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Fire Resistance Evaluation through Artificial Intelligence - A Case for Timber Structures

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ABSTRACT

With the ever-growing surge of new technologies, there seems to be an ongoing inertia towards integrating automation and cognition into various engineering applications. Despite a number of initiatives, and oddly enough of all civil engineering sub-disciplines, the structural fire engineering and fire safety community continues to embrace a classical stance to tackle the problem of fire. In support of growing demands to adopt performance-based solutions, this paper showcases the potential of integrating Artificial Intelligence (AI) as a unique technology to assess performance and fire resistance of structures. More specifically, this study sheds light on the proper use of AI to derive temperature-dependent material models for wood, together with simple expressions that can be used to trace thermo-structural response of timber elements/components (i.e. floor assemblies, beams, columns, and connections). These expressions comprehend the naturally complex temperature-induced physio-chemical changes to timber properties, including creep and charring, and hence do not require input of such properties nor special computing software. The outcome of this study clearly shows the merit of utilizing AI to modernize fire resistance evaluation given that the developed AI-models have high degree of perception (i.e. learn from past behaviors) and ability to improve their prediction capability through independent and unsupervised learning.

Keywords: Fire; Artificial intelligence; Timber; Structural members; Material property; Charring.

1.0 INTRODUCTION

The past few years have witnessed the rise of a momentum towards realizing sustainable and green infrastructure. Inspired by nature and determined to reduce the burden on the

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environment, the number of upcoming projects utilizing timber as main construction material is seemingly rising. Common timber buildings (of two- to four-story) are now being replaced with taller buildings (of greater than six-story), much of which are primary built with improved engineered timber products [1]. As an example, the University of British Columbia (UBC) announced the completion of the 18-story, 53 m tall *Brock Commons* student residence, claiming the title of tallest timber structure in 2016 [2]. More recently, the city of Tokyo in Japan announced plans to build a 70-story, 350 m tall skyscraper made of 90% wood and 10% steel. This skyscraper, named *W350*, is expected to utilize more than 18.5 million cubic meter of timber and to be completed by 2041 [3]. Projects of this magnitude not only challenge our knowledge of timber construction but also add practical complexities on a number of fronts.

Fortunately, there has been a good amount of research on traditional issues arising when designing (or building) a tall timber structure, i.e., weathering of wood, seismic and wind actions etc. [4]. On the other hand, extreme loading effects; such as fire, is one research area that continues to be deficient [1, 5]. The complexity of fire, both as a phenomenon and a load action, exponentially intensifies in case of timber construction, simply due to the fact that a structural system made of timber has the tendency to combust when exposed to fire. Not only that this structural system becomes vulnerable to fire-induced collapse, issues related to timely evacuation of occupants and proper firefighting in presence of high levels of smoke, especially when the main loading bearing system is burning, also become of critical importance [6]. Thus, predicting thermal and structural response of timber structures (or structural systems/members for that matter) is of a great interest to the civil engineering and construction community [5, 6].

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In a traditional sense, fire resistance of timber members/assemblies can be evaluated through standard fire testing. It is quite amusing to note that such standard testing not only remains virtually unchanged for most of the last century, but is also costly to conduct, requires specialized testing facilities and attendance of certified personnel. Alternatively, fire resistance rating of commonly used timber elements can be obtained from tabulated data (or listings) complied from previous fire tests; whether published by testing agencies or listed in building codes and fire standards [7].

In more recent years, this community seems to lean towards adopting advanced calculation methods as a mean to evaluate fire performance of structures. These methods apply rational engineering principles, mostly at section or member level, to determine fire resistance rating of timber members i.e. beams etc. Advanced calculation methods may encompass development of highly nonlinear finite element (FE) (or finite difference (FD)) numerical models that besides requiring a large number of input parameters and high computational capacity (e.g. workstations), they can only be developed by especially trained engineers/designers [8]. A side note to remember is that the validity of such numerical models stems from prior calibration against experimentally conducted fire tests. This, when combined with the fact that there is a serious absence of guidance on proper validation procedure, and more importantly on standardization with regard to selection of input parameters, computing capabilities and training expertise etc., present some of the main challenges that continue to hinder the use, as well as acceptance, of advanced calculation methods in fire engineering applications.

Interestingly, many of the aforementioned challenges associated with standard fire testing and advanced calculation methods can be overcome by integrating a modern form of evaluation

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methods. This form capitalizes on the concept of Artificial Intelligence (AI) to capture implicit relations, with varying levels of complexities, between various input parameters associated with fire phenomenon in structures. These approaches have been extensively used in a variety of engineering applications including structural engineering [9], material sciences [10], extraterrestrial exploration [12] etc. At the time of this study, a thorough examination of published works shows that the integration of AI-based techniques into structural fire engineering and fire safety applications is lacking, especially in the case of timber structures [12].

One of the earliest studies to apply AI in fire engineering applications was carried out by Chan et al. [13]. These researchers developed a simple artificial neural network (ANN) to predict temperature-induced degradation of compressive strength of concrete. The developed ANN was first trained using data points obtained from small scale material tests and then this ANN was used to predict compressive strength of concrete with different mix batches under elevated temperatures [13]. In another study, McKinney and Ali [14] also developed an ANN to qualitatively evaluate fire-induced spalling phenomenon in concrete cylinders. Lazarevska et al. [15] developed a fuzzy-neural network (FNN) to predict fire resistance rating of reinforced concrete (RC) columns exposed to fire conditions. This FNN proved suitable in situations where there is limited data available on features of RC columns.

Erdem [16] developed an ANN to predict flexural capacity of RC slabs under fire conditions. This ANN accounted for various parameters such as compressive strength of concrete, yield strength of reinforcement, duration of fire exposure etc. and managed to achieve high accuracy with a correlation coefficient of 99.75%. Naser [17] managed to incorporate genetic algorithms (GA), a modern form of AI, to derive temperature-dependent material models for structural steel. The AI-derived models were rigorously tested against actual structural members tested in full-scale fire tests and showed high prediction capability when compared against commonly used material models. In a notable study, Rein et al. [18] also integrated GAs to examine the kinetics of polyurethane foam in smoldering combustion scenarios.

At the time of this work, there seems to be virtually no AI-based studies carried out to examine temperature-dependent properties of timber or response of timber elements under fire conditions. Thus, this work aims at developing AI-based models that utilize a hybrid combination of AI technologies, namely artificial neural network (ANN) together with symbolic regressions and genetic algorithms (SR & GAs), to comprehend the complex fire behavior of timber at the material and element (member) level. For a start, this study derives universal and temperature-dependent constitutive material models for wood with due consideration to charring and creep effects. Further, this study also derives simple expressions capable of accurately evaluating fire resistance rating, temperature rise and deformation history within timber elements including floor assemblies, beams, columns, and connections. These expressions take into account critical parameters such as geometric features of timber members, level of applied loading, and fire exposure duration. A distinctive feature of these expressions is that they implicitly account for temperature-dependent material properties and hence do not require input of such properties nor special computing platform/software. These models can be used to predict thermo-mechanical behavior of timber members at any time of interest or throughout fire exposure duration until failure of element. The validity of these expressions was examined and cross-checked against fire-tested timber members collected from open literature. Finally, the compiled databases used to develop the AI-models, which contains over 12,000 data points, will be made available for interested researchers to further expand upon with the hope of enhancing accuracy of the derived expressions and development of improved models.

2.0 ARTIFICAL INTELLIGENCE – A BRIEF BACKGROUND, AND INSIGHTS INTO MODEL DEVELOPMENT

The first mention of artificial intelligence (AI) as a strategy to solve problems that defy solution through traditional computational techniques was noted at a workshop held in Dartmouth College in 1956 [19]. This concept mimics the cognition capability of the brain to exploit hidden patterns and implicit relations within data sets as to understand interaction between input parameters and then draw conclusions to physically represent a solution (or set of solutions) to a given problem or phenomenon [19]. Nowadays, AI is more of discipline that is built through close collaboration between various fields including computer science, mathematics, information theory, neuroscience etc. A quick review of literature shows that this discipline covers a number of techniques such as neural networks (NN), machine learning (ML), pattern recognition (PR) etc. A thorough discussion on history and differences between these technologies is not presented herein for brevity but can be found elsewhere [19, 20].

From the point of view of this study, AI is a modern technology that seems to best suit the needs of fire engineering community for a variety of reasons. For a start, fire, a destructive force in nature, not only encompasses different fields (i.e. civil engineering, material sciences, fluid dynamics etc.) but its effects on structures are still not fully understood. Secondly, in a given fire-based engineering problem, say design of a timber beam to achieve a satisfactory fire performance, a large number of variables (e.g. geometric and material features, load level, fire intensity etc.) exist and with high variabilities. Further, fire tests, the holy grail of evaluation methods, often

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carried out to examine the response of structural members seem to suffer on a number of fronts, specifically those related to accessibility, reliability and reproducibility of test results. This is unlike other sub-disciplines in civil engineering, where experimental testing is more controlled and of high consistency. Moreover, codal provisions for fire design of structures are still immature, as compared to traditional loading actions, and these provisions significantly vary between countries and practicing engineers. This discussion clearly infers how our community is tackling a very complex phenomenon in which traditional assessment methods seem to struggle to adequately resolve. An attempt to integrate principles of AI into this field could be promising.

Compared to traditional approaches, AI does not rely on pure mathematical models nor guidance to start an analysis. But rather, AI attempts to simulate the human-like thinking process in order to understand a phenomenon and is specifically suitable in scenarios where a large amount of inputs is available. By utilizing heuristic search enabled through evolutionary algorithms, an AI model tries to capture hidden patterns through adaptive learning and via systematic analysis of inputs and targeted output(s). Once an initial pattern is identified, this pattern becomes the first step to grasp the nature of the phenomenon on hand as to discover improved patterns with higher prediction capabilities. In essence, an AI model comprises of a number of visible and/or hidden layers and processing units; commonly called neurons. Neurons are often arranged to form an intelligent system (or network), with a similar layout to the human brain, that maintains a continuous interaction between functioning neurons and layers. In this network, the first layer contains the inputs (predictors) and is connected to a number of hidden layers with the ability to establish linear and/or non-linear models. The hidden layers are also connected to the output layer comprising of target variable(s) (or output(s)).

In this study, a number of phenomena related to fire response and performance of timber are examined on two scales; at the material and elemental (member) level. At the material side, thermal, mechanical and special temperature-dependent material properties of timber are collected to derive universal material models that represent how each property changes under elevated temperatures. These properties include density, thermal conductivity, specific heat, tensile modulus, compressive, tensile and shear strength of timber, as well as charring rate. At the member level, AI-based expressions that can be used to evaluate thermal response of timber floor assemblies, together with structural response of timber beams, columns and two types of connections, are derived. These models are developed using a hybrid combination of artificial neural network (ANN) provided in Matlab, together with symbolic regression and genetic algorithms (SR & GAs) [21].

