the current and prospective relationship between structural engineering design and machine learning. It goes through the process of creating and validating the models, the algorithms used in its framework, and the future extent of more sophisticated machine learning integration within the field.

Chapter 5 serves as a conclusion to this thesis, summarizing the above information with an emphasis on the potential opportunities should machine learning continue to be developed in the scope of structural design.

Chapter 6 is a list of all references consulted during the formation of this thesis. These references are listed in order of appearance, as denoted by their corresponding numbers.

2. LITERATURE REVIEW

2.1 Overview

This chapter showcases the state-of-the-art research pertaining to this thesis. This review covers some of the big concepts behind structural fire engineering, and then presents as an argument for the adoption of performance-based fire design of buildings. To this end, after a brief summary of concepts, there is a literature review regarding the implementation of performance-based design and analysis in fire engineering. This review is split into three sections: past and current uses, alternatives, and recent innovations. This review will include a variety of sources, both in physical origin and in content covered.

2.2 Conceptual Review

2.2.1 Structural Engineering

Structural engineering is a discipline of civil engineering, responsible for designing and analyzing structural systems primarily for, but not strictly limited to, buildings and bridges. These analyses are typically focused on stability and serviceability requirements. Stability references the strength of the system; will it suffice for its purpose, or will it fail? Does its moment and shear capacity allow for the expected loading of its occupancy and location? Serviceability, on the other hand, refers to deformation, vibration, and other factors that influence how comfortable and safe the occupants feel while in the building, without any knowledge of structural engineering or the principles that went into the design of it [16-17].

While designing any structure, the final product must be suitable for a number of different conditions. Some conditions are dependent on the expected function and/or use of the building, mainly when considering the magnitude and type of loading that any given element in the building can be expected to encounter, along with a reasonable margin for error to account for material inconsistencies, future adaptability of the structure, and more general uncertainties of design. Other situations depend on events occurring outside of the building, mainly natural disasters like earthquakes, hurricanes, and fires. The emphasis on these mainly depends on the location of the building (for example: California cares more about earthquakes than hurricanes, as that is the phenomenon the buildings are more likely to experience in their lifetime, while Florida is the opposite). But fire is not geographically bound, therefore poses a threat unique to any other.

While buildings could be designed to withstand any and all circumstances they could run into for the next hundred years, that design probably wouldn't be very economically feasible. Therefore, engineers must use some judgment to decide to what extent to design the buildings. This judgment is heavily supplemented with codes and standards to make sure all practicing engineers are being safe and practical in their decision making, along with reasonable expectations of what the client desires out of the project regarding durability and economy. These codes are available at all levels: national, state, and local, and the design must meet all the relevant ones.

2.2.2 Masonry Analysis

While structural design typically follows the same broader process, no matter what the material of the element may be, there are a few idiosyncrasies that go along with each material. To combat this, most of the popular materials have design guides and manuals to ease the burden of the engineer and encourage the use of that particular material. For structural steel, there is the American Institute of Steel Construction (AISC) Manual that streamlines the design process for the engineer to the point where most of their calculations can be looked up in a few tables [18]. For wood, there is the National Design Specification published by the American Wood Council [19]. For masonry, there is the Masonry Society's TMS 402/602 [20]. And those are the design guides specific to the United States; there are more when considering the different methods of structural member design worldwide. That being said, no one building code stands alone, most have intrinsic interactions with other codes; for example, the TMS code mentioned before defers to the International Building Code for any discrepancies or gaps in information [21].

Masonry is split into two different categories: bricks and blocks. Bricks are the typical clay material that comes into mind when a historical red-brick house is mentioned. While blocks or Concrete Masonry Units (CMU) are a bit hardier construction, made of concrete (hence the name) with Portland cement. Both types of masonry come in standard rectangular sizes, though the strength of the material can vary depending on the cost and the needs of the specific project. Structural analysis for masonry design is similar to that for concrete design in that there are two acceptable methods: allowable stress design and strength design. Allowable stress design deals with service (unfactored) loading, and strength design deals with the ultimate capacity of the material. It gets a bit more complicated when the masonry is reinforced with steel rebar for additional tensile strength, as different regions of the resulting stress-strain curve correspond to the different methods of analysis (the uncracked region is linearly elastic, the cracked region requires allowable stress design, and the ultimate capacity relates to strength design). These methods are used to check axial, flexure, and shear capacities, or the interaction of a combination of the aforementioned, typical of any structural member regardless of the construction material it is made out of.

2.2.3 Structural Fire Engineering

The job of any structural fire engineer is to identify the risks involved and design safeguards to mitigate the effects of fire, including preserving human life and, to a lesser degree, minimizing economic consequences. To do this, there are typically three goals: to prevent a fire, confine the fire to a particular region of the building (thus preventing spread), and extinguish the fire.

As touched on before, structural fire engineering design is mainly split into two approaches: prescriptive and performance-based design. The prescriptive approach, prevalent especially in the United States, specifies the fire resistance rating for each individual structural element based on standard fire curves [3]. Figure 1 depicts the time-temperature curves for the 'standard design fire' used in ASTM E119 and ISO 834 test specifications.

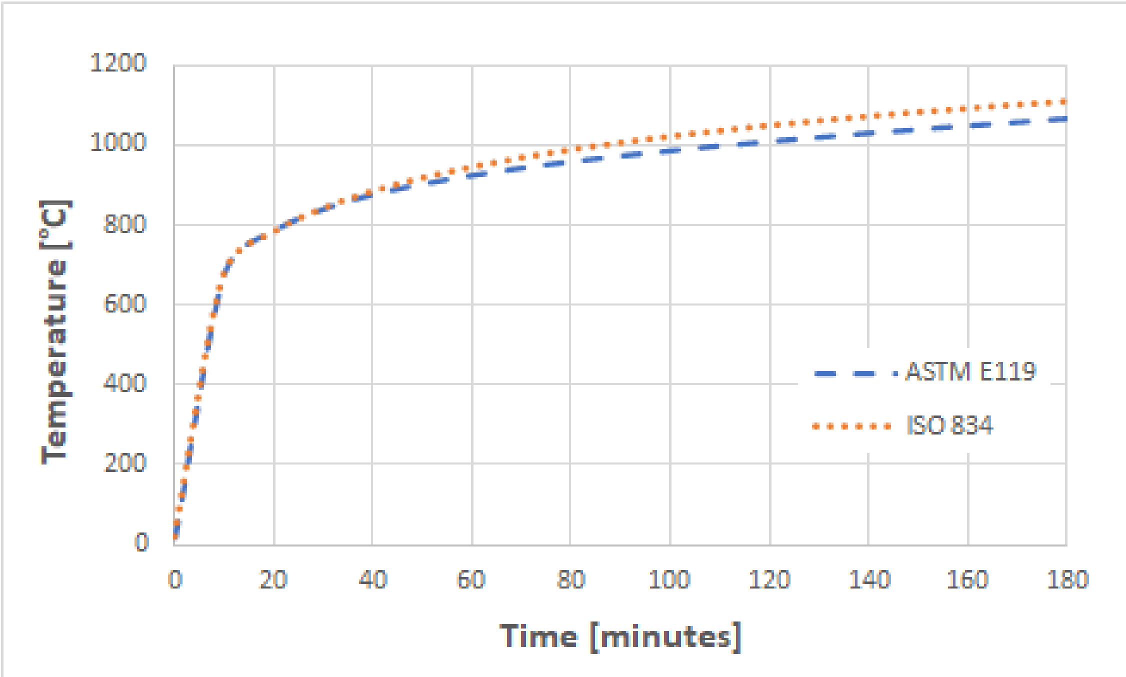


Figure 1: 'Standard fire' design curves [10-11].

The process for the prescriptive approach happens on the component level. Theoretically, if a building is composed of all elements up to a certain fire resistance rating, the requirement of which is based on the occupancy classification of the structure, then the building as a whole will stand up to that rating. Each element is given a conservative fire resistance rating based on previous broadly applicable research with standardized design fires and fundamentals of structural analysis; these ratings are then simplified to hour(s) or fractions of hour(s) to be easily comparable among different building codes. Rating can be categorized into generic ratings, proprietary ratings, and approved calculation methods. Genetic ratings refer to the fire resistance of popular construction materials, given mainly in building codes. In contrast, proprietary ratings are based on the manufacturers of the product. They will have full-scale fire resistance tests completed on their behalf within certain guidelines to determine the rating used for each individual product. Approved calculation methods are just as they sound – a set of calculations the engineers can run to verify that their proposed design work. This method is the least popular of the three, as it requires more labor on the part of the designing engineer.

Prescriptive methods, while simple to incorporate into a design, can be a bit conservative and inconsistent. The fire rating system was created as a simplified, uniform procedure based on risk probabilities; this means the resistance of the members themselves is evaluated with standardized furnace test heating [22-24]. Since fire is such a variable event, the correlation between the behavior of the element under testing and under actual fire conditions it may face is bound to fluctuate wildly. That's not to mention the entire fire-rating system was originally only supposed to apply to "common" buildings. This makes a bit of a grey area for buildings with unique geometry/features or mixed-use occupancy. Best practices developed over the years have given practicing engineers guidelines to minimize these concerns, but they've come into question in recent years, leading most countries to take on a more holistic approach to structural fire engineering.

Outside of the United States, the standard approach is the performance-based design approach. Performance-based design is specific to each project; it sets specific performance goals for when the structure is exposed to elevated temperatures rather than regulating the construction side of matters. The performance-based approach thus allows for more innovation and imagination for the engineers, as it doesn't restrict the design process as long as adequate safety can be demonstrated, equal to that required of the prescriptive approach. When comparing performance metrics like deflection and thermal analysis for designs with each approach, the performance-based designs retained similar load-bearing capabilities to the prescriptive approach when taking into account the required fire-resistance rating [25]. While both approaches are theoretically similar in terms of performance metrics, the performance-based design “offers more flexibility and potential cost reductions, owing to the fact that it takes into account system behavior and/or more realistic fire exposure” [26]. This makes it desirable to clients, as it can be more efficient should it be done correctly. Both approaches have their advantages; the performance-based approach can be adapted to unique designs or to cut costs without sacrificing safety, while the prescriptive approach has more conservative results and is typically easier for the engineer to implement.

The movement towards a more holistic approach to structural fire engineering can, in part, be attributed to the recent advancements in modeling and machine learning. With these new resources available, performance-based designs can be as efficient in terms of time or labor from the designated engineer as the prescriptive approach. As stated before, fire is particular in that it is not dependent upon geographical location or the seasonal timeline, but it is very much dependent upon the surrounding environment where it starts and where it spreads. The geometry of the room, the materials in it, air ventilation, and more contribute to the behavior of fire. To get an accurate representation of the effects of fire on a certain structure without the need for complex calculations and specialized education, software is commonly used. Basic software, like OZone, depicted in Figure 2, is single-zone models for determining the temperature in post-flashover room fires [27].

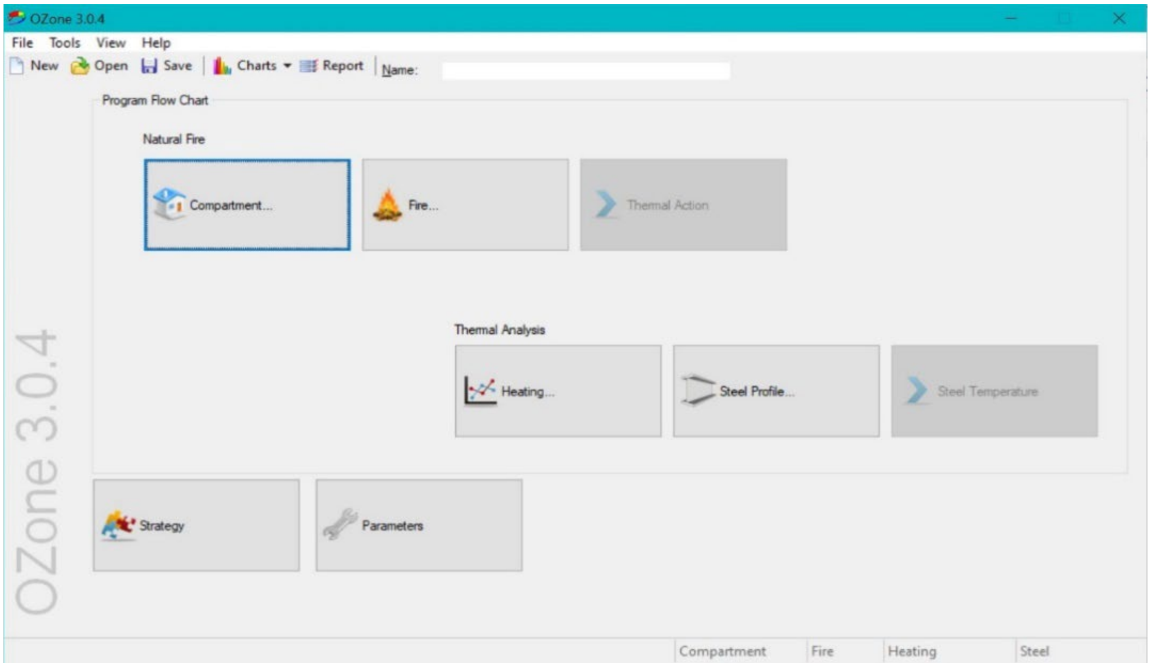


Figure 2: Sample of previously developed fire-resistance software, Ozone [27].

Depending on the sophistication of the modeling software, the models can also take into consideration thermal expansion, material nonlinearity, large deformations, and temperature dependent properties. Software packages like this include SAFIR and FiRE (Fire, Radiation, and Egress Model).

With the complication of the software comes the addition of required knowledge for the engineer. The programs are completely dependent upon the inputs plugged into them – they don't have the judgment of an engineer to decide whether or not an answer seems reasonable, and thus cannot tell if a mistake was made in the creation of the model. The results are only as good as the information used to get them. For the model to have any worth, the producing engineer should have at least a basic understanding of the internal workings of the program, how varying each input affects the final results and what physical phenomenon the input represents, both in magnitude and with appropriate units. Weighing this knowledge against the knowledge used to defend performance-based fire designs without the use of modeling software still makes it a significant improvement, but it needs to be said that the programs alone cannot act as justification for performance-based design; the engineer still bears all responsibility.

The current trend is that as more advancements are made in modeling and predictive programming capabilities, more countries and their practicing will engineers make the shift toward performance-based design because of its increased efficiency and adaptability. This trend spills out into periphery topics; as the field begins to incorporate machine learning into its accepted practices, the same is to be expected.

2.2.4 Machine Learning

By definition, machines cannot think creatively or spontaneously like higher-level beings (e.g., people), but they can follow algorithms and other procedures to "learn" and get better at whatever their objective is; this is called artificial intelligence. Machine learning is a subset of artificial intelligence, wherein the machines can get better without explicit programming but rather from exposure to more data sets. There are three different categories of machine learning: supervised, semi-supervised, and unsupervised [28]. A more in-depth breakdown of the categorization relevant to this project can be found in Figure 3 [29]. This thesis will focus mainly on the yellow highlighted areas of supervised regression strategies, decision trees, and random forest algorithms.

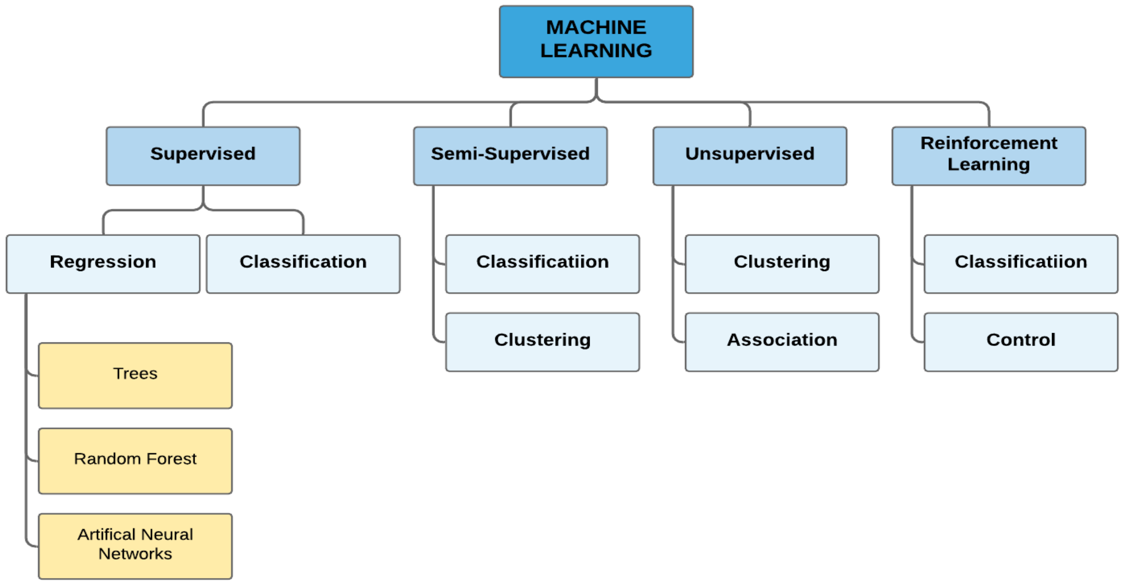


Figure 3: Hierarchical categorization of machine-learning strategies.