In each case, input parameters were selected through a systematic procedure. For example, past and recently published works disseminating results of standard fire tests were first studied to identify critical parameters that influence fire response of wood and timber structures. These critical parameters were also selected based on observations and recommendations of previous works in order to arrive at expressions with optimum size and complexity that do not require complex computations and/or special software. Overall, the rationale behind identifying critical parameters stems from engineering judgment as well as findings and recommendations of various research articles and reports [22-68].

For example, the structural response (i.e. mid-span deflection) of timber beam at any given point during exposure to a standard fire is said to be a result of stresses generated due to applied loading, P, as well as degradation to the beam's sectional capacity (a function of geometric features

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and material properties). Since P is constant during fire, then the mid-span deflection in this beam at a specific point in time is dependent upon the degradation in material properties and (i.e. how much timber has degraded till that point in time) as well as loss in cross section. Imagine this, for two identical timber beams made of the same wood and exposed to the same fire conditions, both beams will experience similar temperature rise and degradation in sectional capacity. However, in case one of the beams is loaded with P_1 (where $P_1>P_2$ and P_2 is applied to the second beam), then this beam will, 1) experience higher levels of deflection, and 2) fail at an early point in time (see Fig. 1).

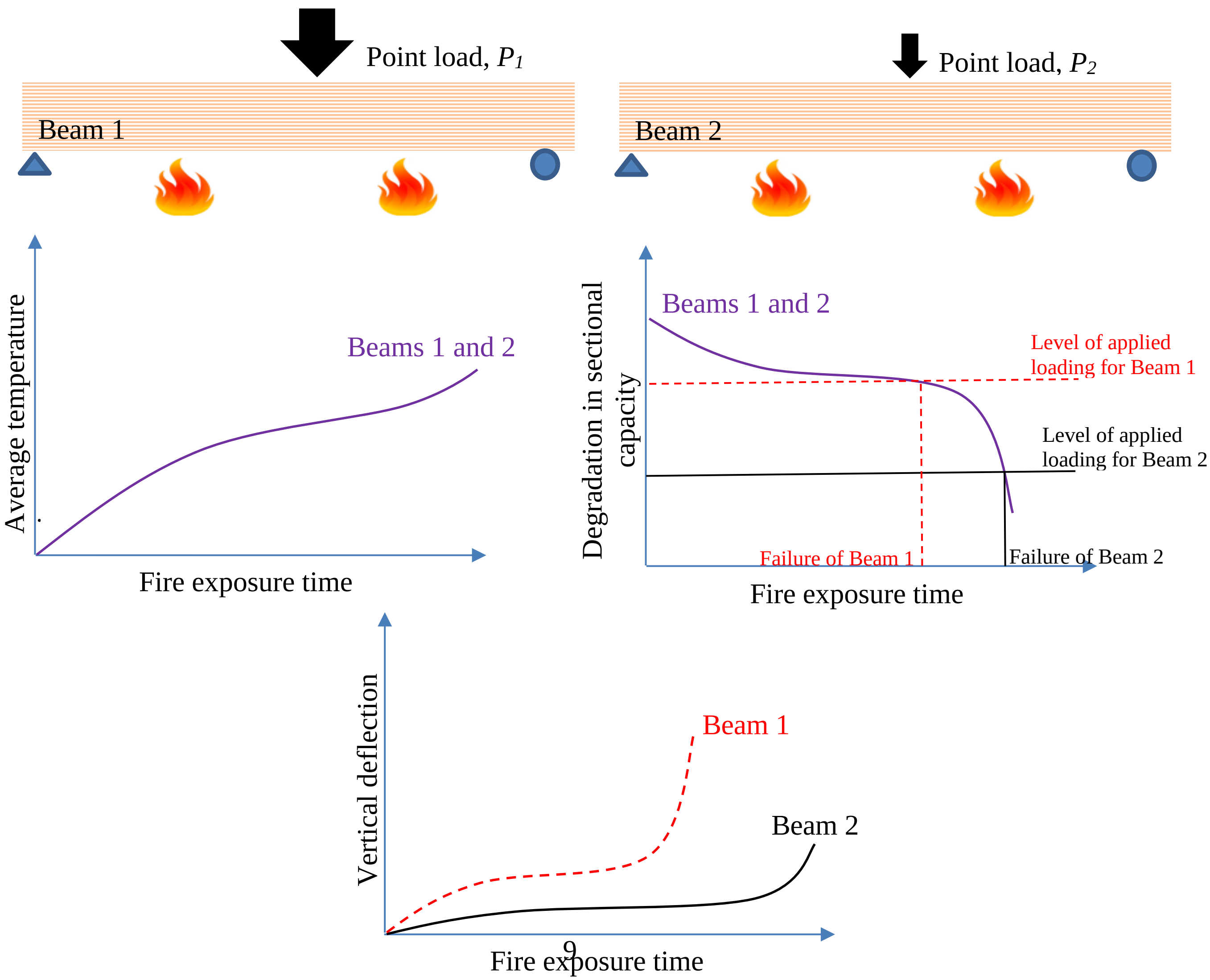

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Fig. 1 Illustration on effect of critical parameter for timber beam

Thus, this study hypothesizes that in order to obtain mid-span deflection of a timber beam, all that is needed is duration of fire exposure, *t*, load level, *P*, initial depth and width, *D* and *B*, of the beam, in addition to the relation that connects these parameters to mid-span deflection. This relation is quite complex as it is a function of various parameters i.e. charring rate, properties of wood etc., yet can still be obtained by properly applying principles of AI. In other words, the rationale behind AI modeling is that since the final effect of fire (i.e. mid-span deflection, temperature rise across a member) is of interest, and since this effect is known (measured in fire tests), then a relation connecting such effect to loading (gravity and fire) as well as material and geometric features of a timber member can be obtained through AI. It should be noted that discussion on other critical parameters selected to represent timber floor assemblies, columns, and connections is provided in their corresponding sections.

A number of databases are compiled to develop AI models. These databases were collected from actual fire tests obtained from open literature [22-68]. From each test, critical parameters (i.e. values of deformation at each point in fire exposure time as observed in the fire test and measured in time intervals of 1 minute, i.e. say 10 mm at 60 minutes, 12 mm at 65 minutes etc.) are collected. This procedure was replicated for various points in time for a particular timber member (e.g. floor, beam, column, connection) as well as for all other members selected to develop the AI models. Through this procedure, a particular AI model can relate fire exposure time to geometric features and applied load level on the timber beam and then derives an expression that relates fire effects (temperature rise, mid-span deflection etc.) to these parameters while implicitly accounting for material properties of timber. Hence, there is no a need to input temperature-dependent material

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properties in the process of predicting temperature rise or deflection in a timber member. It should be noted that whenever possible, other factors such as loading configuration, timber type etc. were kept within an acceptable range (10-20%) of that the most commonly reported values.

While it is true that selecting a few parameters, as discussed in the above rationale, simplifies the very complex behavior of timber structures under fire conditions, the following sections will show that this procedure still manages to capture the essence of thermal and structural response of timber structures with high accuracy. In any case, the developed AI-based framework is flexible and has the potential to include >15 independent (or dependent) input parameters for each timber element. All that is needed is to collect information on a new variable (i.e. moisture content) and to add this as a new input parameter to the AI model.

Due to complexities associated with fire testing, and different styles in reporting outcome of fire experiments, a number of issues can arise. For example, in the case where a particular parameter such as moisture content, is only reported in few studies (and not all studies). This parameter was not selected to be a critical input parameter in order to maintain homogeneity and unbiasness between all input parameters. In the case where such a parameter is deemed necessary, then data points associated with tests in which moisture content of timber is not reported would need to either be "removed" from the databases or given "assumed" values. One should note that applying the first action reduces the amount of available input data points for training the AI model, and that applying the second action might jeopardize prediction accuracy of the AI model. Some of the numerical techniques that can be used to accommodate similar issues will be briefly highlighted in a later section towards the end of this study.

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3.0 DEVELOPMENT OF DATABASES

As discussed earlier, the development of an AI-based framework requires collecting large number of inputs covering material properties, as well as thermal (cross sectional temperature) and structural (deformation, failure time) points obtained from actual fire tests on wood and timber structural members. Thus, the first step into developing fire test databases to be input into the AI-based models entitles conducting a thorough literature review to identify notable and related works in which timber elements were tested under standard fire conditions. This section highlights some of these studies and provides further insights into the development of the proposed models. It should be noted that over 12,000 data points were collected and will be made be available for use and download upon request.

3.1 Material level

The fire response of timber structures is mainly governed by thermal, mechanical and special properties of timber. While thermal properties determine temperature rise and propagation within timber, the mechanical properties govern degree of temperature-induced loss in strength and stiffness and eventually magnitude of fire-induced loss in load carrying capacity. In general, thermal and mechanical properties vary with temperature and are highly influenced by timber material phase changes (i.e. pylorisis) that occur at elevated temperature. The representations (relations) of how material properties of timber change (degrade) with temperature rise are often available in fire design codes and standards (i.e. Eurocode 5), as well as published studies [22-68]. A closer examination of these relations reveals that there is distinct variation in describing temperature-dependent material properties. This is attributed to the differences in testing methods, testing set-ups, specimen sizes and styles of reporting. It is due to such differences that fire design

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of timber continues to be a complex procedure. In fact, this is the driving force behind this study as the application of AI is intended to derive unique and universal material models that can best describe the behavior of wood and timber members under elevated temperatures. Since timber is an anisotropic material with hundreds of species that can be used in construction, this study mainly uses published properties accepted for general fire design of timber structures (i.e. parallel to grain). A typical database for a material property (i.e. thermal conductivity) is shown in Table 1.

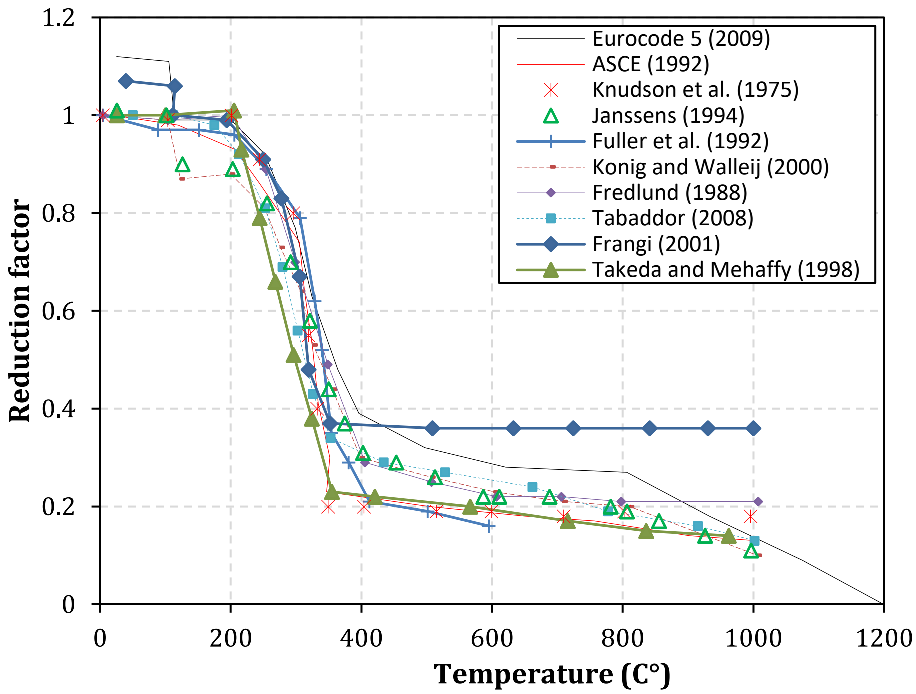
Table 1 Sample database for a material property (i.e. thermal conductivity)

Source	**Temperature (°C)***	**Value of thermal conductivity (W/m.K)**
Eurocode 5 [22]	20	0.12
	…	…
	200	0.15
	…	…
	1200	1.5
ASCE [23]	20	0.11
	…	…
	1000	0.165
⋮	…	…

*Temperature increments were taken to be in 10°C.