Note. Adapted from *Machine Learning: Algorithms, Real-World Applications and Research Directions*, by I. Sarker, 2021, p. 160. Copyright 2021 by Springer Nature [30].

Algorithms are the equivalent of neural pathways in humans; it's how they learn. Decision trees and random forest are two types of logistic regression algorithms. Decision trees outline specific decisions for a given scenario and all the possible consequences for each of those decisions, which are arranged like tree branches splitting from the single trunk, seen in Figure 4. This type of algorithm has been indoctrinated into the fire engineering community [31-34], so by itself, its use will not spur any innovation.

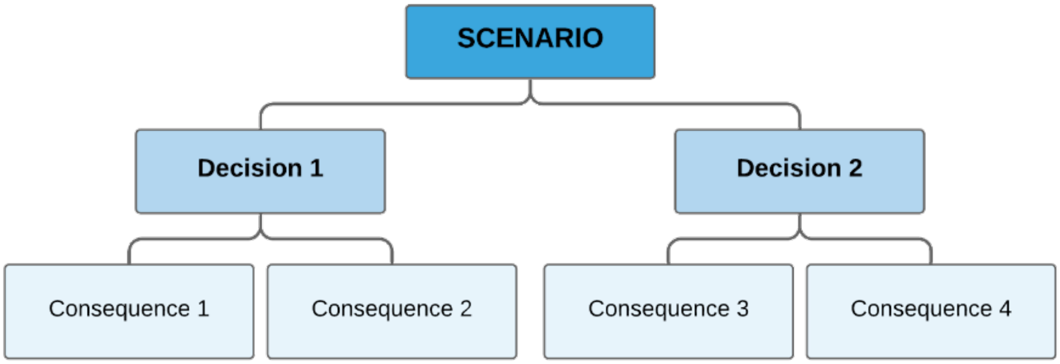


Figure 4: Illustration of the decision tree algorithm.

Note. From *Mechanistically Informed Machine Learning and Artificial Intelligence in Fire Engineering and Sciences*, by M.Z. Naser, 2020, p. 2752. Copyright 2021 by Springer Science + Business Media, LLC. Society of Civil Engineers [30].

The random forest algorithm is an expansion of the decision tree, integrating multiple trees into one algorithm to run. Therefore it requires two parameters to use: the number of trees and the number of variables to be found [35]. There is one predicted outcome for every tree in the algorithm; the final output of the random forest is the average of all results, assuming it is a regression problem. Decision trees and random forests can be used in classification problems as well, though their uses will not be highlighted here. An illustration of the random forest algorithm is shown in Figure 5 to better visualize the process it entails. This is only one example of a type of algorithm with applications in structural engineering. It's not the only type of function currently used, and there is potential for even more, but it idealizes a fundamental understanding of how algorithms work.

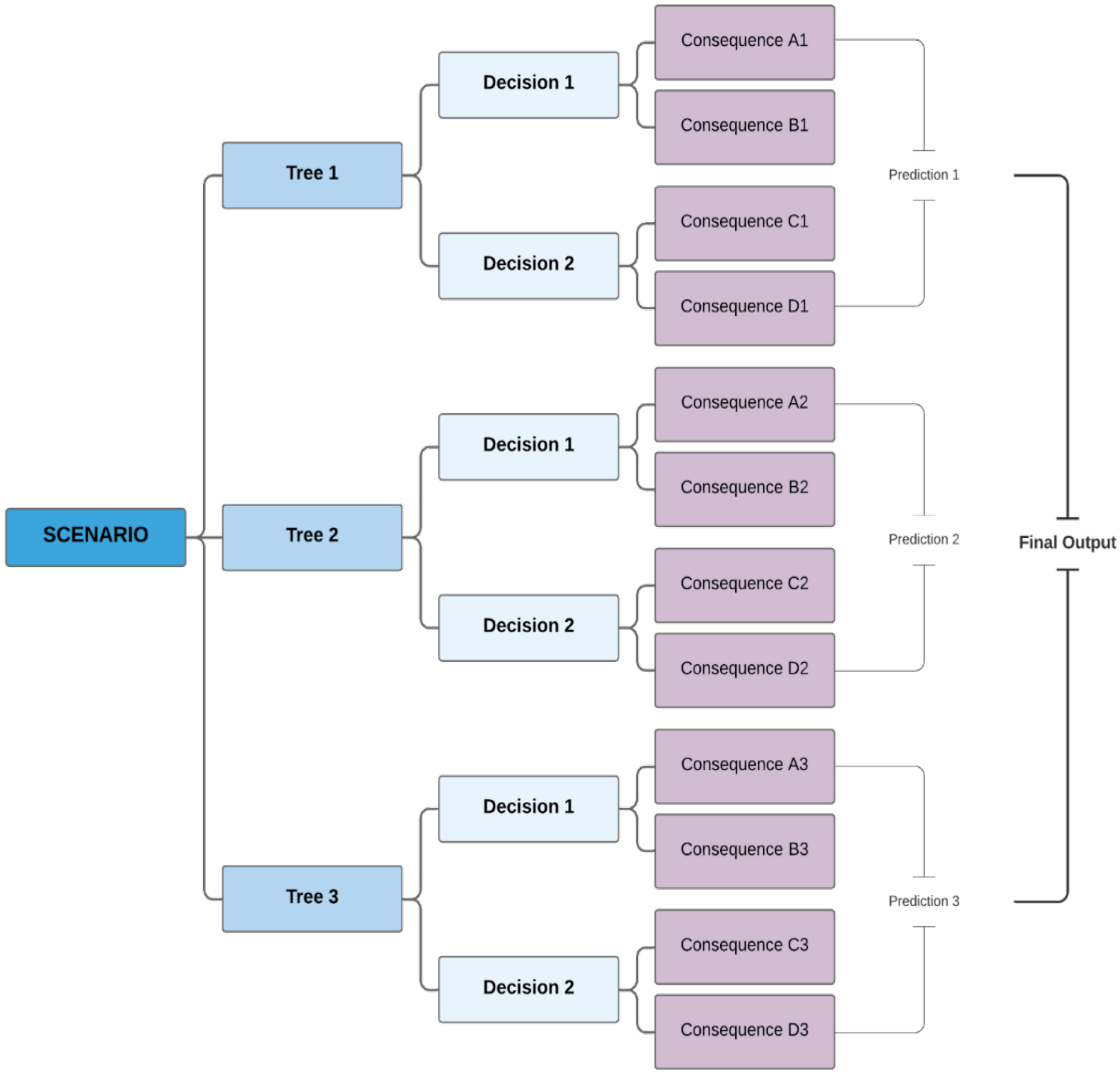


Figure 5: Illustration of the random tree forest algorithm.

Note. From *Mechanistically Informed Machine Learning and Artificial Intelligence in Fire Engineering and Sciences*, by M.Z. Naser, 2020, p. 2752-2753. Copyright 2021 by Springer Science + Business Media, LLC. Society of Civil Engineers [30].

2.3 Performance-Based Fire Design

The job of any fire engineer is to identify the risks involved and design safeguards to mitigate the effects of fire, including preserving human life and, to a lesser degree, minimizing economic consequences. To do this, there are typically three goals: to prevent a fire, confine the fire to a certain region of the building (thus preventing spread), and extinguish the fire. The methods by which a structural fire engineer may design a building are mainly split into two approaches: prescriptive and performance-based design, represented in Figure 6. The prescriptive approach, mainly used in the United States, specifies the fire resistance rating for individual structural elements based on standard fire curves. Performance-based design is specific to each project; it sets specific performance goals for when the structure is exposed to elevated temperatures rather than regulating the construction side of matters. The performance-based approach thus allows for more innovation and imagination for the engineers, as it doesn't restrict the design process as long as adequate safety can be demonstrated, equal to that required of the prescriptive approach. A basic outline of this is depicted in Figure 7. Performance-based structural fire engineering treats the structure or system as a whole rather than a sum of its individual parts. For the field as a whole, there has been a definite shift trending towards the performance-based end of the spectrum, though a project or engineer's position on that spectrum is a function of where they are located.

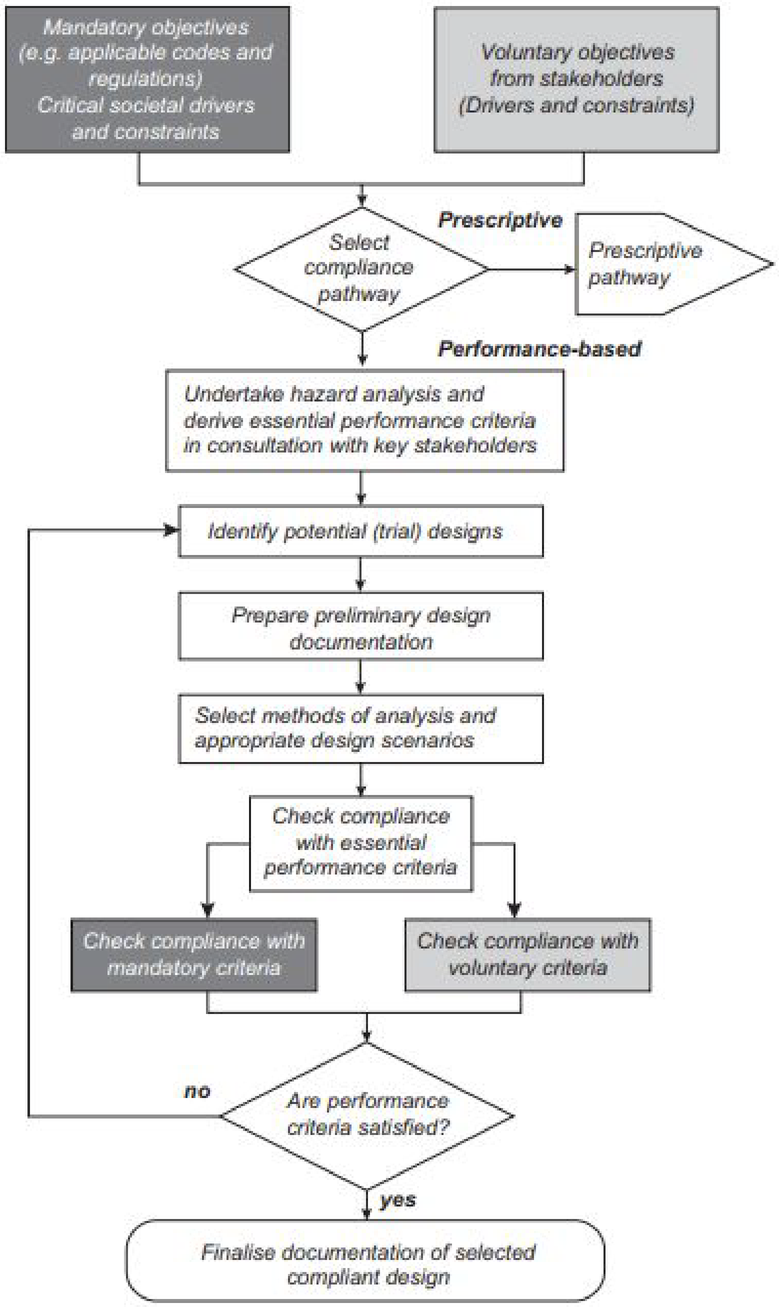


Figure 6: Overview of the structural fire engineering process.

Note. Reprinted from Performance-based design and risk assessment in *Fire Safe Use of Wood in Buildings*, by England et al., 2022, p. 374. Copyright 2022 by CRC Press [36].

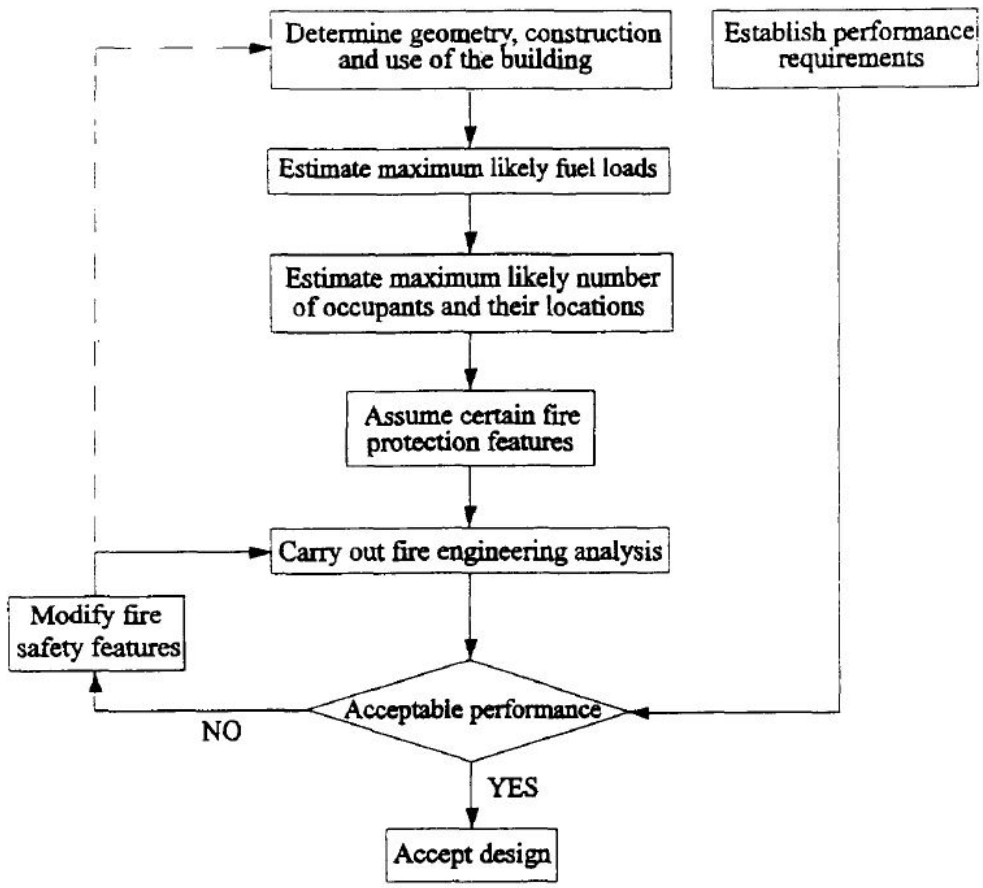


Figure 7: Outline of a performance-based fire engineering design procedure.

Note. Reprinted from *Fire Engineering for a Performance Based Code*, by Andrew H. Buchanan, 1994, p. 6. Copyright 1994 by Elsevier Science Limited [37].

As more and more countries around the world make the transition to performance-based fire codes, the United States is being left behind. A limited catalog of these performance-based fire codes, standards, and guides can be found in Table 1, though this brief list does not begin to cover all of the references currently accessible to practicing engineers.

Table 1: Limited catalog of performance-based design guides and standards.

Global
SFPE Handbook of Fire Protection Engineering [38]
ISO standards: 16732-1, 16733-1, 16733-2, & 23932-1 [39-42]
Europe
Eurocode 1 Actions on Structures – Part 1–2: General Actions – Actions on Structures Exposed to Fire [43]
Fire Safety Engineering – Comparative Method to Verify Fire Safety Design in Buildings. Inter-Nordic Technical Specification [44]
Fire Safety Engineering – Guide for Probabilistic Analysis for Verifying Fire Safety Design in Buildings. Inter-Nordic Technical Specification [45]
UK
Application of Fire Safety Engineering Principles to the Design of Buildings – Code of Practice [46]
The United States
Performance Code for Buildings and Facilities [47]
NFPA 5000 – Building Construction and Safety Code [48]
Australia
Handbook – Fire Safety Verification Method [49]
Australian Fire Engineering Guidelines [50]
New Zealand
Verification Method C/VM2, Framework for Fire Safety Design [51]
Fire Engineering Design Guide [52]

Note. Adapted from Performance-based design and risk assessment in *Fire Safe Use of Wood in Buildings*, by England et al., 2022, p. 378. Copyright 2022 by CRC Press [36].

While the prescriptive code works well enough for structural stability, performance-based codes allow more fluidity and adaptability on the part of the engineer. That will come in handy as technology continues to evolve, bringing structural design and analysis along with it. More and more innovation is being done on the subject in the rest of the world, while those in the Unites States struggle to make substantial heading incorporating modern advances into such a rigid established framework. That is not to say no progress is being made in the United States, but for those who are choosing to develop new ideas and methods, that makes them the outlier, not the rule. In the meantime, even excluding the use of complex software and specialized education, performance-based structural fire design provides a way to mitigate the economic costs of an overly conservative code without risking the safety of its occupants. Similar to how there must be short- and long-term plans of supporting the engineers during a shift in governmental code for it to be a success, there are also short- and long-term advantages that the shift may reap.

Hopefully, this review will serve as an organization of thoughts and knowledge to be called upon if and when the U.S. decides to join the rest of the contemporary world and make the switch. The review will cover literature regarding past and current uses of performance-based fire engineering design around the world, acceptable alternatives (mainly focusing on the prescriptive method described previously), and a very brief summary of recent innovations with the highest future potential in the field. As there is no available literature regarding the use of performance-based fire design for masonry, it will be excluded at this time, although it is the hope that once more research becomes available, performance-based codes will quickly be adapted to accommodate this. It is, yet, worth noting that early efforts in our domain are prospering [53-56].

2.3.1 Past and Current Uses

Performance-based design in itself is not a new concept. Its origins can be traced back all the way to 2250 B.C. to the Code of Hammurabi, which states, "a house should not collapse and kill anybody" [57]. The first time it appeared in building code was not until quite a bit later, in the last half of the 20th century. Its most widely accepted definition came from E.J. Gibson, a member of the International Council for Research and Innovation, who said, "the performance approach is the practice of thinking and working in terms of ends rather than means. It is concerned with what a building or building product is required to do, and not with prescribing how it is to be constructed [58-59]." However, the implementation of performance-based design in the fire engineering field is a bit more recent. Most of its early uses in the field concerned evacuation protocols, smoke control, and exit designs. As technology has developed, its applications have broadened to include the structural design side of projects. As stated before, the level to which the performance-based approach is accepted in structural fire design is dependent upon the location both of the designing firm and of the project itself, in addition to the previous experience of the designing engineer. Therefore, this portion of the review will be organized based on the geographical location of the projects and codes that it evaluates.

Structural fire design was first incorporated in Eurocode EN 1991-1-2, released in 2002, identifying both prescriptive and performance-based approaches to be used by practicing engineers [43]. These approaches are outlined in Figure 8.

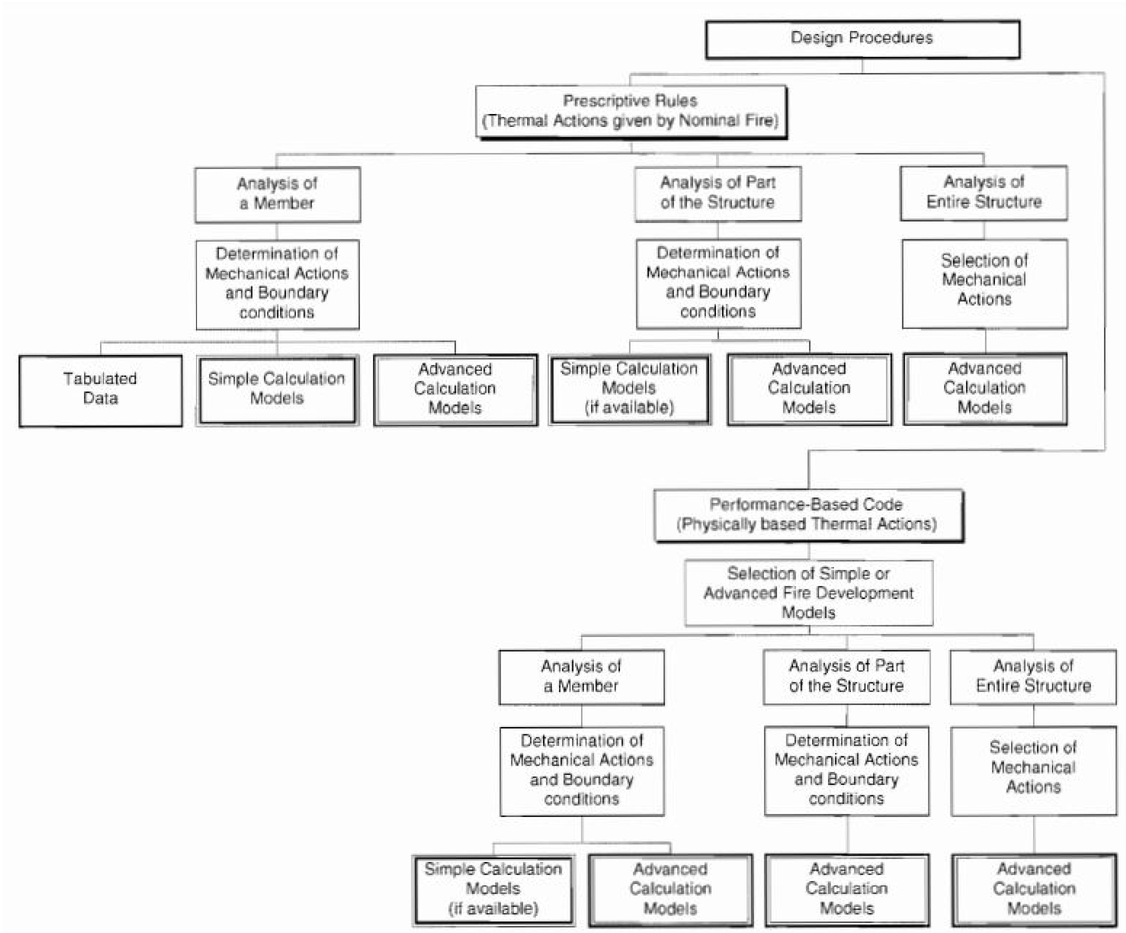


Figure 8: Alternative design procedure for Structural Fire design.

Note. Reprinted from *EN 1991-1-1 General actions – Actions on structures exposed to fire*, by the European Union, 2001, p. 8. Copyright 2002 by European Committee for Standardization [43].

In the years following its creation, the Eurocode practices were slowly adopted into national fire codes of European nations, beginning with the UK. Heinisuo and Laasonen presented a case study on the Salmisaari Sport Centre, located in Helsinki, Finland [60]. At the time of this study, performance-based design was already included in the national fire codes of the Czech Republic, UK, Finland, Hungary, and Italy. Performance-based fire design was used for the floor and roof trusses, with fire actions considered both for their intended occupancy and for special cases such as plastic-slide fires and stage fires (among five others). Computer modeling was used to incorporate the effects of the rest of the structure, as performance-based design treats the structure as a whole, not as a sum of individual components. The software used was National Institute of Standards and Technology Fire Dynamics Simulator version 5.2.5., based on computational fluid dynamics fundamentals to create a three-dimensional rectilinear grid congruent to most other finite element software [61]. The grid size was set with an upper limit of 200 mm in the area with elevated temperatures, based on a previous study by the same author [62]. At the end of the configuration, the simulation created temperature-time graphs for control points in each case of the evaluated fire actions, with an estimated 20% model and technical measurement uncertainty.

Petrini et al. conducted another case study, this one on the Duomo of Modena Cathedral in Italy [63]. The cathedral presented a unique case, as it contained an impressive amount of valuable content in the form of art pieces while being quite an important building by itself but was also lacking a fire suppression system due to its historical construction. This case study was split into three sections: fire risk analysis, fire dynamics, and structural behavior. This involved the event-tree method, thermo-fluid dynamics models, and advanced nonlinear thermomechanical finite element models, informed by the guidelines of the Confirmation of Fire Protection Associations [64]. These models used the same NIST FDS software, summarized in a group temperature-time and displacement-time graphs with the hope that the information they convey could help engineers work in conjunction with fire-fighters to establish a better-informed plan should a relevant incident ever occur.

Though more generalized geographically, Vacca et al. had an intriguing spin on the same line of research. Rather than compartment fires that originate in the structure through electrical mishaps or loose cigarettes, their paper focused on the concern of wildfires with the increasing intensity of climate change [65]. The growing severity of the wildfires and the enlargement of the wildland-urban interface (WUI) settlements both posed a need for the adaptation of lower-level software to account for relevant variables like wind, inclined group surfaces, etc. Without these parameters taken into consideration, the software failed to accurately simulate and predict the effects of real fire exposure [66]. Headway was being made to rectify this, most of which again surrounded the NIST FDS, as it had already been heavily verified and accepted as common place practice in the area [61]. The authors offered procedures and considerations for uses of the computational fluid dynamics program to identify fire-vulnerable concern areas in the glazing systems, roofing & gutters, and uneven building envelopes, all informed on the qualifiable knowledge gathered throughout the years from others on fires in the wildland-urban interface.

Moving on to Asia, Luo et al. put together a rather apt historical review of the role of performance-based fire engineering practices in China, focusing on the last three decades of advancements [67]. The trends in China mimicked that in the UK, discussed earlier in this chapter, rather well, with about a decade delay in governmental policy publication. Hong Kong SAR appeared to be the trend-setter, with their policies influencing the mainland's industry best-practices. Within that pattern, the Code of Practice for Fire Safety in Buildings in Hong Kong SAR was released in 2011 [68], while a formal performance-based code still had not been released regarding Mainland China at the time of publication. That is not to say that the practice was never used, though. While progress in this specific area of fire engineering lagged a bit in the 1990s with its popularization in other parts of the world, the 2008 Beijing Olympics seemed to put it in overdrive [69]. While most of the paper was focused on evacuation protocols and smoke management, structural components were considered both on an element-by-element basis (prescriptive) and for full-frame verification (performance-based), with respect to the "credible worst fire scenarios rather than the standard fire curve" used when following guidelines like the ISO or ASTM standards.

As stated previously, the Hong Kong SAR Code of Practice for Fire Safety in Buildings was released in 2011. Lo et al. offered the unique perspective of engineers before the official addition of performance-based design to their respective governmental building codes [70]. Moreover, this piece was formed as a conceptual system dynamics model, meaning it focused mainly on the qualitative process of structural fire and fire safety engineering rather than the quantitative modeling that has dominated the field in recent years. While it was helpful in allowing visualization of the relationships between components, it, more importantly, gave practicing engineers a place to start when the code was not yet up to the task, along with a reasonable expectation of how the approach was integrated into then-current building ordinances. After the model was presented, numerous simulation experiments were run to demonstrate how the model worked and to predict the effects on the field of fire engineering in general (in Hong Kong). The simulation produced many results, the most important of which was that the rate of fire engineered design projects would increase (with respect to the total projects approved) – precisely what occurred over the years following the publication of this paper.

In variation to the papers covered so far focused on the building side of structural engineering, Rujin et al. attempted to fill a rather large hole in the existing literature by considering the influence of elevated temperatures on the structure of bridges [71]. While fire is not the most common method for causing failure in a bridge, vehicle-induced fire is a threat that continues to grow with the ever-increasing amount of transport in the world. Of course, full-scale fire tests are optimal in terms of learning applicable information, but they are extremely expensive and not to mention imperfect regarding environmental/safety concerns. For more practical methods, this author went back to the FDS so commonly referred to in Northern European industry to stitch together previous, more narrowly focused, research projects that were involved in solving this issue. After outlining a proposed method design framework using this software, they then went on to walk through a case study, assumed to be fictional as its location was not given, step-by-step to verify it provided all the information necessary for any practicing engineer. As a whole, the process seemed to be an adequate solution to bridge fire analysis. It's fairly easy to follow and considers multiple facets of design, though the impact of a few of its parameters needs independent research before the process can be expected to be used in the industry.

Turning the spotlight to Oceania, New Zealand first introduced performance-based structural fire design in their 1992 Building Regulations, where Clause C6 detailed the functional and performance requirements for structural stability [72]. These requirements dealt both with the direct effects of the fire on the structural members and also any effects resulting from the prevention/aftermath of the fires (weight of sprinkler systems, safe access for fire-fighters, etc.). Buchanan introduced these new code developments and discussed the reactions to the changes directly after their implementation [37]. He stated, “[a] holistic performance-based code require[s] a probabilistic performance statement for the whole building, including all aspects of the fire safety system,” which is reflected very prominently in the organization of the new fire code. Once the changes in the code had been discussed, as well as any background information necessary to understand its purpose, he then went on to create a design guide in terms of executing the new requirements. This guide covered fire safety and structural fire engineering, just like the code it is based upon, in the same order for ease of comprehension. All calculations necessary were listed, as were recommendations on the resources with which to find them. As this was before the computational programs were created, these resources mainly consisted of well-known textbooks and handbooks written by fire engineering organizations. To go further, they also advocated for further education for design professionals on the matter, pointing to workshops and seminars from institutions all over the country. The author later wrote a textbook about the same subject, aptly titled Fire Engineering Design Guide, around a decade later, once the performance-based design code was a bit more established [73]. This version included peer reviews, computer modeling, updates to the code (again), and more.

Akin to the FDS tool in Europe, New Zealand has its own tool titled B-RISK [74]. According to its official website, it was created to “allow fire simulation results to be presented in a probabilistic form and allows the variability and uncertainty associated with the predictions of the fire environment to be quantified" [75]. In preparation for its development, Baker et al. compared multiple user-input options for the design fire used in the software [76]. It was found that the design fire generator (created with B-RISK) and parametric heat release rate (calculated using statistics) curves were found to have similar results regarding the growth phase and fully developed phase with a few minor variations. Other details regarding the fire growth rate and location of burning objects were discussed, with the conclusion that the results gathered from the B-RISK simulation were very conservative when compared to the VM2 Verification Method in the 2012 New Zealand Building Code [51] and international research.

Pau et al. presented a case study analogous to the one described before by Petrini et al. It contained the same considerations for heritage buildings, though this paper referred to the McDougall house in New Zealand rather than a church in Italy [77]. The building underwent multiple earthquakes in 2010 and 2011, leading to damage to the chimney and fireplace. The fire engineering design method used was taken from the same VM2 Verification Method in the 2012 New Zealand Building Code as the literature previously touched upon [51]. It also had an added layer of objectives, as the goal of the project was to conserve as much of the building's historical/heritage value as possible while still ensuring the safety of its occupants. This paper followed the same pattern of addressing fire safety engineering concerns (evacuation and ventilation) before moving on to the structural/construction side of matters (material choices, member repair). The approach used appeared to be a mixture of performance-based and prescriptive methods, as performance-based methods were used to qualitatively identify areas of concern, and prescriptive methods were used in the restoration of the fire resistance of the structural elements. The case study ended with a table detailing the updates of all the fire protection systems; for structural elements, this included 30-minute rated plasterboard on the floors, ceilings, and walls. All structural steel was enclosed in the same material, achieving the same fire rating, which was found to be in compliance with New Zealand Building Code and thus acceptable to the engineers.

Before his work on the McDougall house case study, Fleishmann wrote his own piece, years prior, on the impact of the engineers' discretion in interpreting the qualitative guidance of performance-based design criteria [1]. Differences in these interpretations could lead to widely varying results and safety levels for structures that, on the outside, look like they should be fairly similar. While variation in the product itself was not necessarily a bad thing, it could lead to some issues should careful consideration not be taken place. In terms of safety, one of the more important conditions was that the available safe egress time (ASET) be larger than the required safe egress time (RSET) by a reasonable margin of error. The ASET was determined by computer modeling based on the performance criteria, predicting how the structure will behave, while the RSET was an estimate of how long people have to evacuate before the building is unsafe, therefore predicting how its occupants will behave. The issue was that these calculations relied on parameters that were not necessarily constant and/or provided, such as the design fire scenarios, design fires, and acceptance criteria. The author then concluded their remarks with a call for more quantitative guidance for the aforementioned criteria, which was shortly answered with the VM2 Verification Method in hopes of providing the engineers in New Zealand with a more clear and more efficient method for performance-based structural fire design.

Just because the performance-based design approach is not the most popular route for structural engineers in the United States to take, does not mean that it's never done. The American Society of Civil Engineers first incorporated performance-based structural fire design into their code in 2016 [78], later than most countries discussed before, but still established enough for the subsequent literature to have a decent amount of practical experience behind it. Most of the literature focuses on steel structures, as steel tends to be a fairly uniform and predictable material. Fischer, Varma, and Agarwal wrote one such piece of literature, concentrating on compartment fires in medium-sized ten-story steel construction office buildings [25]. These buildings had their structural fire protection designed using the prescriptive method but then were analyzed with performance-based methods to see if any improvements could be made (and they could). The buildings were analyzed using nonlinear inelastic three-dimensional finite element models, with two phases: the first of which evaluated the heat transfer due to the emergence of the compartment fire and the second of which detailed the structural response following that heat transfer. These finite element models were done through the ABAQUS software [79]. The results from these models indicated that changing the elements that the fire protection was attached to increased the fire resistance of the buildings as a whole,while improving their efficiency of it.