3.1.1 Thermal properties

The thermal material properties are those that influence temperature rise and distribution across a cross section made of timber. These properties comprise of density, thermal conductivity, and specific heat and their behavior depend on the composition and characteristics of timber species and moisture content. The density of timber, ρ (kg/m^3), defined as the mass of a unit volume, is often in the range of 300-700 kg/m^3, wherein density of white cedar ≈ 300 kg/m^3, Douglas firs (430 to 480 kg/m^3), southern pines (510-580 kg/m^3), and hickory ≈ 700 kg/m^3. Due to the continuous evaporation of moisture and drying, the density of wood tends to decrease with rise in temperature, reaching about 20-40% at 350°C (see Fig. 2) [22-28].



(a) Density

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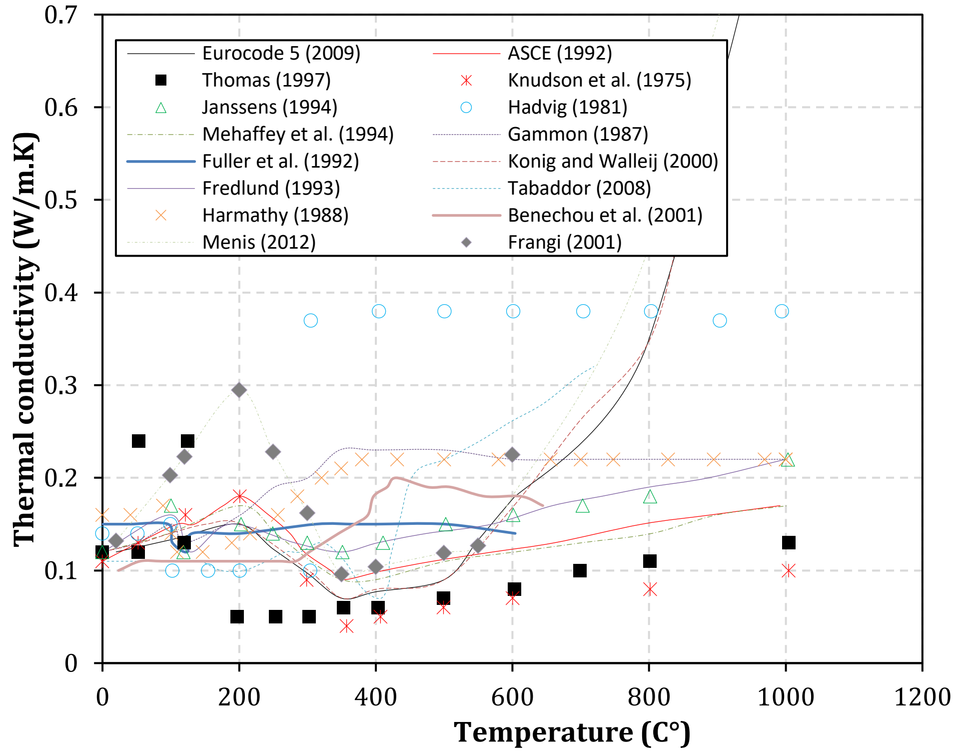
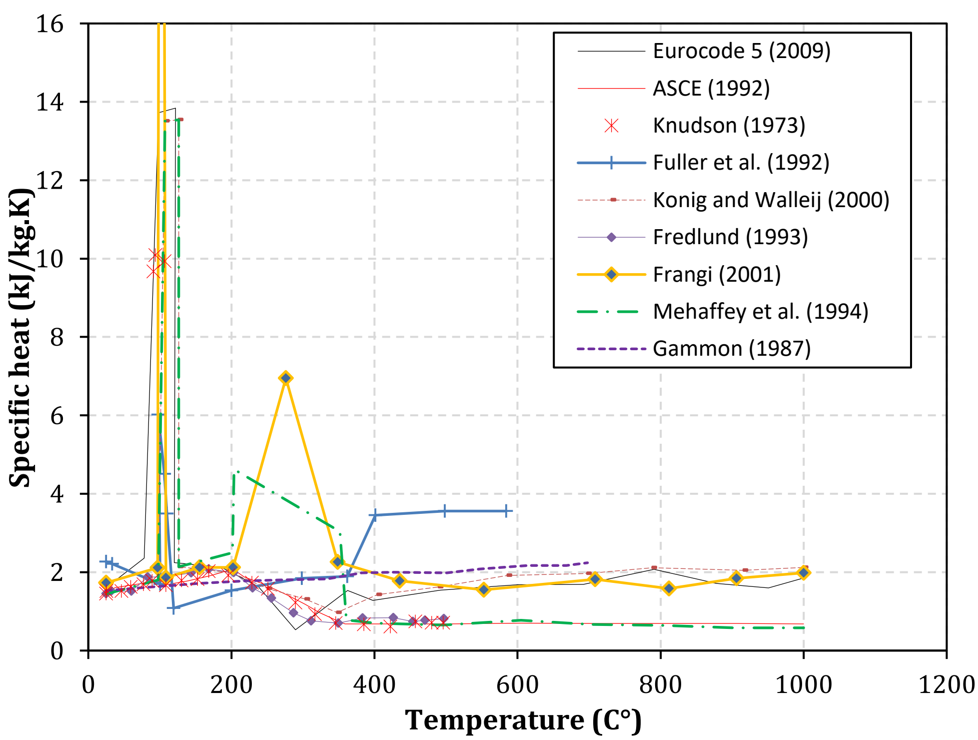


(b) Thermal conductivity



(c) Specific heat

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Fig. 2 Thermal properties of timber at elevated temperatures

Another thermal property is thermal conductivity, *k*. Thermal conductivity, a measure of how timber conducts heat, has a value of ranging between 0.1 to 0.2 W/m.K at ambient conditions and up to 200°C. The thermal conductivity of timber generally reduces between 200-320°C and then increases due to the higher conductivity of dry layers [26-29]. Finally, the specific heat, C_ρ, is a property that describes the amount of heat required to raise a unit mass of timber a unit temperature. The specific heat of timber is about 1.8-2 kJ/kg.K at ambient conditions and raises with a sharp peak once temperature in timber reaches 100°C to represent the latent heat of vaporization of the water within the timber (if not dry). After this point, specific heat of timber drops to a level close to its value at room temperature.

A good amount of documentation is available on thermal properties of timber under elevated temperatures. For example, Eurocode 5 [22], AS 1720.4 [30] and American Society of Civil Engineers (ASCE) structural fire protection manual [23] provide recommendations to such properties in terms of graphs and tabulated values. Other notable studies include those carried out by Adl-Zarrabi et al. [31], Bénichou et al. [32], Menis [33], Frangi [34], and [35-46]. Data points complied from all of these studies are plotted in Fig. 2. As stated earlier, data plotted in this figure clearly show that there is a large variation in describing temperature-dependent thermal properties of timber.

3.1.2 Mechanical properties

The mechanical properties of constituent materials determine the extent of strength loss and stiffness deterioration in timber. These properties mainly comprise of Young's modulus (E), compressive (f_c), tensile (f_t) and shear strength (f_v) of wood. Unlike tests carried out to evaluate thermal properties of wood, the mechanical properties of wood were mainly reported up to 250-

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350°C. This is because timber tends to lose much of its load bearing capabilities beyond this temperature range. Similar to thermal properties, the open literature contains a good amount of documentation on mechanical properties of wood under elevated temperatures. Some of these studies are listed herein and include Eurocode 5 [22], AS 1720.4 [30], ASCE structural fire protection [23], Thomas and Buchanan [47], Ostman [48], as well as [49-61]. It is worth noting that a thorough review on mechanical properties of wood at low and elevated temperatures is presented by Gerhards [61].

Figure 3 presents how mechanical properties of wood deteriorate at elevated temperatures. This figure shows that mechanical properties generally decrease with rise in temperature. This degradation follows a linear trend and can start at relatively low temperature slightly exceeding 75°C. It is interesting to note that some material models, such as that proposed by Jong and Clancy [53] shows that modulus of wood reduces to about 20% of its initial strength at 100°C, while other models such as that adopted by Eurocode 5 [22] and ASCE [23] show degradation of about 50% and 5%, respectively (possibly due to the fact that these models were carried out on moist timber and/or account for temperature-induced creep while others do not). Similar observations can also be made in the case of compressive and tensile strength properties of wood.