Alasiri, Chicchi, and Varma wrote a paper regarding a very similar structure [80]. It was also a ten-story office building made with steel perimeter moment frames. This building, though, had the added concern of being in a high seismic region; therefore, the authors chose a very niche topic: assessing the impact of the damage caused by previous earthquakes on the behavior and stability of the structure during a fire. The simulated building was designed up to American standards, with the required fire resistance determined by the International Building Code [21]. The authors then created performance-based parametric studies using ABAQUS [79] of the simulated building being exposed to fire after having previously undergone eleven earthquakes. These parametric studies "indicate[d] that partial or full collapse of the building structure [could] be prevented by sufficiently increasing the structural design (size) or fire protection (fireproofing thickness) of the critical gravity columns," thus providing multiple practical options for the designated engineers.

While, as stated before, most of the established literature regarding performance-based design in the United States is in reference to steel structures, there appears to be the beginning of a shift, or rather an expansion of subjects. Khorassani et al. completed a parametric study regarding performance-based structural fire design of composite floor systems [81]. This nine-story office building (with steel moment frames of course) was used to investigate the influence of many of the structural engineers' decisions regarding fire engineering, including "modeling approach, fire curves, applied gravity loads, and hazard scenarios (fire-only vs. post-blast fire)." To do so, the MACS+ tool was utilized to simulate the composite slab under an ISO standard fire [82-83, 11], the results of which are found in Figure 9. The performance-based design of the slab was found to be acceptable, able to temporarily withstand losing a column, allowing for complete evacuation of the building.

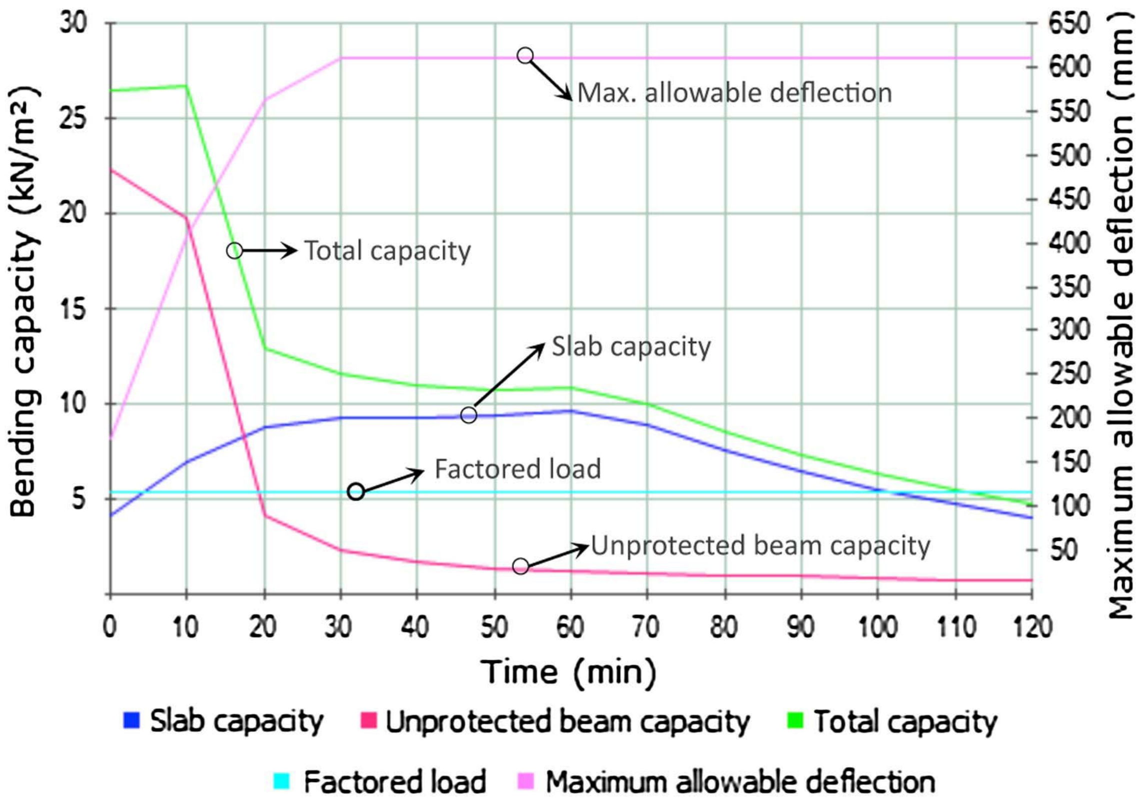


Figure 9: Fire resistance of performance-based design done with MACS+.

Note. Reprinted from *Parametric Study for Performance-Based Fire Design of US Prototype Composite Floor Systems*, by Khorasani et al., 2019, p. 9. Copyright 2019 by ASCE [81].

2.3.2 Alternatives

While this thesis provides a literature review and argument for the popularization of the performance-based design approach in structural fire engineering, it would be remiss not to recognize the alternatives. More precisely, the next section of this review will cover comparisons between the performance-based design and prescriptive fire resistance methods.

Khorassani, Germany, and Fang, who also wrote the previous paper discussed, composed a comparative study about the very same subject [3, 84] prior to the publication of the parametric composite floor analysis. Actually, the same nine-story office building was used in this comparative study, though this paper was equally focused on evaluating both methods rather than trying to prove one is better than the other. In this study, the same building was designed in two different ways: one following current prescriptive guidelines to get as close as possible to a real-life design in the U.S. (spray fireproofing with each individual element acting alone [21, 18]) and one that employed performance-based design to adjust reinforcement in the slab such that it achieves tensile membrane action. The two structures were then modeled with a non-linear finite element program named SAFIR, which allowed for thermal analysis and subsequent transient structural analysis of building members at elevated temperatures [85]. These models were exposed to both the standard ASTM E119 fire curve and a two-zone CFAST model that provided a bit more adaptive and realistic results [10, 86]. Both methods were found to be adequate when exposed to both kinds of fire, which showed that the performance-based approach was an acceptable alternative. Though, the labor and resources required to prove this fact call into question whether or not it is worth it for the practicing engineer to take it into consideration until performance-based design has more thorough guidelines and best practices available that are integrated into the national codes.

Sanctis, Faber, and Fontana had a slightly different approach to comparing prescriptive and performance-based design; they compared them by proposing a method of quantifying the level of safety that each design would achieve [87]. This methodology could also be used to verify what is "equivalent" between the two design approaches. Mathematical models were created for each step of the methodology, describing anything from the limit state on the temperature domain to the influence of the fire brigade intervention. The level of safety for each method was found through a reliability analysis of these models, which was outlined in terms of fire ignition, the effect of the fire on the structure, and finally, structural failure. The reliability analysis found that the probability of failure using the prescriptive design approach depended on building properties, which makes sense as those are not considered in the guidelines themselves. The probability of failure when following the performance-based indicated it is more removed from building specific properties.

While some of the literature discussed here attempts to be objective about the methods adopted by each nation, others make their opinion very clear. Such is the case with O'Loughlin and Lay, in their article titled "Structural fire resistance: Rating system manifests crude, inconsistent design," referring to the prescriptive method [88]. Their problem laid in the 15-minute increments that the fire resistance of any given product is normally categorized as. As with any other procedures, the accuracy of the final results is only as strong as the accuracy of each step within the process. More eloquently put by Elms, 'the choice of level of detail in any part of an engineering procedure must to some extent be governed by the crudest part of that procedure'' [89]. As the field of engineering rapidly develops, as structural fire engineering has in the past few decades, the progress might not be uniform across the field, causing a weak link in the chain. Figure 10 shows a rough interpretation by the author of the relative progression of different aspects involved in structural fire design. This view was then backed by a hypothetical study, though more research would have to be done by an independent party for it to have any substantial effect on national codes.

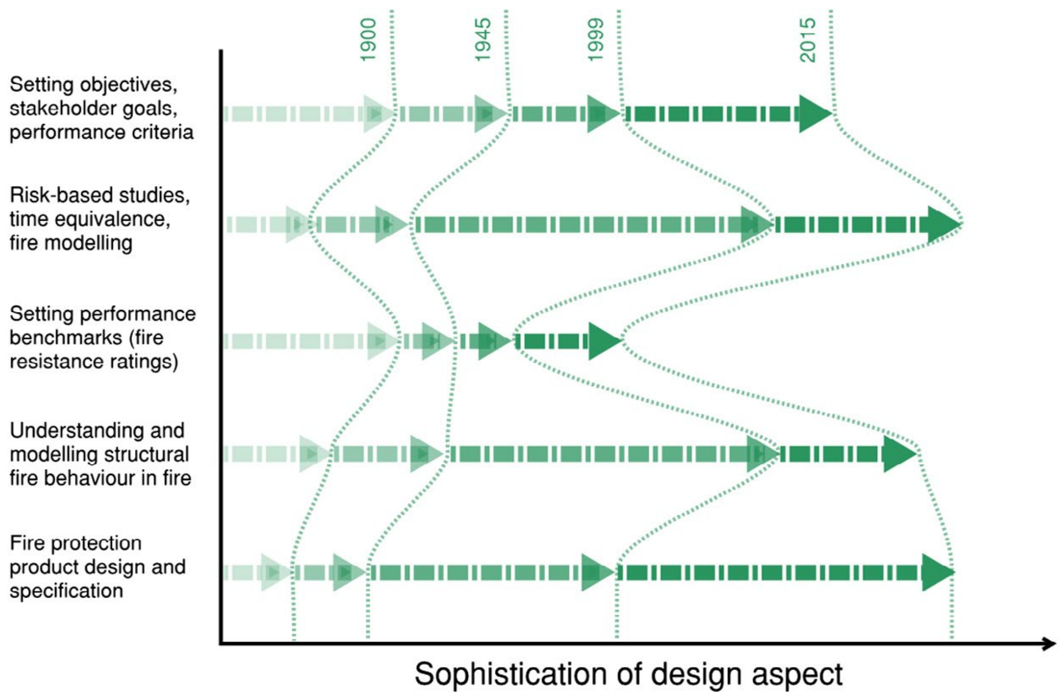


Figure 10: Relative progression of various facets involved in structural fire design.

Note. Reprinted from *Structural fire resistance: Rating system manifests crude, inconsistent design*, by O'Loughlin and Lay, 2015, p. 39. Copyright 2019 by Elsevier Ltd [88].

Tavares attempted to do just that: influence code at a national level. This was done through a comparison of the two methods, done both in terms of objective economic impact and through a cultural lens specific to Brazil [90]. The first objective was completed fairly easily, with the advantages and disadvantages of both systems easily presented in charts. Based on the information there, the prescriptive codes were nice in the way that fire safety engineers with high levels of qualifications were not required, but there was a lack of flexibility and innovation to help reduce costs. Performance-based design had that flexibility and potential for economic efficiency, but it was difficult to quantify the criteria or validate the methodologies. After addressing how other countries shifted from prescriptive to performance-based codes, the focus shifted towards potential problems specific to Brazil, mainly the fear that the then-current fire codes were not well known or efficiently applied; therefore, how could any new ones be? Culturally, not much stock was put into fire risks, so while the long-term goals might've been to shift to performance-based design, there was much groundwork that needed to be laid before the country was ready for that. Perhaps this has changed in the years since the article was written, or perhaps not. Either way, it shows that while performance-based design has its clear advantages for the contemporary world, it does not necessarily mean it is the best for every case.

Meacham went one step beyond just comparing prescriptive regulations with performance-based; he added market-based into the mix [91]. Another unique note is that this paper was geared towards the influences of different types of regulations on buildings formed with modern methods of construction (MMC). This was in reference to buildings that are comprised of components prefabricated off-site, which makes construction move very quickly once the pieces have all been transported to their final location. This created issues specific to MMC, like the fact that the components are closed from view when they are inspected on-site, which limits what information can be gathered about their condition. Market-based regulations are similar to performance-based codes in that they are very objective based; the only difference is that the responsibility lies with the owner and/or developer rather than the involvement of any governing body. In the case of MMC, none of the three approaches were deemed to be admissible without caveats. Any objective-based code needed entire "systems" testing to be worthwhile, while prescriptive design was based on standard fire tests that weren't always applicable to the finished assemblies. Therefore, all methods needed to find a way to adapt to complex systems, as our industry and technology advance.

2.3.3 Recent Innovations

As all prevalent methods of structural fire design have been addressed, with a clear preference towards performance-based design, this section will focus on literature published within the last couple of years that have particularly inspired and innovative additions to research regarding performance-based structural fire design. This will provide a sense of where the extent of the application currently is, and furthermore where its future potential lies.

Germany and Khorasani presented a very thorough archetype for computational analysis with their study of a steel-framed building with composite floor slabs [92]. The paper was similar to that with one of the same authors discussed before, namely the piece by Khorassani, Germany, and Fang, with the exception of the multiple different models with increasingly larger scales and the iterative design process based on their analysis, which was the main draw of the paper. It began with an in-depth performance-based analysis of the structure after being exposed to elevated temperatures using computational modeling. Three different models were created: single slab, single slab with restraint, and full building. Each of the models was designed with the performance-based approach, as they "adopted a set of performance objectives for the structure based on a rigorous definition of fire hazard scenarios informed by probabilistic considerations…iteratively by acting on several design parameters affecting the thermal and structural response of the building." These designs were verified by the nonlinear finite element analysis, including scenarios of single- and multi-compartment fires, as well as if should a fire break out following column loss. This analysis concluded that the full building model was most optimal, as it was the most realistic to be used in the case of extreme events like multi-compartment fires.

Danzi, Marmo, and Fiorentini recently released a new parametric method titled Fire Risk Assessment Method for Enterprises (FLAME) [93]. This risk assessment, or rather risk index, method combined the strategies from several established methods, including the Gretener method, the Fire Risk Assessment Method for Engineering (FRAME), the Building Fire Safety Evaluation Method (BFSEM), and the Dow Fire and Explosion Index [94-97]. This method was meant to be used as an alternative to complex computational fluid dynamics models briefly touched on before; performance-based design is not necessarily synonymous with simulated design, and this method intended to prove that. It went back to the fundamentals, basing its property risk evaluation tree structure on the NFPA Standard 550 Fire Safety Concept Tree, depicted in Figure 11 [98]. Rather than organize the results in reference to time periods, in this method, "the fire risk [could] be described by a number of key attributes while considering the fire strategy in place and the facility conditions." The semi-quantitative parametric method was used in several case studies involving healthcare facilities, which found the method comparable to the Italian Fire Code prescriptive measures.

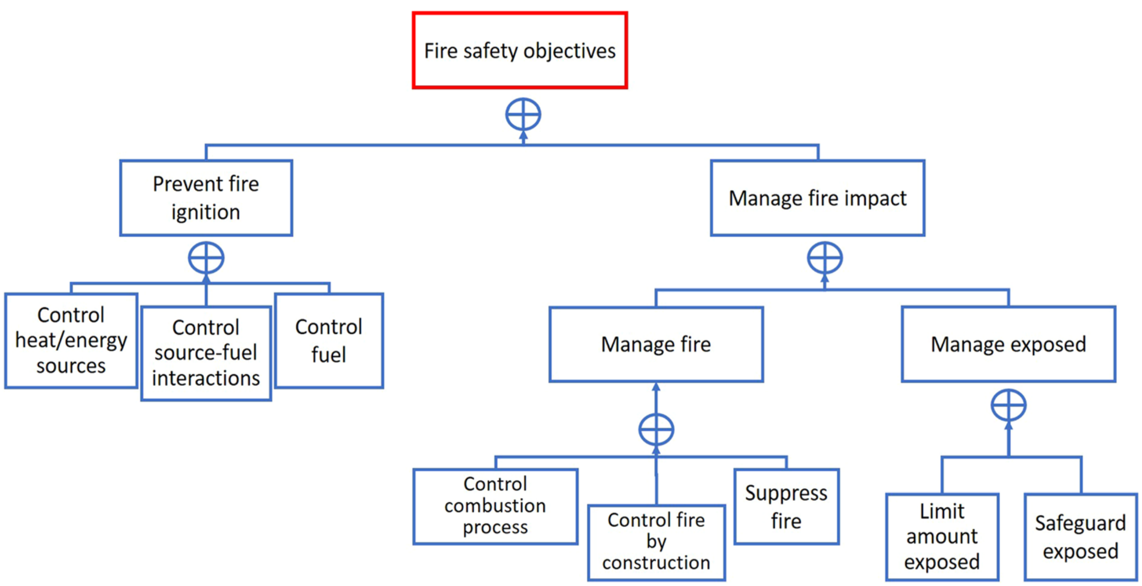


Figure 11: NFPA Standard 550 Fire Safety Concept Tree.