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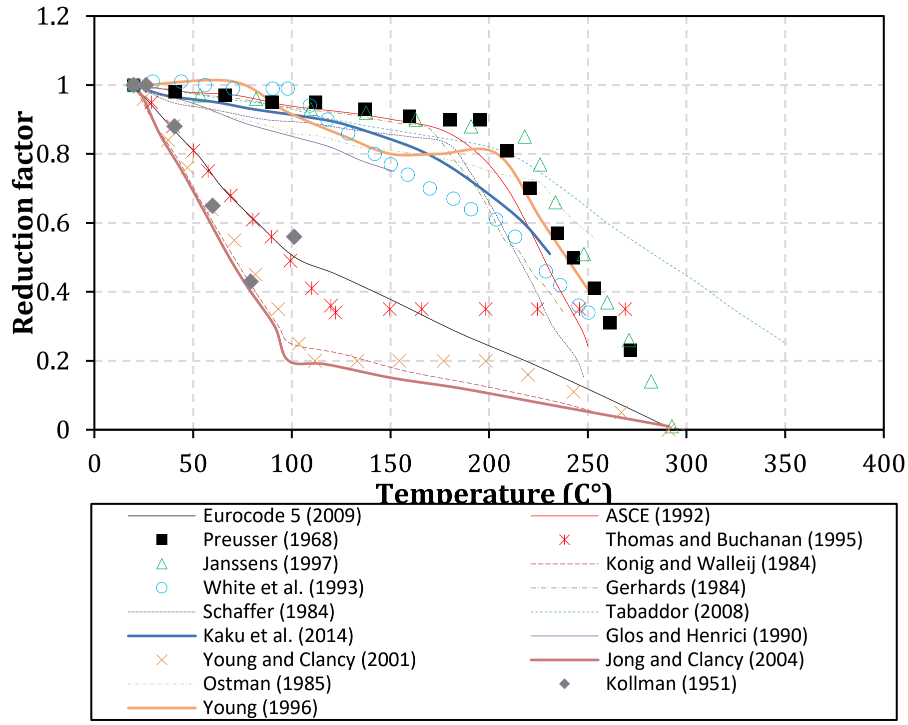
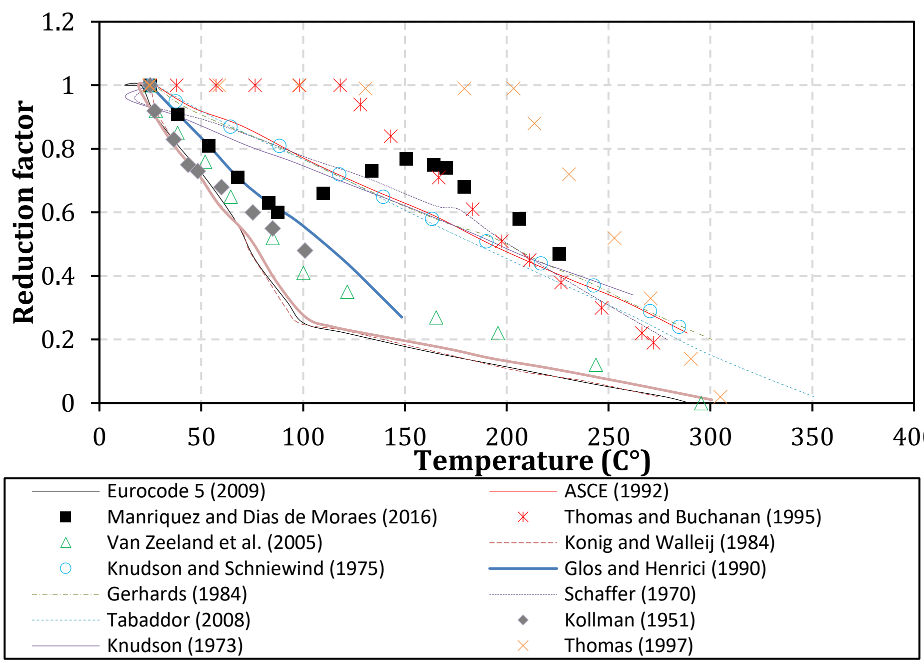


(a) Young's modulus (in tension)



(b) Compressive strength

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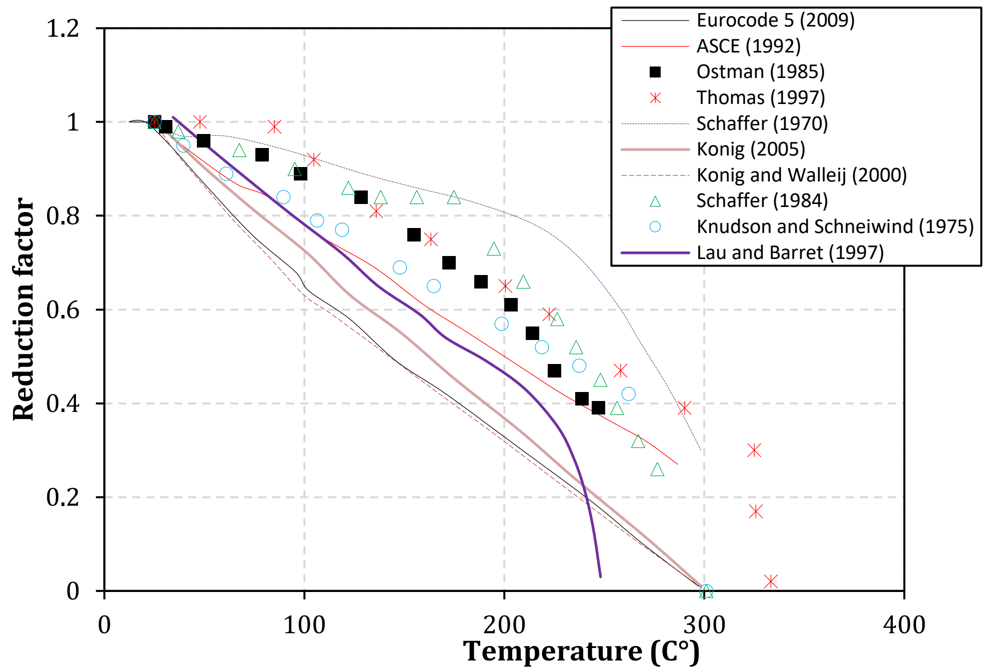
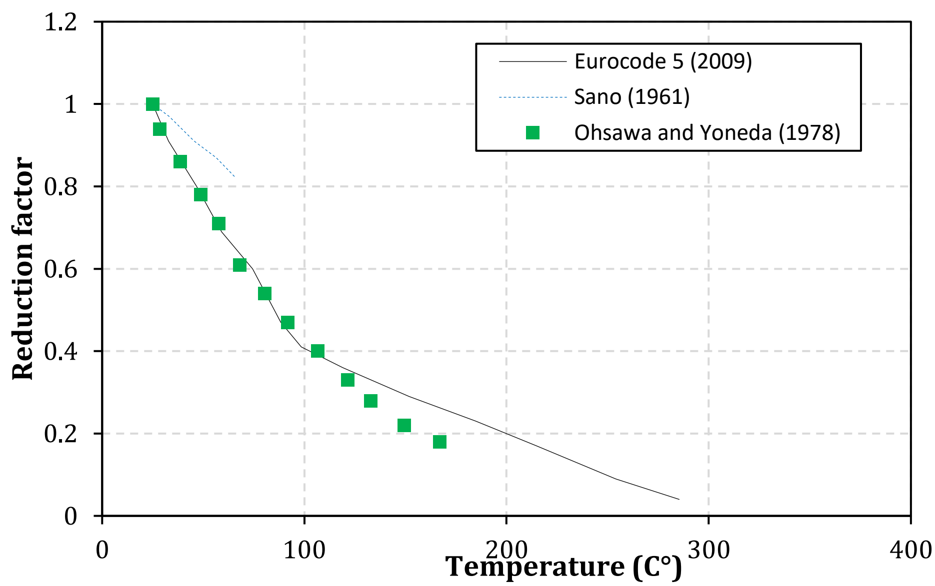


(c) Tensile strength



(d) Shear strength

Fig. 3 Mechanical properties of wood as a function of elevated temperatures

3.1.3 Special property (Charring)

Charring is a unique property of wood. Charring occurs as a result of pyrolysis of timber and takes place in the narrow temperature range of 260-300°C [22, 23]. Charred wood has virtually

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no strength and low thermal conductivity. It is due to this low thermal conductivity that charred layers thermally insulate interior (core) of wood. Charring rate is governed by a number of factors including wood species and fire exposure etc. Although charring rate may reduce as the insulating charred layer grow with extended exposure to fire, charring can still be considered to occur with a constant rate throughout the duration of fire. Many design codes specify constant charring rates in their provisions. For instance, Eurocode 5 gives a charring rate of 0.6-0.75 mm/min for softwood and 0.5 mm/min for hardwoods. Figure 4 shows charring depth as a function of exposure time to standard fire as proposed by fire codes and researchers such as AS 1720.4 (1992), White and Nordheim (1992), Lawson et al. (1952), Schaffer (1967), Schnable and Turk (2006), and Fredlund (1988). In general, the charred depth increases linearly with fire exposure time.

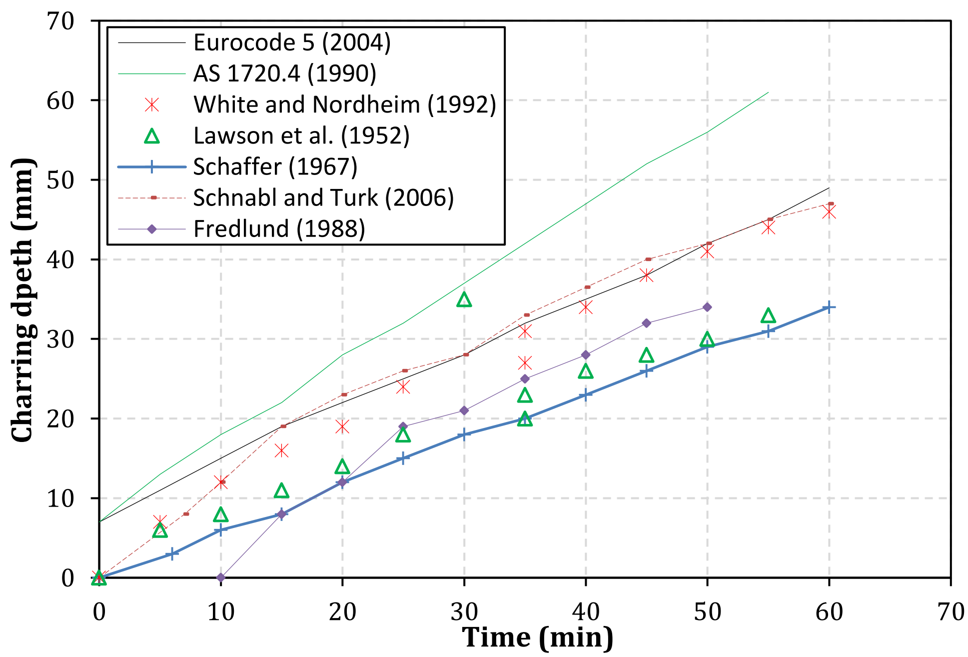

Fig. 4 Charring depth in wood exposed to standard fire

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3.2 Element (member) level

Databases were also developed to be input into another set of AI models specifically designed to derive simple expressions that can be used to evaluate thermal or structural response of timber structural elements. These elements include, floors assemblies, beams, columns, and two types of connections (nail-based and finger-joints). These expressions take into account critical parameters such as geometric features of elements, adhesive type, fire exposure duration, among others. A unique feature of these expressions is that they implicitly account for temperature-dependent material properties of timber as well as associated fire phenomena; such as charring. Another feature is that these models can be used to predict fire response of timber members at a particular point in time or throughout fire exposure duration until failure of element. Due to the different objectives of each AI-derived expression, specific details on developed database for each type of members is presented in corresponding sections below.

3.2.1 Fire tests carried out on floors assemblies

Sultan et al. [62] carried out an extensive experimental program at the National Research Council Canada (NRCC) to examine fire resistance and performance of unrestrained lightweight wood frame floor assemblies protected with Type X gypsum board. This program comprised of over 70 fire tests in which full-scale load-bearing wood joist floor assemblies were exposed to the ULC/ASTM standard fire exposure (which is similar to ASTM E119 standard fire). Sultan et al. [62] investigated a number of parameters including; gypsum board screws spacing, insulation type and installation process, joist spacing and depth, resilient channel installation, sub-floor topping, number of sub-floor layers, and load magnitude. A typical configuration of these assemblies is shown in Fig. 5.