Note. Reprinted from *FLAME: A Parametric Fire Risk Assessment Method Supporting Performance Based Approaches*, by Danzi et al., 2020, p. 723. Copyright 2020 by the authors [93, 98].

Siddiqui et al.had a different spin on integrating computer modeling into fire engineering, or rather the other way around [99]. As part of an international collaboration with BIM Standards Organization buildingSMART, a strategy was developed to incorporate fire safety engineering-specific information into the exchange of data involved in building information modeling (BIM). BIM creates virtual or simulated buildings with a combination of objects and information about those objects. Development of any given aspect of that information is given a level based on what information is available in the model and in what format it is given. The format controls what can be done with the information without the need for a third party or manual recreation of data by the engineer. The goal was to eventually get this information into a cloud-based environment where data could be called upon by any of the participants and easily integrated into other relevant programs. This paper outlined a three-step strategy to get to that goal, namely enhancing Industry Foundation Classes modeling specifications for fire safety engineering, implementing those specifications, then improving fire and evacuation modeling tools to support BIM.

The next couple of articles reviewed looked toward the future of machine learning. While its use has been well developed in other fields, structural fire engineering has just begun to realize the possibilities of its implementation. Zhao, Chen, and Wu developed a simulation model, created with a relatively new ensemble-learning method titled XGBoost [100]. This model accurately predicted fire resistance of concrete-filled steel tubular columns using the balancing composite motion optimization algorithm previously proposed by Le-Duc et al. [101]. That is all to say that they created a model that learns from the data it receives using algorithms, until it could accurately predict the behavior of concrete-filled steel sections when exposed to fire. This model was limited in the number of tests available for it to learn from, so it will only continue to improve in the time to come.

Naser et al. had a bit of a broader view as their paper explored a multitude of algorithms that can be applied to structural and fire engineering [102]. The algorithms described and later tested were Decision Trees (DT), Random Forest (RF), Extreme Gradient Boosted Trees (ExGBT), Light Gradient Boosted Trees (LGBT), TensorFlow Deep Learning (TFDL), and Keras Deep Residual Neural Network (KDP). They were chosen due to their expected application to structural fire engineering regression and classification problems. The authors then went on to present a framework for validating these algorithms through datasets tested against six databases, which were made of both physical tests and finite element simulated data. Those tests showed that Extreme Gradient Boosted Trees and Light Gradient Boosted Trees seemed to do the best, although no one algorithm appeared to dominate above all the rest, so it was the authors' suggestion that multiple algorithms be used in any future machine learning analysis.

2.4 Concluding Remarks

In summary, performance-based design has been around since the beginning of structural engineering – but it's only recently been written into code. The debate between prescriptive and performance-based approaches to structural fire design is intense, but at the end of the day, both methods seem to get the job done adequately. Prescriptive methods are easy to understand and implement, but they are restrictive in their uses and overly conservative in accounting for the variability in parameters that they do not take into consideration in their process. Performance-based methods allow for more flexibility and experimentation on the part of the engineer, permitting them to increase efficiency and minimize costs where possible, so long as it is verified that the safety of the occupants is not being sacrificed. That verification, however, tends to involve computational software capable of running complex calculations or professionals with specialized education, should the governmental codes not be sufficiently streamlined. These codes can often be left up to interpretation, as there can be qualitative benchmarks depending on the code's origin.

Despite the complications in the process, performance-based design has many benefits over the prescriptive approach, which will only continue to grow as the field evolves. This is evident in the way computational modeling and building information modeling (BIM) have been integrated into structural fire analysis already. While they are not necessary for performance-based design, they certainly widen the possibilities for the project, allowing for all sorts of material and geometrical configurations to be included. Going further into the realm of innovations, towards the trends just starting to horizon, is the concept of machine learning. Algorithms are now being verified for use in structural fire design and while it is still in the early stages, the potential for these models looks to be immense.

Performance-based design is not for everyone, however, so the most desirable option appears to be putting emphasis on performance-based design to give the method the resources it needs to develop to its full potential while providing a secondary way for simpler projects, where it does not seem worth the extra effort or labor for the designing engineer, to keep the ease of prescriptive methods. This is much in how performance-based design is seen as a secondary alternative to prescriptive codes in the United States. In any event, based on the information presented, there is a major argument to be said for the benefits that professionals would reap should performance-based methods for structural fire engineering be incorporated more considerably into the United States fire codes.

3. EXCEL-BASED DESIGN TOOL

3.1 Overview

This thesis is motivated by the fac that there's not any significant amount of literature currently available for performance-based structural fire design of masonry products. Most of the past work regarding the influence of fire has been done through behavioral and material testing, similar to the testing that prescription-based codes are based on. However, that does not mean that advancement has come to a halt until that information can become available; there is still plenty of innovation to be had in the increasing efficiency and automation of structural fire masonry design. To that end, this chapter describes the creation of a new tool capable of adjusting member capacities to account for the degradation caused by exposure to elevated temperatures (at the heating and post-heating phases), thus incorporating the material testing information available into the design aspect of the field.

The chapter is formatted such that a brief literature review is first presented to form an elementary foundation of information for masonry design, then subsequently followed by the description of the tool accompanying this thesis, split into three sections: Purpose, Creation, and Limitations & Future Development. The first section describes the purpose and need for such a tool. The second outlines the creation of the tool, both the process of actually constructing the tool and the code fundamentals/design principles that it is based on. The final section details the limitations regarding what the tool can currently do, and its potential for future development for more specialized cases or detailed designs.

3.2 Literature Review

This section composes a very brief literature review in order to provide context for the coming excel tool. As such, it is not to be seen as representative of the quantity of sources available, but it does provide a good range of literature in terms of the breadth of information covered. For this review, the literature will be split into three categories: behavioral tests, material property studies, and predictive modeling.

3.2.1 Full-Scale Fire Behavioral Testing

Nguyen and Meftah conducted a parametric experimental campaign focused on the behavior of clay hollow-brick masonry walls when exposed to fire, the first part of which was an experimental analysis [103]. The overarching goal of this project was to build a database for the degradation of clay masonry walls under fire conditions for the purpose of completing performance-based design using that verified information in existing sophisticated models, akin to the purpose of this thesis. But first, the data must be collected. The authors completed fire-resistance tests, heating the walls on one face with air temperature that evolved with the passage of time, simulating the conditions of a real fire. The thermal behavior and standard design criteria of each of the four specimens tested were analyzed, and it was determined that the structural walls had localized spalling that gradually propagated through the wall thickness, causing eccentricity in vertical loading that ultimately led to failure. The out-of-plane deformations coupled with the mechanical degradation of joints indicated that simplified two-dimensional modeling would not suffice for accurate prediction of spalling, to be discussed in detail later.

Jazouli and Tsangouri compiled a similar report on stone masonry structures [104]. These authors were mainly interested in local (Belgian) historical construction and restoration. As such, the stone masonry analyzed was composed of limestone, sandstone, and quartzite. The masonry was treated according to ASTM E119 fire exposure protocol [10] to determine the decline of strength in a three-point bending test following ASTM C99 [105]. Once the specimen had failed in flexure, a portion of the end was cut off to be used for a compression test. As a general trend, the sandstone appeared to have less significant degradation of flexural and compressive strength when compared to the other specimen tested, while limestone had the highest drop of mechanical properties. The authors went on to detail the role of micro-cracking in the grains in this phenomenon, along with its relationship to physical properties like density and p-wave velocity.

For concrete masonry units, Oliveira et al. published an experimental analysis of the behavior of CMU walls after fire exposure [106]. The experiment was done by heating walls made of three-cell calcareous aggregate concrete blocks on one side according to ISO 834 standards [11] while the walls were subjected to serviceability in-plane loading. The temperatures were measured on the side of the wall not heated, along with both in-plane and out-of-plane displacements. The authors found the masonry to be a highly heterogeneous material, stressing the importance of moisture content in the masonry on its thermal properties, namely specific heat. The experimental results were then compared with Eurocode's simplified calculation method [43], where the Eurocode's method was found to overestimate the fire resistance of the applicable specimen by over 20%, showing a need for a more accurate, if more complicated, method for predicting fire-resistance.

3.2.2 Material Properties

Deware and Naser have recently made their mark on this niche field. In addition to writing a literature review of their own outlining previous testing for mechanical and thermal properties of masonry blocks [107], the same authors also completed fire tests of their own [108]. These tests formed the basis of generalized temperature-dependent models for the degradation of compressive strength in masonry due to fire [109]. The fire tests will also form the basis for the tool accompanying this thesis, which this chapter is focused on. The authors used the empirical results to test three different methodologies to determine which regression model could yield the most accurate results with the simplest procedure, though they found the difference between models was minimal, suggesting that the models would eventually converge and yield comparable results.

Andreini De Falco and Sassu conducted a parametric study for stress-strain curves of (clay and concrete) masonry based on the results of a previous experimental campaign [110]. This experimental campaign tested approximately 200 cylindrical specimens, measuring their compressive strength both at ambient temperature and at elevated temperatures, in addition to a test determining the thermal behavior of the specimens. The authors then developed a numerical relationship or constitutive law, using the Levenberg-Marquardt algorithm and Popovič model, for each different type of material (clay, lightweight aggregate concrete, mortar, etc.). These relationships were then validated through an adapted k-fold cross-validation procedure. Based on a comparison with the corresponding curves from the Eurocode, the constitutive laws seem adequate to be used as an alternative or to provide a basis for finite-element analysis of masonry structures.

3.2.3 Predictive Modeling

Going back to Nguyen and Meftah, the second half of the project regarding clay hollow-brick masonry walls under fire, presented in a companion paper, consisted of the completion of a spalling assessment with three-dimensional finite element modeling [103], as two-dimensional was proven to not be capable of predicting spalling accurately under the given conditions. Basic thermo-mechanical equations were incorporated into elastic nonlinear material models in Cast3M [111] to complete the analysis in two stages: heat transfer and iterative mechanical analysis. The first stage made sure the fire was being accurately represented, and the second confirmed structural integrity, yielding the final results. The end result was a fully functional spalling assessment simulation, displaying satisfactory predictive capacities for both load-bearing and non-load-bearing walls with traditional mortar joints.

In terms of developing new finite element models, a program called MasSET was developed by Nadjai et al. [112-113]. This model was created to predict the thermal behavior of masonry walls exposed to fire by analyzing a slice as a two-dimensional column strip. This model is a bit simpler to use compared to the one discussed before, but it has some drawbacks, such as the temperature distributions must be explicitly assigned rather than pairing a secondary thermal analysis program to define them. This model focuses on cracking and crushing failure of the masonry, as opposed to spalling, which isn't necessarily a drawback but does come with some responsibility on the engineer to ensure that spalling is not a risk for the specific projects that it is used for. This model was validated using experimental results; then a parametric study was completed to determine the influence of slenderness ratio, load eccentricity, and boundary conditions on the maximum temperatures that the masonry walls can withstand before failing structurally; it was found that the slenderness ratio had the greatest impact on structural integrity.

3.3 Purpose

As stated earlier, there is not much literature about the effects of elevated temperatures on masonry, a direct contrast to other natural disasters like hurricanes and earthquakes, and what little literature there is about the subject is based on outdated testing and 'standard' fire curves that fail to accurately simulate real fire situations. While this gap in the literature is slowly being filled, most current progress revolves around the degradation of material properties when exposed to fire. This lays the foundation for those in the design part of structural engineering, but as of now, no one has yet to make the jump over.

This tool attempts to correct that by creating a practical, easy-to-use tool to encourage the consideration of fire criteria in masonry projects without the need for complex finite element simulations or the extensive theoretical knowledge needed to wield them accurately. The machine learning predictive model outlined later in this thesis will go through a similar process; it will just be more automated with less exposure on the inner workings, whereas Excel lays all the intermediate calculations out for those who know where to look.

3.4 Creation of the Tool

The excel tool is based on the building code design procedure for masonry structures outlined in The Masonry Society's 2016 manual TMS 402/602 [20]. More specifically, the procedure follows the strength design method for unreinforced masonry, found in Chapter 9 Section 2 of the TMS Code. It should be noted that while another version of the code has been released in 2022, none of the relevant sections have been changed. The design procedure used is split into a flexural check, an axial check, and interaction diagrams for members with both flexural and axial loading. In general, the structural limits are given in terms of stress; the compressive stress cannot exceed 80% of the specified unit strength (f'_m), while the tensile stress cannot exceed the modulus of rupture (f_r). It should be noted that regarding the modulus of rupture, the prism strength and unit strength are said to be equivalent for the purposes of the tool. No matter, to get the stress in terms of the moment or axial capacity, Equation 1 is used, split into compressive and tensile stress, respectively:

$$f_a + f_b \leq \Phi 0.8\, f'_m \tag{1a}$$

$$-f_a + f_b \leq \Phi\, f_r \tag{1b}$$

where $f_a = \frac{P}{A_n}$ and $f_b = \frac{M}{S_n}$.

These equations can be rearranged to isolate M and P to calculate moment and axial capacities. The nominal axial strength can also be calculated using Equation 2. It should be noted that the axial tensile resistance of unreinforced masonry is to be neglected, so the following equations refer only to compressive strength.

$$\text{for } \frac{h}{r} \leq 99 \qquad P_n = 0.8\left\{0.8A_n f'_m\left(1-\left(\frac{h}{140r}\right)^2\right)\right\} \tag{2a}$$

$$\text{for } \frac{h}{r} > 99 \qquad P_n = 0.8\left\{0.8A_n f'_m\left(\frac{70r}{h}\right)^2\right\} \tag{2b}$$

For members experiencing both flexural and axial loads, an interaction diagram can be created to account for the different possible combinations of flexural and axial loading that would lead to structural failure, shown in Figure 12. The diagram is split into two easily defined sections: compression-controlled and tension-controlled. As each requirement is calculated separately, the interaction diagram is made of two equations with an ultimate strength limit cap. Note that the diagram does not fall below zero for axial strength, as compression is considered positive and tensile strength is neglected. This would change if reinforcement was added to the member.

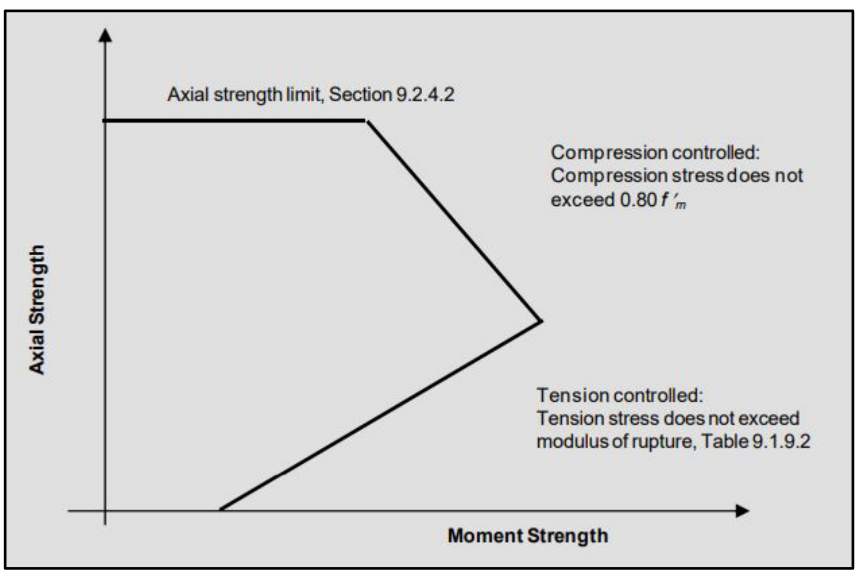


Figure 12: Interaction diagram for unreinforced masonry members.

Note. Reprinted from *Building Code Requirements for Masonry Structures and Commentary*, by The Masonry Society, 2016, p. C-131 [20].

These equations give the design capacities of masonry at ambient temperatures; exposure to fire, however, effects the mechanical properties of the masonry, and thus effects the design capacities. To incorporate the effects of this degradation, reduction factors were used for both the compressive and tensile strength of the concrete masonry units. These factors were estimated based on previous literature. Daware et al. examined the mechanical behavior of concrete blocks when exposed to elevated temperatures, using experimental testing to estimate accurate reduction factors for the compressive strength of concrete masonry at 25, 200, 400, 600, and 800 °C [114]. These factors were found both for the 'hot state' (during the elevated temperatures simulating a fire) and 'residual state' (when temperatures returned to ambient). For the Excel tool, each 'state' has its own sheet and the reduction factor for any other temperature value is found using linear interpolation.