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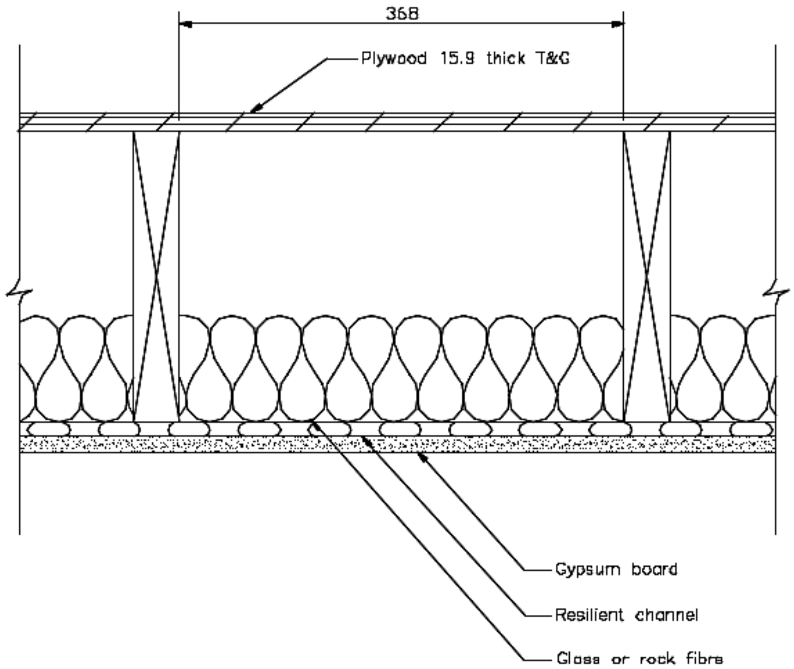

Fig. 5 Typical configuration of selected assemblies for analysis [62]

Due to the large number of studied parameters by Sultan et al. [62], and for the sake of this study, only fifteen floor assemblies were identified to showcase how AI can be used to derive a simple expression that can be used to predict thermal response (i.e. temperature rise) across a floor assembly. These assemblies were made of similar wood joists (depth = 235 mm and spacing = 406 or 610 mm), installed with resilient channels, and subjected to varying magnitudes of loading (3830-5027 MPa)[*]. The key parameters in these floor assemblies are fire exposure duration, t, number of layers in ceiling finish, C, thickness of sub-floor, k_{th}, as well as type of insulation used in cavity, I. The output obtained from the AI model is temperature rise in the plywood subfloor

[*]It should be noted that an assumption is made herein that the magnitude of loading does not affect temperature rise in the floor assembly.

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located at inner face of cavity. Table 2 lists the selected input parameters used to developed AI-based model.

Table 2 Sample database for AI model used to derive an expression to predict thermal response of floor assemblies.

Parameter/ Assembly no.	**Inputs**						**Output**
	Time, *t* (min)	**No. of layers in ceiling finish, *C***	**Sub-floor thickness, k_{th} (mm)**	**Feature of cavity insulation, *I***			**Temperature, *T* (°C)**
				No insulation	**Glass fire insulation**	**Rock fibre insulation**	
…	…	1 or 2	15.5 or 19	0	1	2	…

3.2.2 Fire tests carried out on beams

Fahrni et al. [63] tested six spruce glulam beams under four point bending while being exposed to standard fire conditions simulating that of ISO 834 fire. These beams had a span of 3,800 mm and a rectangular cross section of nominal width and height of 158 and 250 mm, respectively. The average bending strength and stiffness in these beams was 35.5 and 12,961 MPa, respectively. The average moisture content in beams was measured at 11%. These beams were exposed to fire from three sides and sustained a maximum bending moment of about 20-30% of their room temperature moment capacity. All beams had an average charring rate ranging between 0.63-0.72 mm/min. This study was primarily selected to show the merit of AI as only the structural response (mid-span deflection) of these beams was reported (and not the thermal response). Unlike

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simplified or advanced calculation methods, structural modeling through AI can be carried out without the need to obtain thermal response of beams first (given that all beams were exposed to similar fire conditions). Out of the six beams, only four were selected to develop a database. The selected input parameters in this database are; duration of exposure to fire, *t*, load level, *P*, height, *H*, and charring rate, *β*, and the output parameter is mid-span deflection, Δ (see Table 3).

Table 3 Sample database for AI model used to derive an expression to predict structural response of glulam beams.

Parameter/ Beam no.	**Inputs**				**Output**
	Time, *t* (min)	**Load level, *P* (%)**	**Height, *H* (mm)**	**Charring rate, *β* (mm/min)**	**Mid-span deflection, Δ (mm)**
…	…	20 or 30	253, 256	0.68, 0.71, 0.80	…

3.2.3 Fire tests carried out on columns

Unlike AI models developed in the above two sections, the AI model herein was primarily developed to understand the relation between critical parameters associated with determining fire resistance rating for timber columns. The required data points needed to develop a special database for such a model was obtained from the works of Malhotra and Rogowski [64] and well as Stanke et al. [65]. These researchers carried out a large number of standard fire tests on glued-laminated columns to examine effect of key parameters (such as wood species, cross section shape, and level of loading) on fire resistance of columns, and to derive simple relations to predict fire resistance ratings. Fortunately, the Technical Report No. 10 [66], prepared by the American Wood Council (AWC), managed to compile both critical parameters as well as fire ratings associated with tested columns by aforementioned researchers. These properties are listed in Table 4 and include, column depth, D, column breadth, B, compressive strength of timber, f_c, specific gravity of timber, S_G, and level of applied loading, P, among others. This database compiled points from 58 fire tests.

Table 4 Sample database for AI model used to derive an expression to predict fire resistance rating of columns.

Parameter/Beam no.	**Inputs**						**Output**
	Time, *t* (min)	**Depth, *D* (mm)**	**Breadth, *B* (mm)**	**Specific gravity, S_G**	**Compressive strength, f_c, (MPa)**	**Load level, *P* (%)***	**Fire resistance, *FR* (min)**
…	…	140-400	140-400	0.31-0.59	22-62	9-41	…

*The level of applied loading was calculated as the ratio between induced load/resisting capacity [66].

3.2.4 Fire tests carried out on connections

Two types of connections were selected in this study, i.e. finger-joint, and nailed joint connection. Thus, a specific AI model was developed for each type of connection. As a result, two separate databases were compiled. These databases were obtained from the published works of Klippel and Frangi [67], and Norén [68], respectively.

Klippel and Frangi [67] investigated fire behavior of solid and bonded finger-jointed timber connections. In this study, 49 finger joints were loaded with a constant tensile load parallel to grain direction with varying load levels while being exposed to ISO 834 fire from two sides. These researchers also investigated the performance of a number of structural adhesives including, emulsion-polymer-isocyanate (EPI), polyurethane (PUR): P2, P3, P4, P6 and P7, melamine-urea-formaldehyde resin (MUF), urea-formaldehyde resin (UF), phenol-resorcinol-formaldehyde resin (PRF) and polyvinyl acetate (PVAc). The finger-jointed connections varied in adhesive type, *A*, width, *W*, charring rate, β, and applied loading, *P*. The AI model used for this connection type was designed to arrive at fire rating, *FR*, of connections (see Table 5). Additional details on these experimental tests can be found in Klippel and Frangi [67].

Table 5 Sample database for AI model used to derive an expression to predict fire resistance of finger-joint connections.

Connection No.	**Inputs**															**Output**
	Time, *T* (min)	**Adhesive type, *A***							**Width, *W* (mm)**			**Load level, *P* (%)**				**Charring rate, β (mm/min)**	**Fire resistance, *FR* (min)**
…	…	Solid = 0	MUF*	EPI = 7	PUR**	PRF = 8	UF = 11	PVAc = 12	80	140	200	20	30	45	58	From 0.57 to 0.80	…

*MUF M1.1 and M1.2 = 1, MUF7.1, 7.2, 10.1, 10.2 =10, **PUR P2 = 2, PUR P3 = 3, PUR P4 = 4, PUR P6= 5, PUR P7= 6.

On the other hand, Norén [68] tested a number of nailed connections loaded in the range of 10-60% of the failure load at normal temperature. The connections were made of spruce wood, conditioned at 20°C and 65% relative humidity, with final moisture content of 14%. The oven dry density of wood used in these connections was reported in the range of 381 to 422 kg/m^3. Norén

[68] tested four series and those grouped under series two were selected for analysis herein. The dimensions of the central members are 120×45 mm and side members of 20×120×280 mm. Both central and side members are joined with nails of 2.8 mm diameter and length of 52 mm. Each connection had 12 nails and was loaded in single shear (see Fig. 6). The point-side penetration including the nail tip was 32 mm. The nails were spaced at distances of 28 mm parallel to the grain and at distances of 20 mm transverse to grain. The distance between nails and loaded edges of the members was 28 mm and between nails and unloaded edges was 40 mm. Since Norén [68] reported results on ten connections (in terms of connection slip as a function of fire exposure time), then the AI model was developed to arrive at expressions that can capture this behavior. The input parameters were, duration of fire exposure, *t*, and load level, *P*. The output is slip, *δ*, at various times.

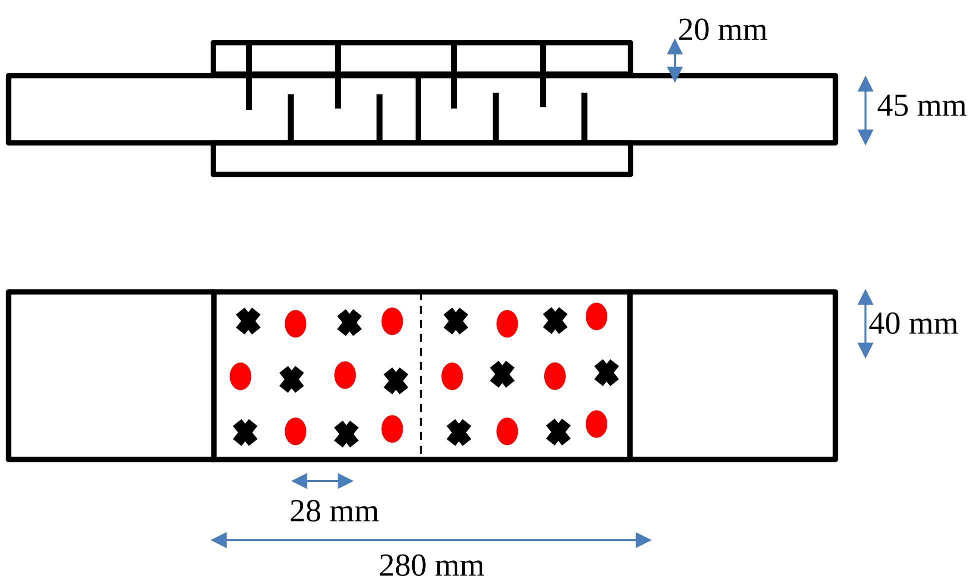

Fig. 6 Layout of nailed connection as tested by Norén [68] (top: side view, bottom: top view)

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4.0 PERFORMANCE AND VALIDATION OF AI-BASED DERIVED EXPRESSIONS

Once the databases were prepared, these databases were first input into the neural network tool in Matlab for analysis and then processed through genetic algorithms [21]. In this algorithm, candidate solutions are encoded with terminal nodes corresponding to variables that best describe a given phenomenon; which in this study cover material property, thermal and structural response of timber and timber structural elements. The candidate solutions are derived using symbolic regressions to describe the unique relation between input parameters, i.e. fire exposure time (t), compressive strength of timber (f_c), applied load level (P) etc., and output (e.g. temperature rise, mid-span deflection, fire resistance rating etc.). Each relation comprises of mathematical functions such as addition, multiplication etc. A fitness function is usually governed by the difference (absolute or squared error) calculated between values predicted by a candidate solution and those measured through fire tests described above, with parsimony corrections to favor simple and compact expressions.