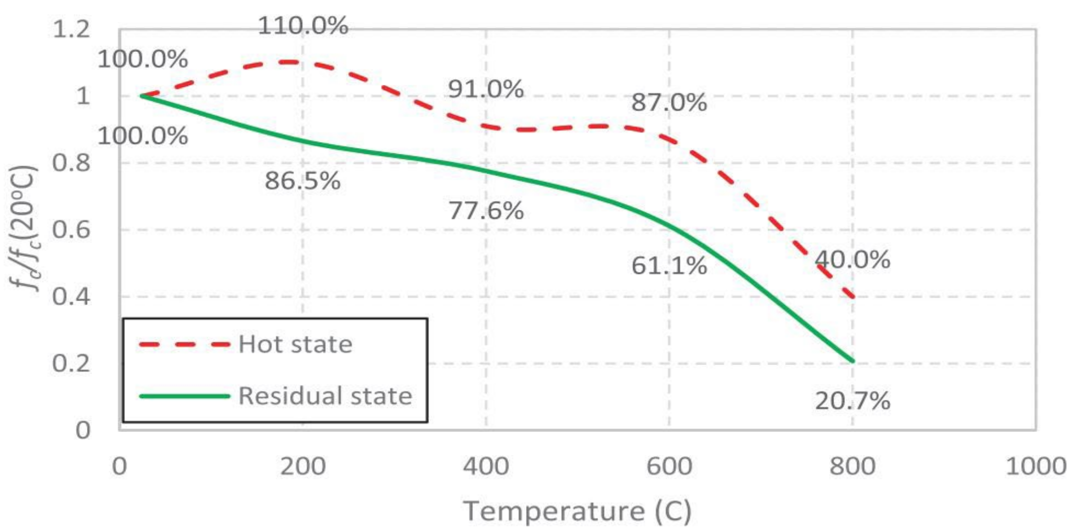


Figure 13: Degradation of masonry compressive strength at elevated temperatures.

Note. Reprinted from *Examining the behavior of concrete masonry units under fire and post-fire conditions*, by Daware et al., 2022, p. 8 [114].

The reduction factors for the tensile strength, governed by the modulus of rupture, were found is a very similar way, this time based off the work of Xiao et al. [115]. Three separate mix proportions were created for the wall blocks to test the effect of recycled aggregates on the masonry's fire resistance. The blocks were tested in the same temperature range as before, though at 20, 300, 500, and 800 °C; the average results of which are found in Figure 14. This reflects only the residual strength of the masonry after the temperatures have died down, which based on Daware et al's results [114], should underestimate the structure's capacity during the event itself, allowing for a safe, if conservative, final member design.

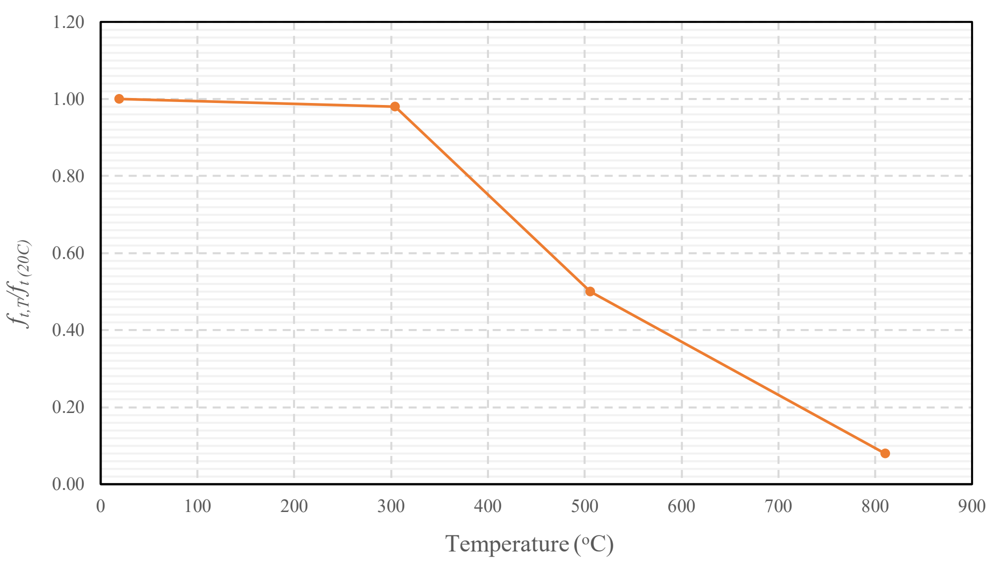


Figure 14: Degradation of masonry tensile strength due to elevated temperatures.

Note. Adapted from *Properties of partition wall blocks prepared with high percentages of recycled clay brick after exposure to elevated temperatures,* by Xiao et al., 2013, p. 60 [115].

Regarding the physical creation of the tool itself, it has been stated many times but bears repeating: the Microsoft Excel program was used. As this is a well-established program that most structural engineers are more than comfortable with, it seemed to be the best choice to encourage practical usage. *Two different documents were created for heating and post-heating phases*. The procedure coded into each document follows the fundamentals described above for the strength design method for unreinforced masonry. The document is split into different pages for different analysis types depending on the loading the member is expected to have (namely flexure members, axial members, and interaction diagrams). Each page functions independently, going through a unique set of checks with a unique set of inputs to fit the requirements set by the engineer. As the sheets design for individual member capacities, it is up to the discretion of the engineer to decide which sheet best describes the anticipated function of the member it is designing for. Should the information for multiple members need to be stored for a single project, it is easy to duplicate a sheet in the same file, without the need for any modifications to the underlying code. Formatting-wise, the document has been cleaned up to minimize the number of inputs required by the user and be easy to follow. All input cells are white and boxed, with a discrete list of options coded into the cells of any variable that requires them in order to ensure the formatting of the inputs works with the coding based on them. Cells with coded functions have been greyed out, so the user knows not to edit them. Intermediate calculations are hidden on a separate sheet, aptly titled 'Hidden Data', where they can be retrieved should the user desire them, but still placed far enough way to streamline the process, saving time and space.

Structural Fire Design of Unreinforced Masonry

Axial Members

Section and Material Properties

Dimensions			Area, A_n (in^2)	Specified compressive strength, f'_m (psi)
Height, h (in)	Radius of gyration, r (in)	Slenderness ratio		
168	6.9282	24.25	180.140625	5000

Fire Properties (for design)

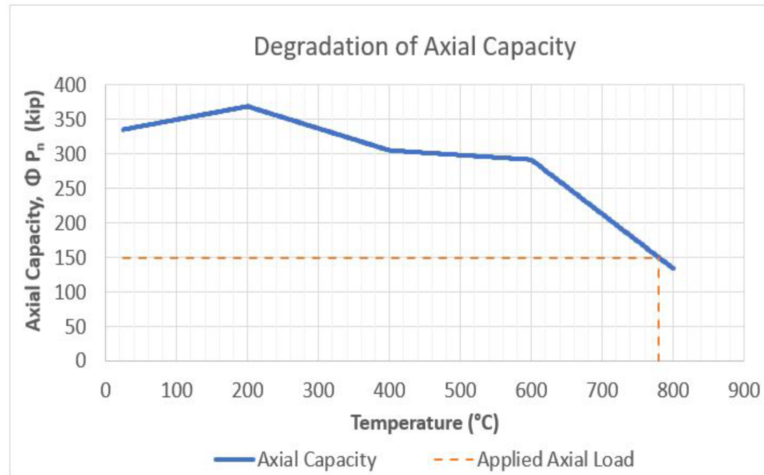
Temperature (°C)	Compressive Strength Reduction Factor	Modified Specified compressive strength, f'_{fire} (psi)
500	0.89	4450

DESIGN Properties

Compressive Stress Limit (psi)	Tensile Stress Limit (psi)	Axial Capacity, ΦP_n (kip)
3560.0	*Neglected*	**298.59**

ANALYSIS Properties

Applied Axial Load, P_u (kip)	Temperature of Failure (°C)	Estimated Time of Failure (min)
150.0	**780**	**18**



Note: this capacity applies to compressive axial load, tensile axial resistance of unreinforced masonry is neglected

Figure 15: Example of completed heating phase 'Axial Members' sheet.

3.4.1 Worked Example

This section of the thesis serves as a worked example of one of the sheets, namely the one for pure Axial loading, of the complementary Excel tool provided alongside this thesis to verify its accuracy. At the top of each sheet is a reminder that the following information refers only to unreinforced members, with a subtitle regarding the loading conditions analyzed (flexural, axial, or influence diagram for a combination thereof). Working down the sheet, the first section asks for the section and material properties of the masonry used, seen in Figure 16. Each cell that is white requires an input. Each cell that is greyed out has a coded formula. These inputs refer to an 8 in. x 24 in. nominal masonry column that is 14 feet tall. Note the area refers to the actual, not nominal area of the column.

The tool has two different applications: design and analysis. For the design portion, a temperature must be inputted for the fire. This refers to the maximum temperature that the member is designed to withstand. The compressive and tensile stress limits (if applicable) are calculated as an intermediate step towards finding the total capacity of the member for whatever loading type the sheet is for at the desired temperature, shown in Figure 17. Note the capacity applies to compressive axial load, tensile axial resistance of unreinforced masonry is neglected. The temperature chosen was 500 °C (932 °F), so the

Section and Material Properties

Dimensions			Area, A_n (in^2)	Specified compressive strength, f'_m (psi)
Height, h (in)	Radius of gyration, r (in)	Slenderness ratio		
168	6.9282	24.25	180.140625	5000

Figure 16: General inputs required to compute the axial capacity.

Fire Properties (for design)

Temperature (°C)	Compressive Strength Reduction Factor	Modified Specified compressive strength, f'_{fire} (psi)
500	0.89	4450

DESIGN Properties

Compressive Stress Limit (psi)	Tensile Stress Limit (psi)	Axial Capacity, Φ P_n (kip)
3560.0	***Neglected***	**298.59**

Figure 17: Inputs and outputs for the axial design approach.

reduction factor for the compressive strength would be linearly interpolated between the hot state value for 400 °C (752 °F) and 600 °C (1112 °F), or 0.91 and 0.87, to get 0.89. This value is multiplied by the specified compressive strength f'_m to get the modified version, f'_{fire}. This strength was then used, along with the net area and slenderness ratio, in Equation 2a (since the slenderness ratio was less than 99), described above, to calculate the axial capacity of the masonry member at the given temperature.

$$\varphi P_n = (0.6)0.8\left\{0.8(180.14\ in^2)(4450\ psi)\left(1-\left(\frac{168\ in}{140(6.9282\ in)}\right)^2\right)\right\} = 2.986\times10^5\ lb = 298.6\ kip$$

For the analysis application of the tool, an applied load must be inputted by the user. This load should already be factored, as it is directly compared to the factored axial capacity, ΦP_n (where Φ = 0.6 for unreinforced masonry). The outputs for the analysis portion of the tool are composed of a graph depicting the degradation of mechanical properties of the masonry (in this case, the axial capacity), along with the temperature at failure and the estimated corresponding time based on the ASTM E119 Standard Fire temperature-time curve [10], as shown in Figure 18. The temperature at failure is shown both quantitatively and graphically, as seen below. The applied axial load can be changed at any time, and all outputs will update accordingly.

ANALYSIS Properties

Applied Axial Load, P_u (kip)	Temperature of Failure (°C)	Estimated Time of Failure (min)
150.0	**780**	**18**

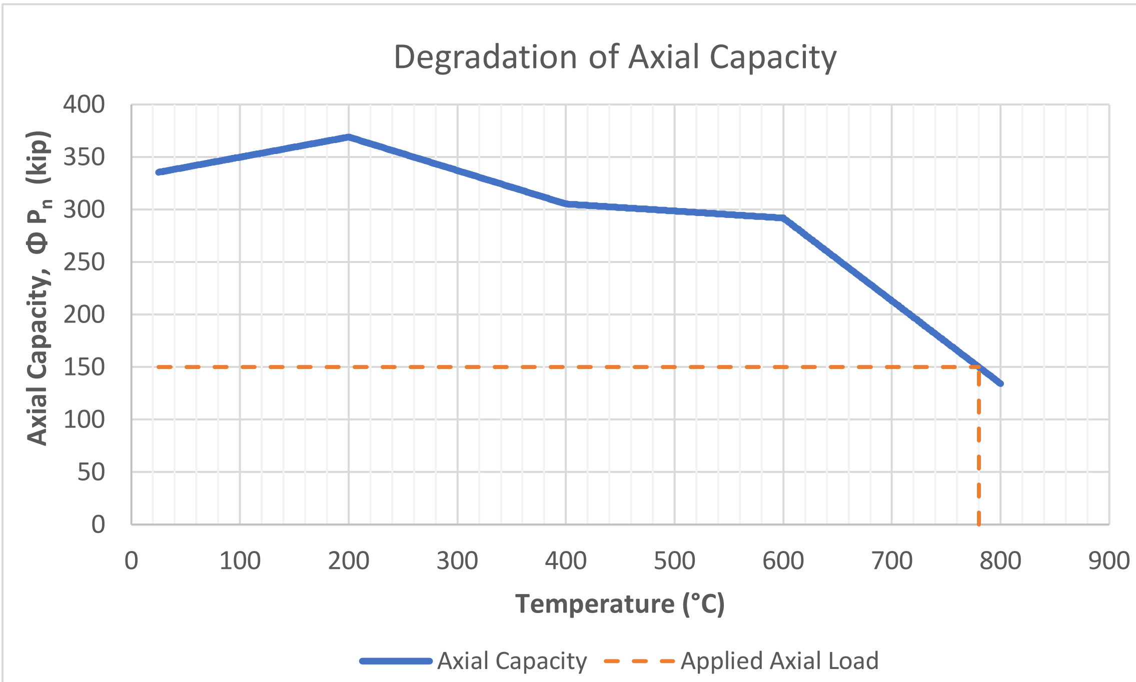


Figure 18: Inputs and outputs for the axial analysis approach.

This worked example refers to the sheet titled 'Axial Members'. Each sheet is slightly different, as they serve different purposes, but overall, the general process should be the same. The 'Interaction Diagrams' section of the tool is a bit different, as it creates a graph depicting all the possible combinations of axial and flexural load that the member can undergo before failure based on a set temperature, rather than as a function of temperature. This was done to ensure that the outputs were in a two-dimensional format that was easy to follow and understand.

3.5 Limitations and Future Development

As discussed previously, this Excel tool serves as an easy-to-use automated tool incorporating the effects of elevated temperatures into the design of structural masonry members. This was an intermediate step towards the inclusion of machine learning in the design and analysis of masonry members exposed to elevated temperatures, which in turn will smooth the way for overall automation of performance-based design of structural masonry members exposed to fire conditions. This was just the first step to a lofty goal with high ambitions and even higher significance; this tool and the coming developments based on it have the potential to save countless lives. But as it is the first step, the tool has quite a few limitations to the scope of its application.

Currently, the tool is geared towards standardized-sized rectangular CMU construction; this is not a hard limit, though, as it can easily be worked around should the user know the net area (A_n) and section modulus (S_n) of whatever the desired shape is. The dimensions are hardcoded in standard sizes up to 36 inches in each direction – this again can be changed by clearing the data verification of the appropriate cells if need be. In terms of slightly more permanent limitations, it was determined that the hassle of inputting the number of variables needed to accurately calculate the net area (A_n) and section modulus (S_n) of any given multi-course arrangement of block and grouting outweighed the benefit of automating this portion of the process. While this could be rectified, for it to be practical, it would most likely need to be on a company-by-company basis, using their specific standards rather than that of the industry in general. To keep the applications as wide as possible, this has been neglected, for now, so the two variables remain user defined.

In terms of structural concept limitations of this tool, it is only designed to check for flexural and axial capacities (and the combination thereof). For any structural design to be complete, shear, deformation, and bearing checks also must be completed. These checks are more conceptual with masonry (or, in the case of shear, the maximum of multiple single-term equations applied conceptually), so they were not seen as necessary to be included in this version of the tool. In order to accurately complete these checks, a large amount of non-quantifiable variables would need to be inputted, the addition of which was not seen as worth the extra effort of the user. Should it continue to be developed, these checks could be added in later. For the flexural check mentioned before, only the nominal strength was determined, P-Delta effects of moment magnification were not. This lies more on the side of the applied moment rather than moment capacity anyways, but as it makes quite a difference on members with high slenderness ratios, it was worth mentioning.