Out of all complied data points, 70% of the collected data is used to train the AI-based cognitive framework and the remaining 30% were used to validate and test the performance of the developed AI-derived expression as recommended by previously published works [14, 15, 17]. Further, additional data points compiled from tests that were not included in the databases were also used to cross-check the validity of the AI models (see Sec. 5.0). In general, the compiled input parameters were randomly arranged in order to eliminate any biasness. In this study, thirteen expressions are derived. These expressions, together with their coefficient of determination (R^2), correlation coefficient (R), and mean average error (MAE) as obtained from the AI-based models are listed in Table 6. Further, plots showing validation of derived expressions (against training data) as well as performance (against published works) are shown in Fig. 7. Overall, the plotted figures show a good agreement between predicted and measured points and this shows the validity and accuracy of the developed AI models. It is worth noting that few numerical examples are provided in the appendix to show how to properly collect input parameters and to use these derived expressions in predicting thermal and structural response of timber elements.

Table 6 AI derived expressions to evaluate fire response of timber elements and components

Case			Derived expressions	Coefficient of determination (R^2)	Correlation coefficient (R)	Mean absolute error (MAE)
Material property	Thermal conductivity (W/m.K)		$k = 0.37 - \frac{6.07}{T} + 0.0006T ln(T) + 7.66 \times 10^{-5} T \tan(0.071T) - 0.0042T - 0.0127 \tan(0.071T) - 9.5 \times 10^{-8} T^2 \tan(0.071T)$	0.99	0.99	0.001
	Specific heat (kJ/kg.K)		$S = 2.48 - \frac{6.12}{T} + 3.6 \times 10^{-6} T^2 + \frac{29.25}{2.8T - 343.6} - 0.004T - 0.0466 \tan(3.9 \times 10^{-9} T^3)$	0.99	0.99	0.004
	Reduction factors (*RF*)	Density	$RF_\rho = 0.8 - \frac{0.00186}{\cos(T)} + 0.389 \cos(T + \cos(T)) \cos(\cos(1.85T)) - 0.0007T$	0.99	0.99	0.005
		Young's modulus	$RF_E = 1.17 + 8.14 \times 10^{-5} T^2 + 1.1 \times 10^{-14} T^6 - 0.0087T - 6.84 \times 10^{-20} T^8 - 3.48 \times 10^{-7} T^3$	0.99	0.99	0.004
		Compressive strength	$RF_{f_c} = 1.17 + 3.19 \times 10^{-5} T^2 + 7.32 \times 10^{-13} T^5 - 0.0076T - 4.31 \times 10^{-10} T^4$	0.99	0.99	0.008
		Tensile strength	$RF_{f_t} = 1.02 + 0.0294 \cos(T^2) \sin(T \cos(T^2)^2) - 0.00195T - 4.37 \times 10^{-11} T^4 - 7.7 \times 10^{-5} T cos(T^2)$	0.99	0.99	0.002

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		Shear strength	$RF_{f_v} = 4.2 \times 10^{-8}T^3 + 5387\tanh(0.07 + 0.174T) - 5362 - 0.0054T - 2.16 \times 10^{-5}T^2 - 4.89T^{T^{0.228}}$	0.99	0.99	0.003
	Charring depth (mm)		$Ch = 1.48 + 0.798T + 0.981cos(1.08T) + 5.34 \times 10^{15}T \times 0.0017^T + 0.037Tcos(0.882T) - 2.46 \times 0.0017^T$	0.99	0.99	0.21
Elemental level	**Thermal response**	**Temperature in floors (°C)**	$T = 11.2 + \frac{k_{th}+0.255t^2}{CI+C} + \frac{0.047\cosh(0.133t\sin(-0.091t))}{\mathrm{asin}(\sin(17.8k_{th}))} - 27\sin(-0.091t)$	97.2	98.6	11.02
	Structural response	**Mid-span deflection in beams (mm)**	$\Delta = 0.0069t^2 + 8.63 \times 10^{-9}Bt^6 + \mathrm{acosh}(PH) - 3.08 - 5.54 \times 10^{-9}t^6 - 0.00022Bt^3$	96.7	98.3	0.9
		Fire resistance of columns (min)	$FR = 44.18 + 19.67\ln(f_c) + 0.0073DBS_G - \sin(0.7DBS_G)\,\mathrm{asinh}(0.0073DBS_G) - 60.36 - 327.95S_G - 19.67\ln(P) - 0.0022DB - 1.1 \times 10^{-9}(DB)^2$	95.3	97.6	2.82

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		Connections	**Slip in nailed (mm)**	$\delta = 2.96 \times 10^{-9} t \cosh(t) + 1.45 t^2 P^3 + 3.55 \times 10^{-6} \cosh(0.22 P t^2) + 0.077 \tan(1.45 t^3 P^4) + \sin(t)$	94.3	97.1	1.63
			Fire resistance of finger-joints (min)	$FR = 20.94 + 0.584W + BA^2 - 134.97P - 0.00016 \exp(A) - 0.055AW - 0.068W tanh(\sin(5.96ABexp(A)))$	93.9	96.9	2.55

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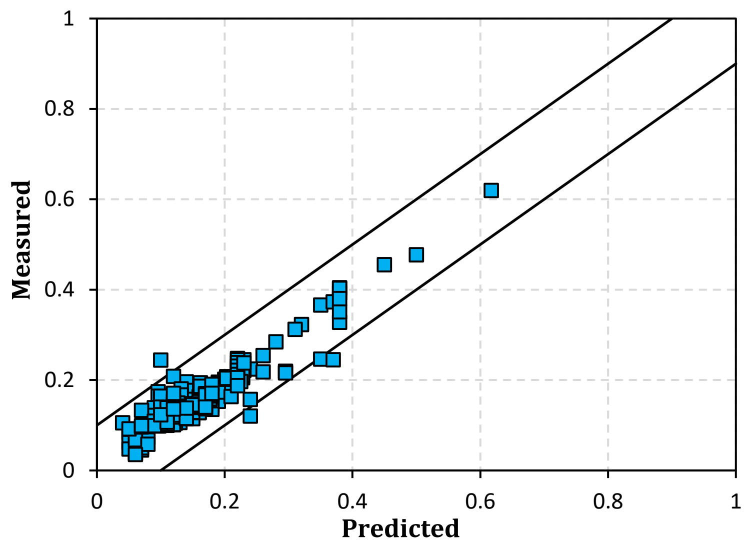
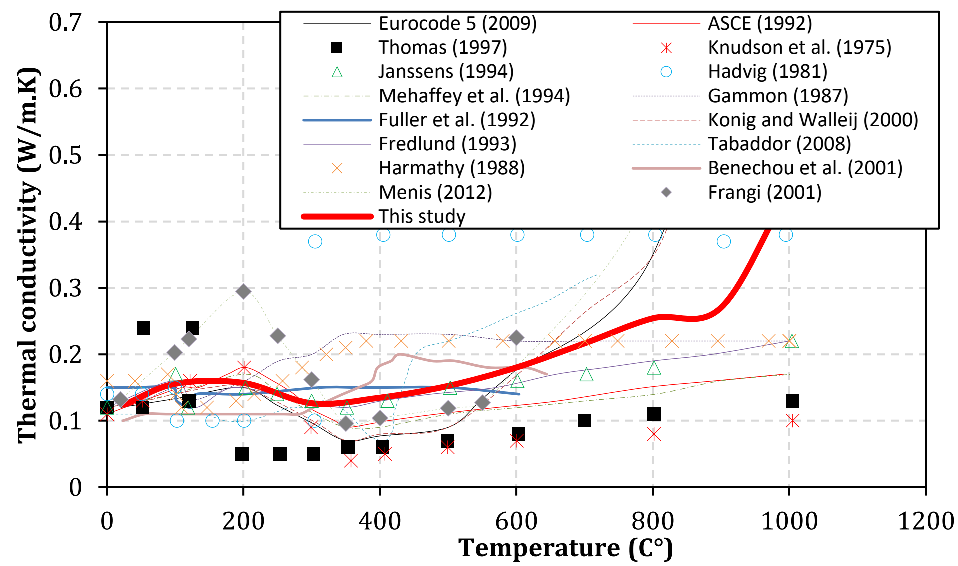
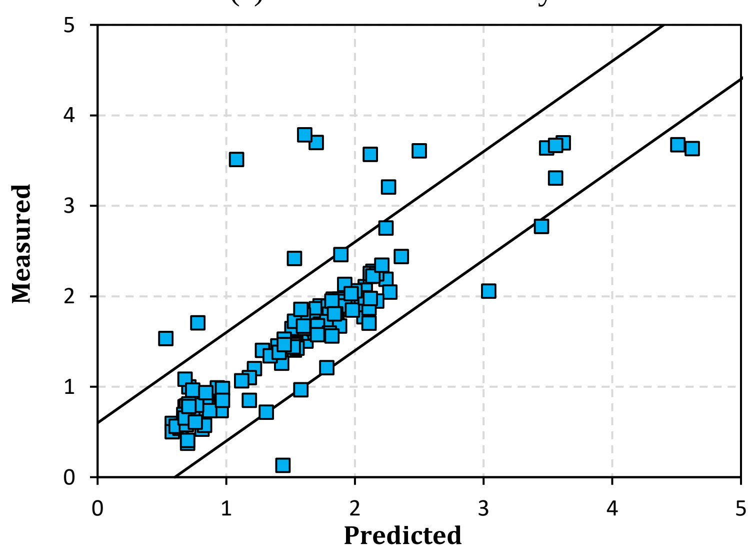
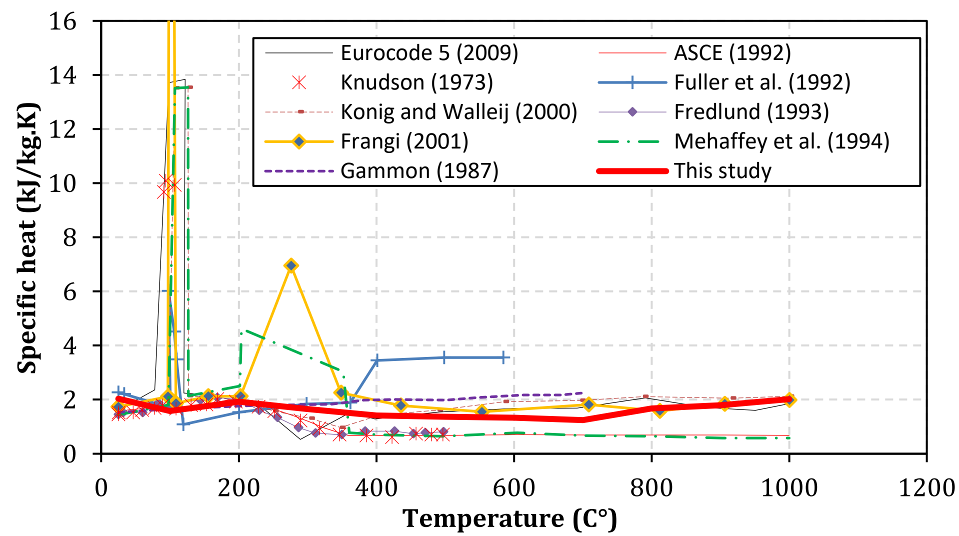