The last limitation of note, but one that is rather important, is that this tool was created specifically for unreinforced (plain) masonry design. In order to adapt it for reinforced masonry, to start with, the strength-reduction factor would change from 0.6 to 0.9. The addition of reinforcement would change both the compression and tensile stress limits (such that it would have an axial tensile stress limit). The equations would get a bit more complicated [20], but since the effect of elevated temperatures on steel and concrete-encased steel has been well documented, the addition is definitely possible.

While this tool could be improved by negating some of the limitations mentioned here, as previously stated, most of the future development of this project rests on the idea of machine learning, to be discussed in detail next.

4. MACHINE LEARNING MODELING

4.1 Overview

The chapter is formatted such that a short overview is first presented regarding the current applications of machine learning in the structural fire engineering field, split into three sections: Fire Criteria, Material-Based Models, and Performance-Based Models. The first section covers literature ensuring that fire is accurately represented in the virtual space of machine learning. The second details some previously created models based on the degradation of material properties like compressive strength due to exposure to elevated temperatures. As stated before and stated again later, there is no current literature regarding machine learning in masonry design or analysis, so that will not be one of the materials covered. The final section does the same for performance-based models, focusing on the intersection of structural fire engineering and fire safety.

This review is followed by an outline for a proposed machine learning model that fills a hole mentioned previously about the role of machine learning in masonry design and analysis. A plan of action will be presented, along with details throughout the process, starting with the selection of algorithm(s) and ending with the quantified validation of the finished model to verify its results. The primary core of this chapter will be focused on the future applications for the created machine learning model and the innovations it will lead to in the field of structural fire engineering, covered last. This will complete the body of the project, leading nicely into the final conclusions.

4.2 Literature Review

Similar to the identically named section of the last chapter, this section will be a brief literature review that will cover the current applications of machine learning in the structural fire engineering field. Again, it is not to be seen as representative of the quantity of resources but rather an overview of the breadth of present-day published content. The literature covered in this review will be split into three categories: fire criteria, material-based models, and performance-based models. As a forewarning, to the best of the author's knowledge, <u>there is not yet any available literature regarding machine learning integration with structural masonry design or analysis</u>, so that will, unfortunately, be absent from the following review. However, trends will be observed based on other material-based models that should be applicable to any future machine learning programs created.

4.2.1 Fire Criteria

Predictive modeling/design of structural members is split into two steps: 1) creating a virtual reality capable of accurately simulating real-world conditions relevant to the desired results and 2) correctly analyzing the behavior resulting from the simulated conditions. This portion of the review will focus on the side of the structural fire engineering field that ensures that fires are being accurately represented through the simulated variable criteria so that the results of the models have significant practical worth in the industry.

Naser makes a case for a machine learning approach on how to create descriptive expressions that represent engineering phenomena, a general category which most fire criteria fall under [116]. The approach, titled 'mapping functions,' uses machine learning techniques to create a model describing whatever the required phenomenon is, then continues on to use physics principles in order to identify the key features in it, referred to as feature selection methods. With such a complicated phenomenon as fire, this can come in handy as there are quite a few variables needed to accurately simulate real fires, with very little ranking organization regarding how each variable affects the final outcome. These mapping functions have already demonstrated satisfactory success in a case study regarding the deformation history of reinforced concrete beams under fire conditions, comparing the machine learning results against 20 experimental specimens.

Similar to the current trend with available finite element software, most of the predictive machine learning programs in structural fire engineering are used in reference to compartment fires. Hodges, Lattimer, and Luxbacher used convolutional neural networking to predict spatially resolved temperatures and velocities (thermal flow-fields) within compartment fires [116]. The model was trained with 100 computational fluid dynamics simulations of two-compartment fires, varying the size and location of the fire, along with the compartment geometry and ventilation configuration. When compared to the Fire Dynamics Simulator [61], 95% of the model's predictions for two-compartment tests were within 17.2% or 0.3 m/s of the FDS results. Zhang, Wang, Wong, Cheong Tam, and Huang used deep learning, another subset of machine learning, algorithms to predict temperatures of compartment fires [117]. The model was trained with 21 compartment tests of different sized fires and openings, resulting in the ability to predict flashover with 20 seconds of lead time and temperature 30 seconds in advance, with less than 10% error. With additional specimens added to the training set, this is expected to improve, but nevertheless shows the potential for firefighting applications.

Ihme, Chung, and Mishra took a more niche approach, focusing on the combustion science aspect of fires [118]. They completed their own literature review on applications of data-driven machine learning techniques on combustion examples like fire/explosion hazards. Combustion science is a field with plenty of data to be had, as opposed to other aspects of fire engineering where researchers would have to seek out experimental tests suiting their needs, or usually, do it themselves. Databases of this knowledge have been used to train regression and dimensionality reduction models, but they leave something to be desired. Some areas of growth for the current applications are interpretability, quantification of uncertainty, and the need for prior combustion-domain knowledge. CombML, a new paradigm offered by the authors for data intense-analyses with combustion machine learning, has the potential to minimize some of these problem areas, incorporating physics-driven inquiry into currently available data-driven models.

4.2.2 Material-Based Models

A review has already been conducted to summarize the use of machine learning to predict fire performance on different types of materials [120]. The review focuses of concrete, steel, timber, and composites, but no matter the material, artificial intelligence was shown to predict the behavior of basic structural components within acceptable margins, including the non-linear relationships that finite element modeling can have trouble with. For the purposes of this review, literature has been further organized based on the material the model is simulating; the categories are as follows: concrete, steel, and a combination thereof, i.e., steel-filled concrete.

Concrete is a rather popular material in the literature, paralleling its use in structural engineering as a whole. While compressive strength degradation due to exposure to elevated temperatures is a fairly well researched topic at this point, some have used machine learning to go above and beyond the normal, usually accounting for the effect of specialized mixture types of concrete like geopolymer concrete [120] or self-compacting concrete [122]. These authors used multiple kinds of regression models to create a prediction program based on the mixture components of the concrete. Rahmati and Toufigh found that curing time and sodium silicate percentage had the largest effect on final compressive strength of geopolymer concrete, while Rajakarunakaran et al. created a Random Forest model with upwards of 95% accuracy for self-compacting concrete. A phenomenon specific to concrete, Naser and Kodur created a machine learning model capable of predicting spalling due to fire, using the compressive strength as one of the many variables inputted into the network [123]. Fan et al. took it one step further; rather than considering a specialized method of failure, they considered a specialized application of service, namely bridges [124]. This approach was mainly similar to that of the literature before, but it took into consideration the unique limitations that bridges have for inspection and quality management.

Steel is the other popular material used in structural fire engineering research. In fact, when validating a machine-learning approach for structural fire response, steel is often the material used as the prototype structure or in the case study verifying the results [125-126]. Since steel is a fairly popular, homogeneous material with a significant amount of research and development already behind it, for machine learning to get involved at this point would require a very specific question to be asked. As such, Tong, Couto, and Gernay created a model for predicting fire resistance of slender steel columns exposed to fire [127]. The large slenderness ratio makes for unique behavior even at ambient temperature, so this study evaluated how that carried over into fire conditions. The same authors completed a similar program from thin-walled beams, for the same reasoning as discussed before [128]. All cited sources were accompanied by sufficient surrogate models that acted as their final results.

Material-based models can also be created for the interaction between different materials. Up until this point, it has mainly been used to detail the relationship between steel and concrete, whether that be steel-filled concrete or concrete-encased steel, but the same idea applies to masonry; it's essentially block filled with grout, two separate materials with separate properties working together through their bond. Mei, Sun, Li, Xu, Zhang and Shen wrote an article regarding mathematical modeling (with experimental validation) of that bond under fire conditions [129]. But the bond is only one source of failure. Moradi, Daneshvar, Ghazi-nader, and Hajiloo created a machine learning program to predict the overall fire resistance and residual strength of concrete-filled steel tubes [130], using the empirical relationships rather than derived mathematical ones.

4.2.3 Performance-Based Models

Beyond the material-based models that consider structures on an element-by-element basis, there are also performance-based models that look at the structure as a whole. In structural fire engineering, that usually focuses on the intersection of fire engineering and fire safety. Xu and Saleh wrote an article on just that, evaluating the use of machine learning in reliability engineering [131]. Most of the current literature is fragmented into niche topics, as academic research often is; these authors attempted to compile all known literature to create a roadmap for creating performance-based machine learning models in the future. These models were broad in scope, but for implementation in structural fire engineering, the most useful potential aspects were the quantification of uncertainties and deep gaussian process/generative adversarial network for reliability applications.

Ouache, Nahiduzzaman, Hewage, and Sadiq had a similar idea; they created a machine learning-based framework for fire safety assessment and proposed a model capable of predicting fire impacts [132]. The method used had four main steps. The paper began with an investigation into current fire safety strategies in multi-unit residential buildings; these strategies were then evaluated based on their effectiveness in relation to fire extent and damages. A model was developed to predict the fire impacts based on the data gathered before, and then analyzed; it was shown to be fairly accurate, with a R^2 value of 85%. After analysis, the model was then optimized to find the combination of strategies that minimized the fire impacts, thus it was able to advise on the fire safety design aspect as well as predict damages.

4.3 Plan of Action

Given the severity of fire-induced degradation of mechanical properties and ensuing failure of masonry, in addition to the lack of resources currently available regarding the subject, this project proposes the development of machine learning-based models capable of predicting fire-induced failure of unreinforced solid concrete-masonry unit (CMU) structural members. These models will iteratively train an existing algorithm with data obtained from the previously described Excel tool, in order to eventually achieve good performance for moment and axial capacities output predictions. The process of creating such a model is outlined in Figure 19.

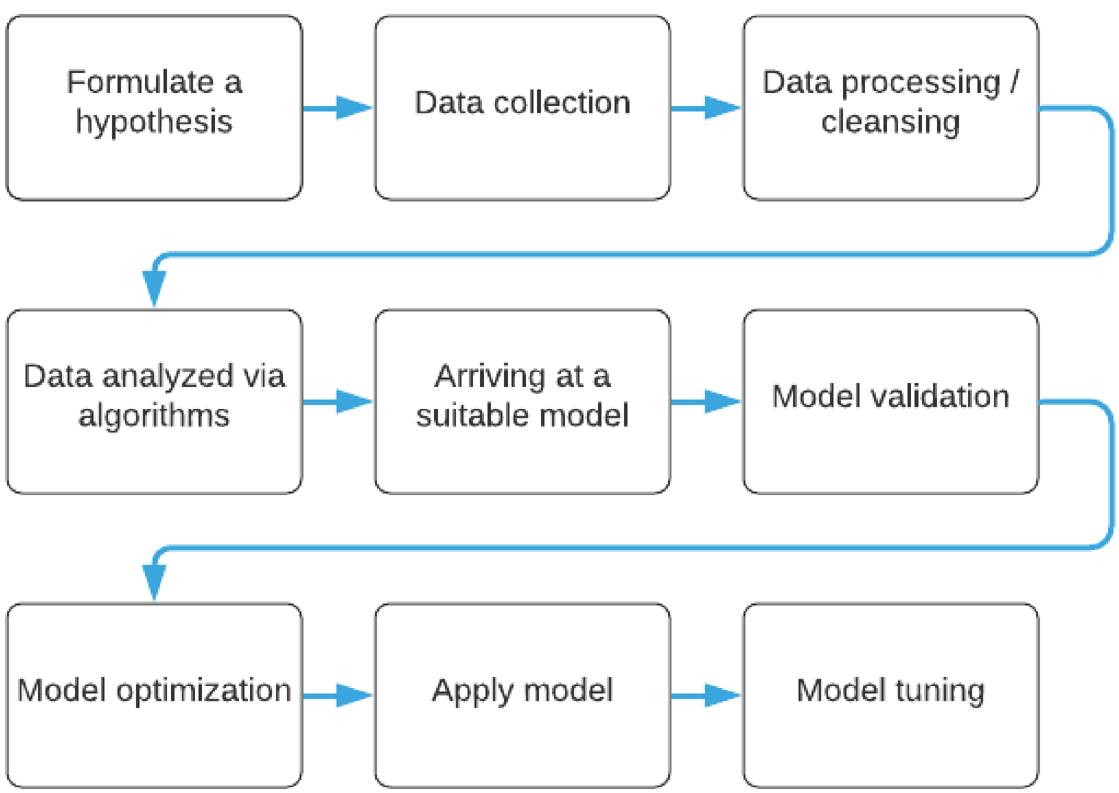


Figure 19: Flowchart detailing the methodology of creating a machine learning model.

The machine learning program will use gradient boosted decision trees to analyze data pulled from the Excel tool based on current masonry design standards, with the goal of collecting a large enough dataset to train the model to sufficiently predict the degradation of mechanical properties due to elevated temperatures. These models will be able to use the understanding of the provided algorithm for predicting multiple different failure types (in this case flexural and axial), thus bypassing the lengthy calculation process typically associated with structural fire analysis and design. The machine learning models will therefore provide solutions that are significantly cheaper (as the deliverables from this research and those following from the same research group will be freely available) and at a faster rate (~500 members per minute) than fire tests or the limited capability of numerical simulations. The model will be optimized and finetuned within the limitations provided by the number of datasets that can be provided to train it. As such, it provides an opportunity for continual advancement, should it be deemed worthwhile to release updated versions of it in the future. The models will also be compatible with traditional computers of its time and will not require specialized hard/software to operate, in order to maximize their potential usage. They will be the first of their kind and its application in the structural fire engineering field, both in research and in industry, will be boundless.

4.4 Creation of Predictive Model

The predictive machine learning models were created using XGBoost. This software's framework falls under the supervised portion of machine learning as a decision-tree based algorithm. The algorithm "assigns a numerical quantity to the tree leaves, [where] the score corresponds to whether the instance belongs to the decision…[At] the end of the training data, the algorithm converts the numerical score into a categorical score leading to an answer for each instance" [133]. The algorithm builds decision tree models sequentially, each trying to predict the error on the previous one, getting more accurate with each iteration until the training set runs out, leaving the final model.

The predictive models were created with the assistance of Moe Albashiti on Jupyter, an open-source web-based computing platform [134]. Two different machine learning models were created for predicting moment and axial capacities, respectively. The predictions were based on 100 data points collected from the excel sheet tool for solid unreinforced masonry members with a modulus of rupture of 267 psi. This data is split into the 'training' and 'testing' sets, with 70% of the data going into the former. With such a limited data set to work with, these models serve as a proof-of-concept that the integration of machine learning into performance-based structural fire design will work, rather than a deliverable to be released to the public as a finished product.

The data used in creating this model is shown via histograms below in Figure 19. As one can see, the data is healthy and uniform (except, and as expected for the output which varies as some members are designed to be naturally of small capacity given the applied loadings and vice versa). The Pearson (linear) correlation matrix between this data is shown in Figure 21. It is clear that there is positive and high linear correlation between the axial capacity and width, depth and strength. There is also a clear negative linear correlation between the axial strength and the rise in temperature (i.e., higher temperatures lead to lower strength).

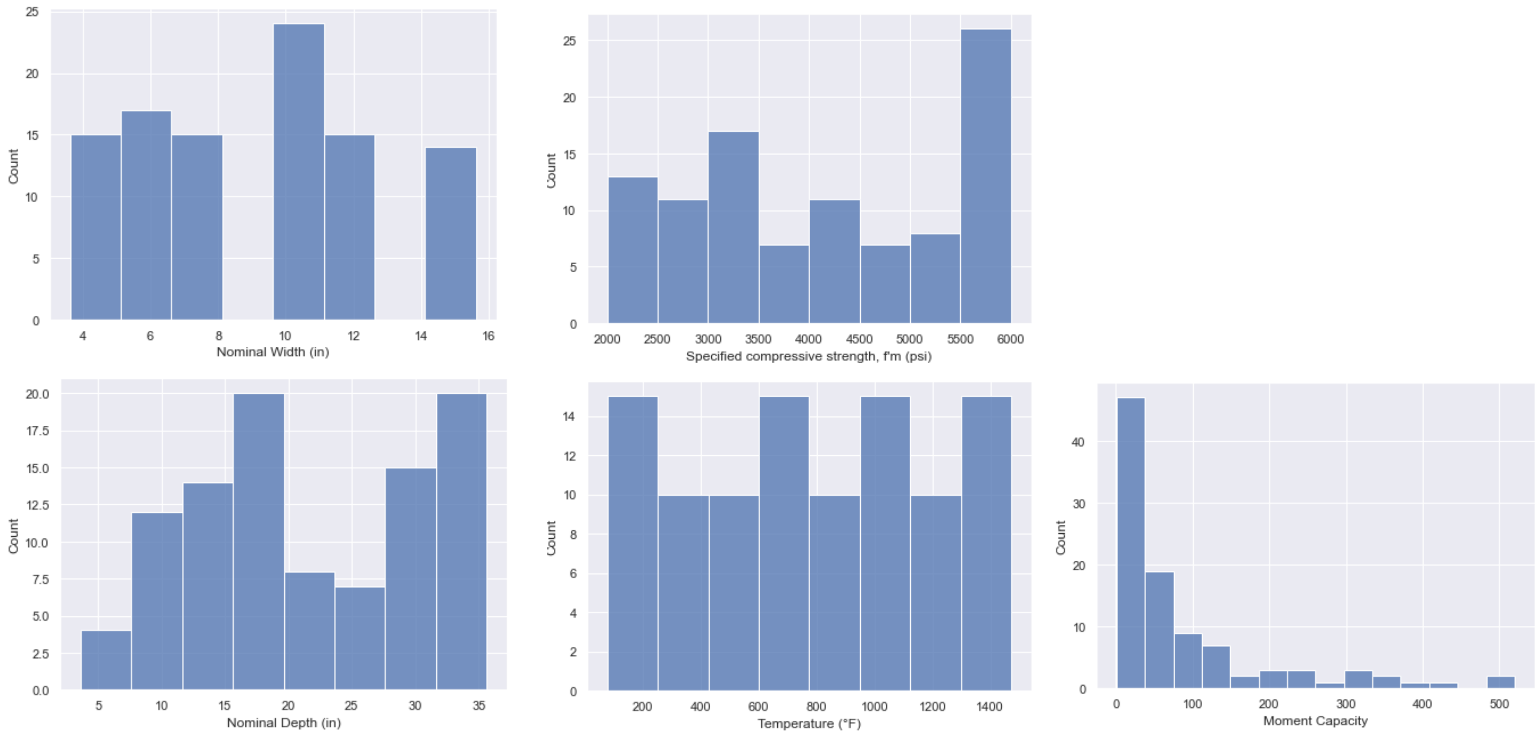


Figure 20: Histograms detailing data used in creation of machine learning models.

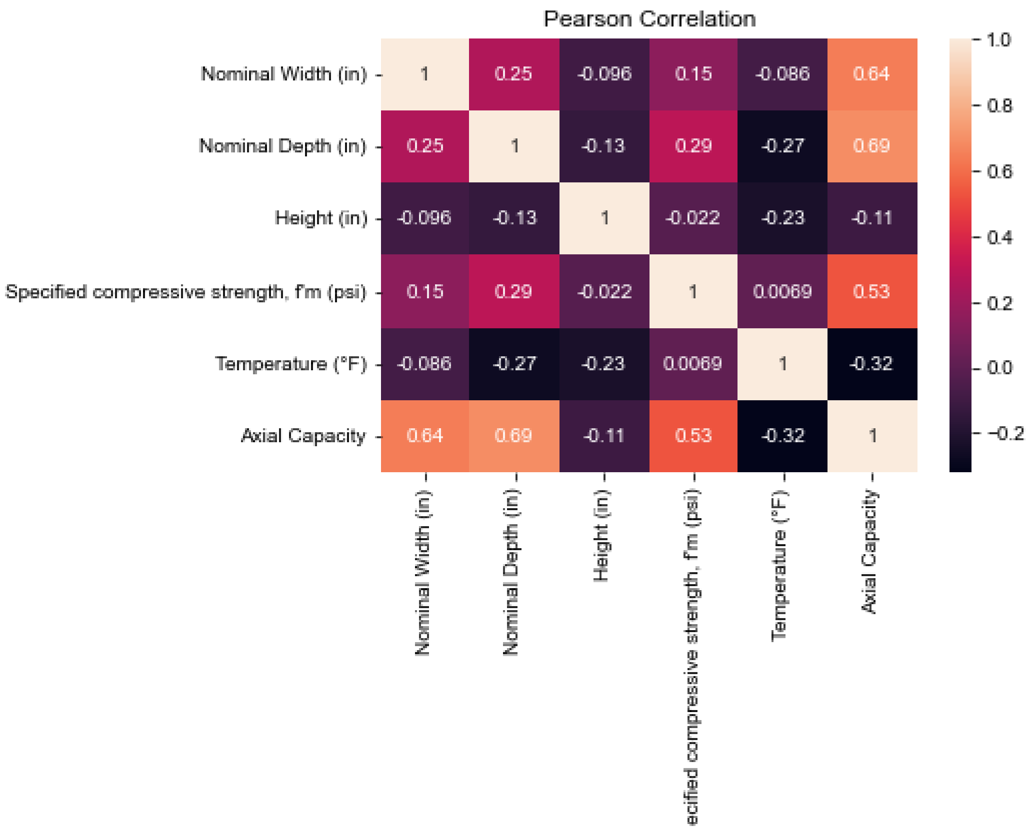


Figure 21: Pearson correlation of the machine learning models.

4.5 Validation of Predictive Model

For methods of validation, the k-fold cross-validation technique was applied in order to minimize the risk of overfitting, a classic problem for all data-driven analysis. This method is an established procedure for estimating the performance of a machine learning algorithm based on the received dataset, used quite often in academic publications of similar research. The technique is similar to the iterative process mentioned before, but in this technique, the data is split into k (a variable) number of "folds"; typically the results get more accurate with an increased number of folds, but that comes with the disadvantage of also increasing the time it takes to properly train and run the model [135]. This value of k is taken as 10 as noted to be common in most structural engineering applications [136].

Anyways, once the data is split into “folds”, the training set is created, consisting of k – 1 folds. Each fold of the training set trains an independent model, each validated on the last fold left for the testing set. The results of each individual model are averaged for the final results of the network. For ease of comparison, the correlation between the model’s output predictions and the testing dataset output values, quantified using R^2 values, was used as a benchmark. R^2 values refer to the coefficient of determination, or the square of correlation. Using Equation 3 below, it quantifies the correlation of two variables on a scale from 0 to 1 [137].

$$R^2 = 1 - \sum_{i=1}^{n}(P_i - A_i)^2 \,/\, \sum_{i=1}^{n}(A_i - A_{mean})^2 \tag{3}$$

The R^2 values of the machine learning moment and axial capacity prediction models are 0.709 and 0.774. The relatively high R^2 values mean that the models can predict both capacities with high accuracy.

For other sources of validation, the results were obtained for both the Mean Absolute Error (MAE) and the Root Mean Squared Error (RSME), using Equations 4 and 5, respectively.

$$MAE = \frac{\sum_{i=1}^{n}|E_i|}{n} \tag{4}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} {E_i}^2}{n}} \tag{5}$$

Both the Mean Absolute Error and Root Mean Squared Error measure the difference between two continuous variables, or how far predicted values are away from the observed values, using a similar scale as the input data [138]. The lower the value, the better the prediction is. For the machine learning models created, the Mean Absolute Errors were 19.7 and 102.1, for the moment and axial capacity prediction models, when the moment capacity has units of kip-in and the axial capacity has units of kips. The Root Mean Squared Errors are 38.2 and 183.9, respectively. Some disadvantages with RMSE use are that it tends to be sensitive to outliers and highly dependent on a fraction of data used, leading to low reliability, especially in the case of such a small dataset like the one for this project, so the values must be taken with a grain of salt [139-140].

Overall, with the validation from the data above, it is safe to say that the machine learning models have sufficient predictions of moment and axial capacities including the degradation of mechanical properties due to elevated temperatures and can thus be considered good proof-of-concepts for the inclusion of machine learning in structural fire design and analysis.

4.6 Results

The products of this portion of the project are the predictive models created by the machine learning program XGBoost, capable of predicting flexural and axial structural failure of masonry members under the influence of elevated temperatures. These deliverables are to be published and distributed to practicing engineers with the hope of encouraging the consideration of fire criteria in industry structural projects of all sizes and in all geographical locations. With the validation methods described above, it is shown that machine learning, more specifically XGBoost, can predict both moment and axial capacity with high accuracy (70%-78%). As such, the machine learning models provide a good prototype for the merit of machine learning in performance-based structural fire design.

4.7 Future Applications

Since this chapter is comprised of proof-of-concept machine learning models capable of predicting the influence of elevated temperatures on masonry design and analysis, most of the future applications would obviously revolve around expanding on those models to increase their practical applications. The limitations regarding the current project's scope are mainly due to time constraints and lack of previous foundational components present at the inception of the project. Machine learning as a whole is a relatively new field, so any progress is limited by the (lack of) building blocks created by others previously. However, the predictive machine learning models created provide a proof-of-concept that the idea will work, and the resulting outputs are reasonably accurate for use in design and analysis structural fire engineering scenarios, so any additional improvements made to the models in the future are just a bonus.

For the research side of matters, masonry is quickly falling behind in structural fire engineering. Verified models have already been produced to quantify the diminishment of mechanical properties of steel and reinforced concrete, the two most popular choices of construction material, due to exposure to elevated temperatures. These models lead to clear equations or coefficients regarding the reduction in the moment, axial, and/or shear capacities, which can be added to existing building codes, providing a clear and easy pathway for engineers to do a few quick checks to account for fire conditions and verify that it is up to standards. Masonry has begun this process but just hasn't advanced enough to see the results of the research in any building codes. Behavioral and material testing has been conducted on a range of masonry types, mainly regarding compressive strength and flexural failure of walls, along with introductory finite-element analysis modeling programs. The next step in extending the application of the research compiled in this project and the machine learning models created based on it, would be to take the fundamental analysis procedure that the finite element and machine learning programs already do and will do in the future, and get them properly verified and included in the corresponding national building codes, namely The Masonry Society's code in the United States where the current project scope was completed.

For the machine learning component's future applications in industry, the general idea is much simpler. The overarching goal for machine learning in structural engineering is to eventually get the programs created to a point where either the corresponding hand calculations would be too complex and time consuming to do by hand, or where the models could intrinsically discover relationships between variables that are currently unaccounted for in building codes without direct supervision from the engineer. While the machine learning program created in this project is to be released to the industry, the proposed adaptations of it would be a significant improvement regarding the breadth of applications that practicing engineers could use it for. They function much like currently available masonry finite element programs or modules already do. Material, section, and loading properties are inputted into the machine learning model, and the output would either be the expected capacity of the member or perhaps reinforcement design, depending on how the future development of the models is formatted and what the next wave of researchers deems to be the most effective solution in terms of labor and usage. In other words, the models created are an extension of the Excel tool provided in such that it analyzes individual members, outputting the capacities for the engineers' use, but it could be modified to go further, actually designing optimized members given the temperature properties of the fire and the geometry limitations provided by the architect or client like higher-level finite element model programs are capable of. Either way would produce an easy-to-use tool that has incredible but very focused practical potential for industry applications in structural fire engineering.

5. CONCLUSIONS

5.1 Summary

Performance-based design has been around in theory since the beginning of structural engineering as a field – but modern incorporation of the practice has only recently been written into building codes. There is a continuous debate between prescriptive and performance-based approaches to structural fire design; both methods work satisfactorily enough but there are some definite advantages and disadvantages to both. Prescriptive methods are easy to understand and implement, but they are restrictive in their uses and overly conservative in order to account for the variability in parameters that they don't directly consider. Performance-based methods allow for more flexibility and innovation for the engineer, which can lead to increased efficiency and minimized costs. But since every design is different, each individual project needs to be verified in terms of the safety of its occupants, and that verification can involve computational software to run complex calculations or professionals with specialized education. Plus, the performance-based building codes are often left up to interpretation, with qualitative benchmarks depending on the code's origin, which can lead to issues as well.

Machine learning has the potential to balance the scales by minimizing those options. In recent times, machine learning has gained more and more popularity, becoming a source of innovation in countless fields, including structural engineering. While its use in the field is still on the newer side, the progress appears to be moving quite rapidly. This progress has yet to include much on masonry design though. Masonry seems to be getting left behind in this specific niche, while models regarding steel and reinforced concrete are plentiful. Any literature regarding masonry under fire tends to be purely from material testing, which, while important, is only the first step in a very long process toward getting integrative machine learning programs capable of evaluating masonry structures under fire conditions using the performance-based design approach. Since that goal seems to be a bit out of reach at the moment, this project settled for a practical design tool in the form of an Excel file capable of analyzing flexural and axial masonry structural members when exposed to fire, using basic user inputs for geometry and temperature, along with an accompanying, rudimentary predictive machine learning model, based on data retrieved with the same process. This provides a good foundation for others in the future to realize the overarching goal of incorporating both performance-based design and full-scale predictive machine learning models in masonry structural fire engineering.

5.2 Challenges and Limitations

As discussed previously, the overarching goal of this project was to incorporate both performance-based design and machine learning in masonry structural fire design. Upon further research, it was discovered that there was very little previous research and literature to provide a stable foundation to work off of, both in regard to the masonry material and in the design aspect. As such, this work can now be considered a foundation in and of itself for future projects to come, discussed in the next section.

In terms of specific challenges, for the first section of this project, while performance-based codes are becoming more popular, there is a lack of literature specific to masonry design and analysis. Trends were discussed and case studies were analyzed, but nothing of note could be directly pulled for masonry, as the literature just doesn't exist yet.

For the second half of this project, focusing on the application of machine learning in structural masonry design and analysis, most of the limitations of the project come down to a matter of time. The integration of machine learning into different fields is new, into structural engineering even more so. Rudimentary machine learning predictive models were created as a proof-of-concept, but a more in-depth analysis using a significantly larger dataset and modifications to increase the breadth of the applicable members are suggested before its implementation in industry. The created easy-to-use Excel tool is limited in that the need for simplicity outweighed the need for inclusivity, both in terms of the section geometry applicable and in terms of additional shear, deformation, and bearing checks. These checks are more conceptual in nature for masonry members, so they were not seen as necessary to be included in this version of the tool due to the high numbers of inputs needed to accurately describe the conditions. The most important limitation to note is that the tool (and thus the predictive model created off of it) is only currently applicable for unreinforced masonry design, with the potential for the inclusion of tensile steel reinforcement should another version of it be published in the future.

5.3 Future Scope

The future scope of this project mainly resides with the second half of this thesis. The Excel tool created has many limitations, discussed previously, so the first order of business would be to expand the application of it. While the tool currently works just fine, basic modification could account for non-standardized sizes of concrete masonry unit (CMU) construction. This modification would be primarily for academic research purposes or for very high-profile industry projects, but it is definitely worth pursuing should the need ever come about. In terms of the actual capabilities of the tool, sections could be added to complete additional checks beyond the flexure and axial checks currently programmed in. These structural analysis checks, including shear capacity, deformation allowance, and bearing requirements, use qualitative factors of the conditions surrounding the masonry in determining the quantitative capacities or acceptable ranges (the outputs). The tool could, and probably should considering standard construction practices in the industry, release an updated version that incorporates the presence of tensile steel reinforcement. This proposed module would accompany the version released with this thesis, as it significantly increases the practical application of the tool's use in industry settings without overlapping roles.

For the machine learning components, the future scope of this project would be to follow the future development outlined in the previous chapter to increase the created machine learning models' applications of designing and analyzing masonry members exposed to elevated temperatures in industry. A predictive model using XGBoost was created for this purposes, but further in-depth analysis of the program and modifications to increase the breadth of the applicable members (both in material and in reinforcement properties) could prove worthy of its own project. The created model was made to fit 100 data points generated by the Excel tool to a decision-tree algorithm. Increasing this dataset would in turn increase the accuracy of the resulting model's prediction capabilities. And going alongside the future modifications of the Excel portion of this project described above, the model could also be trained to incorporate the presence of tensile steel reinforcement. It would require adding in more parameters, which would make it slightly more difficult to train, but the underlying process is the same.

5.4 Conclusions

For final remarks, both performance-based design and machine learning have a bright future in the next wave of innovation for structural fire engineering. The development of both research areas has been progressing nicely in recent years, supported by the respective literature reviews for each part covered in previous chapters of this thesis. The combination of both performance-based design and machine learning in a single tool for any material, not just limited to masonry as this project's scope is, is a lofty but still worthy goal to keep in mind as the field progresses in the future.

In the end, creating a machine learning for systems-wide performance-based structural masonry design could not be completed in the time frame of this project due to the lack of foundation materials. The proof-of-concept machine learning models and Excel tool created for this project, along with the accompanying literature reviews, still present a firm starting point for any future projects to use. The overarching goal is one shared by many engineers, each person chipping away at a different piece of a very large puzzle; any contributions going towards the same culmination can be considered a worthwhile endeavor for the structural engineering field as a whole, this thesis included.

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