(a) Thermal conductivity (b) Validation against fire tests





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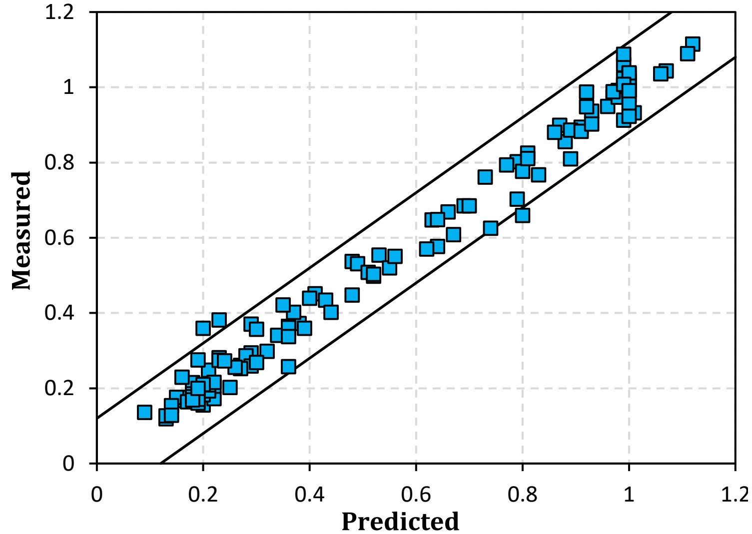
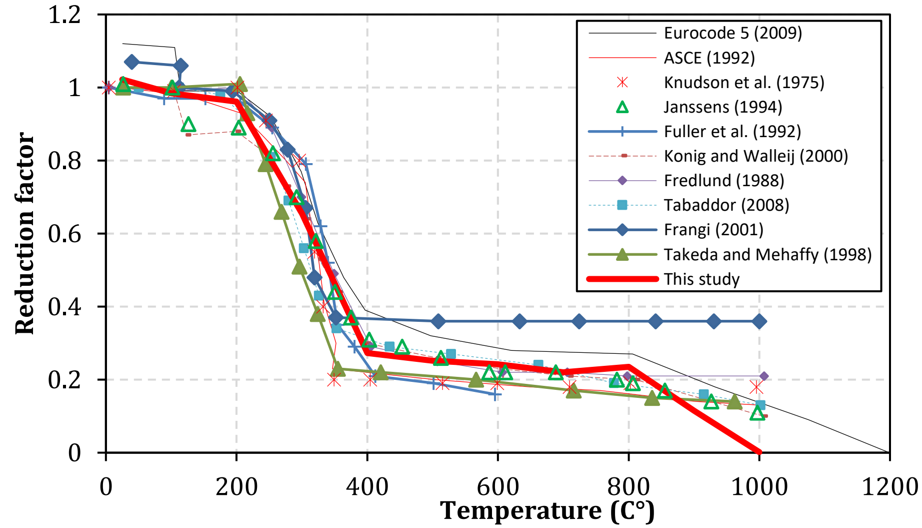
(c) Specific heat

(d) Validation against fire tests





(e) Density

(f) Validation against fire tests

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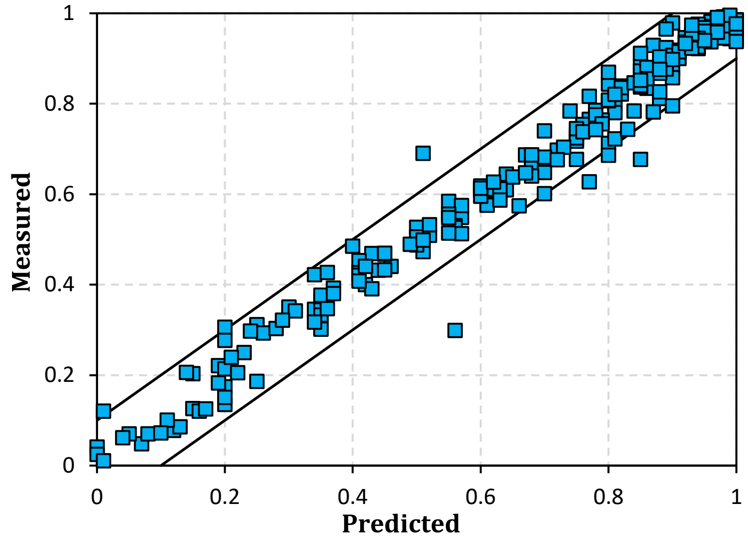
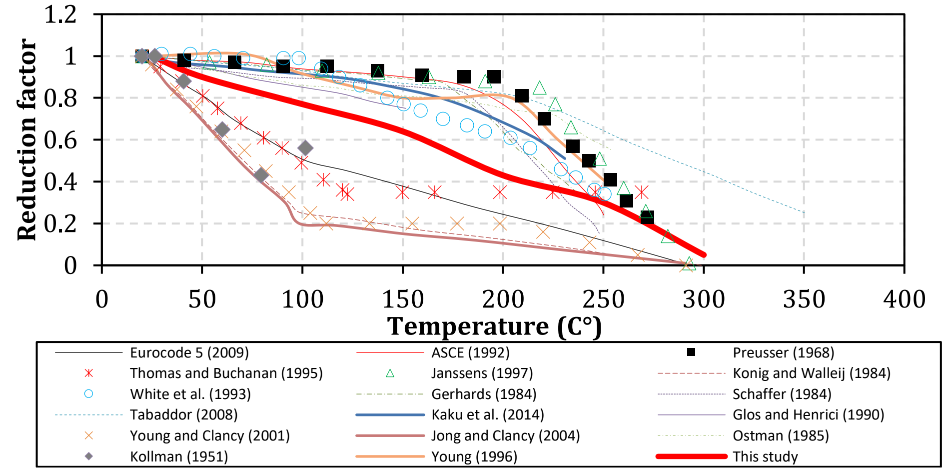
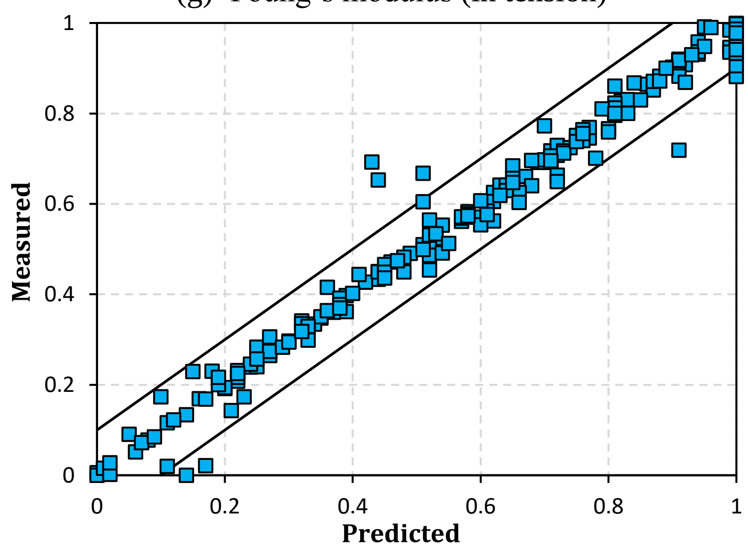
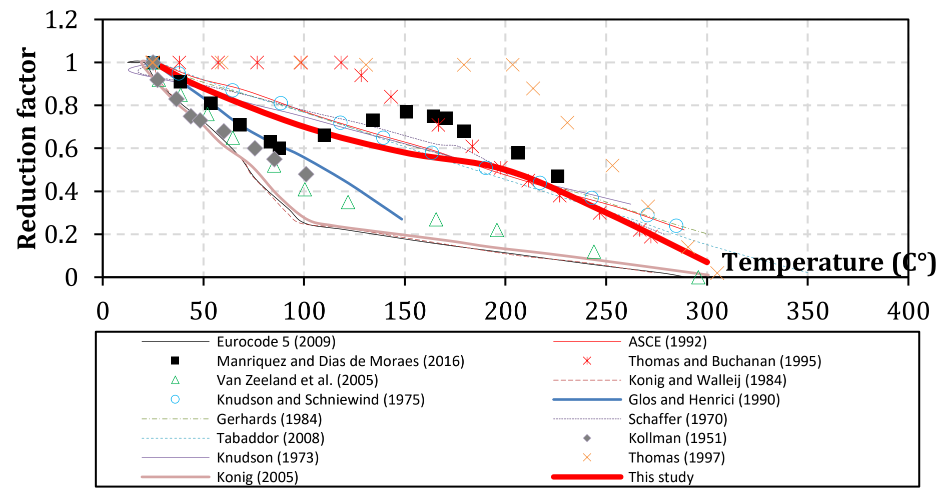


(g) Young's modulus (in tension)



(h) Validation against fire tests





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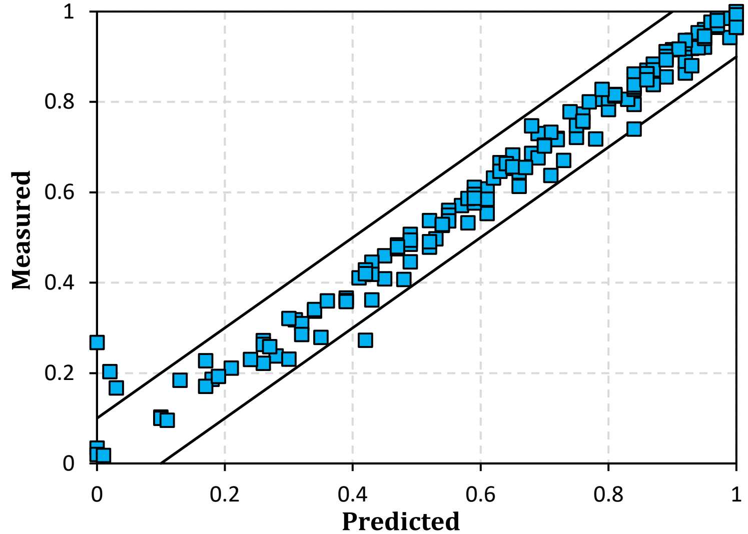
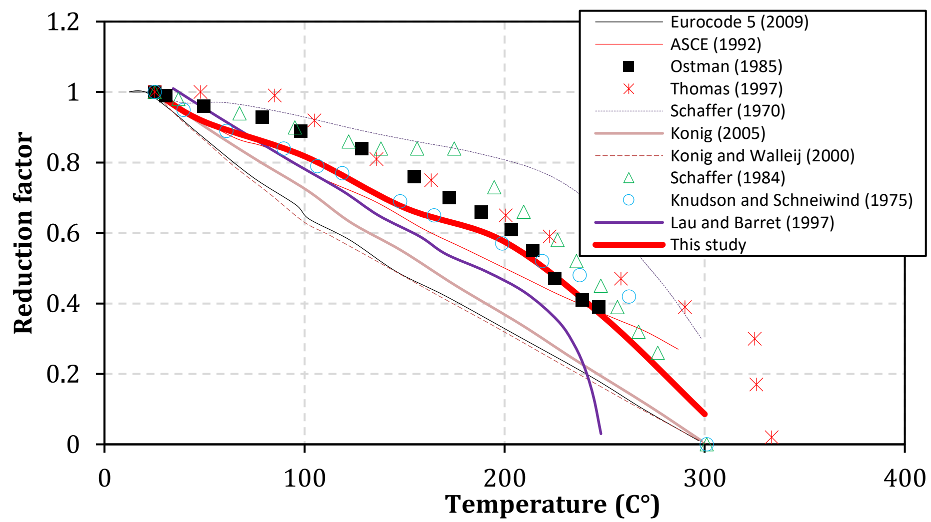
(i) Compressive strength

(j) Validation against fire tests





(k) Tensile strength

(l) Validation against fire tests

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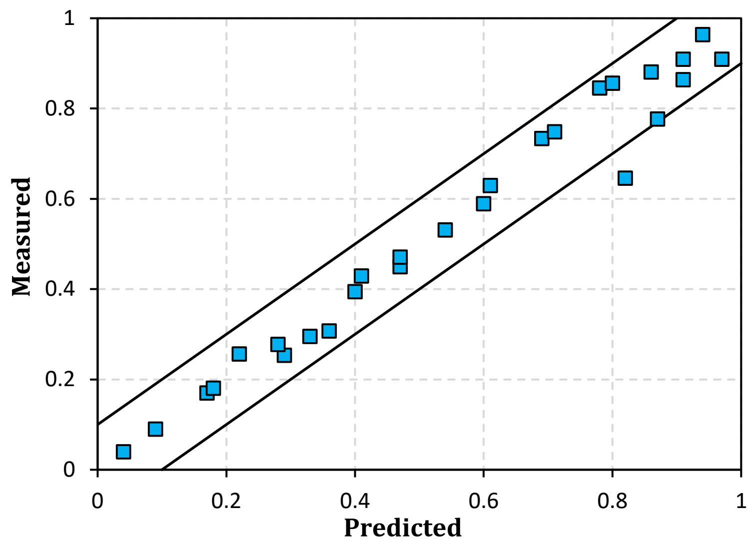
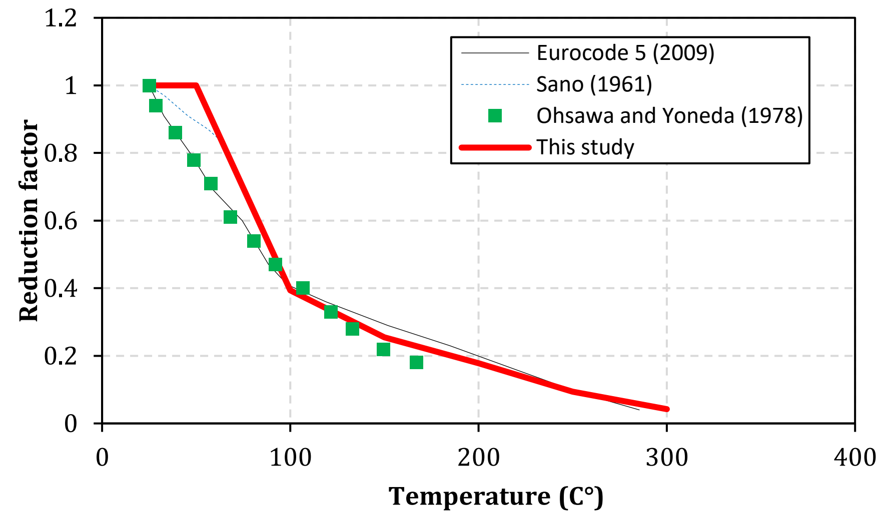
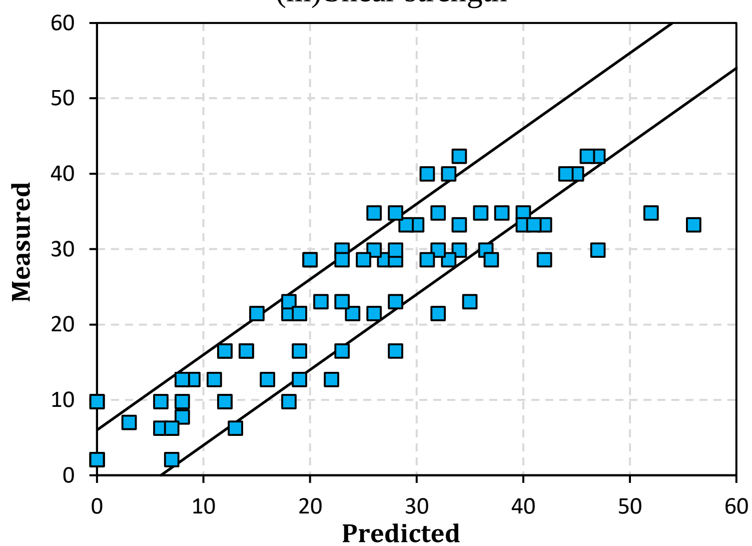
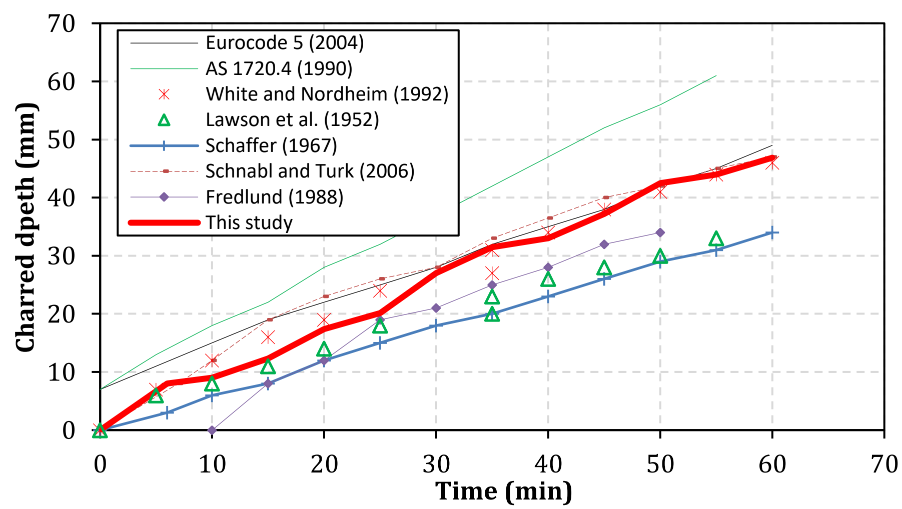


(m)Shear strength



(n) Validation against fire tests





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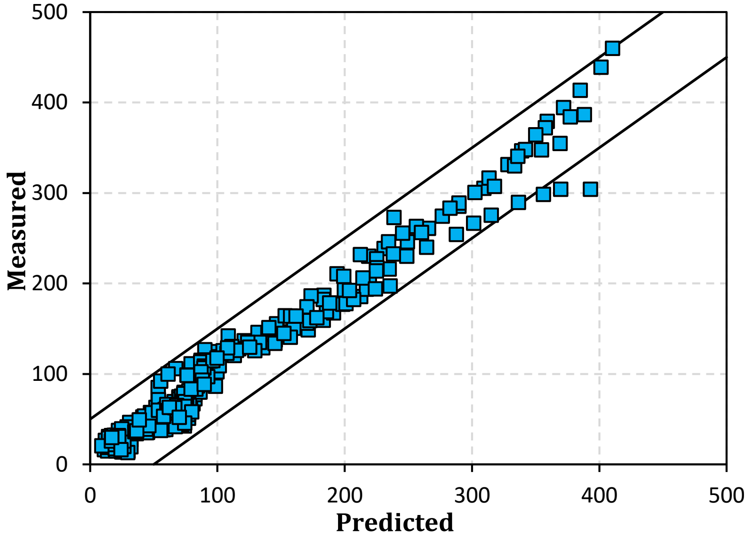
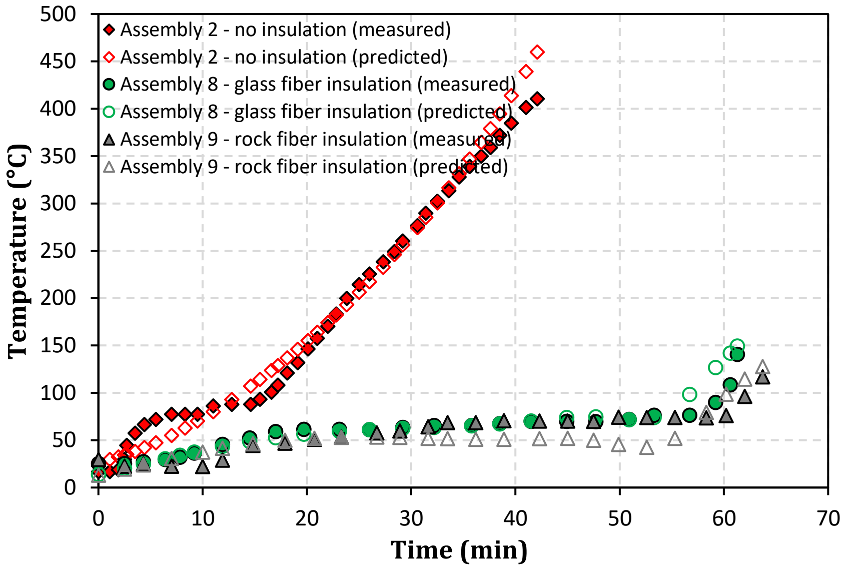
(o) Charring depth



(p) Validation against fire tests



(q) Temperature across floor assemblies

(r) Validation against fire tests

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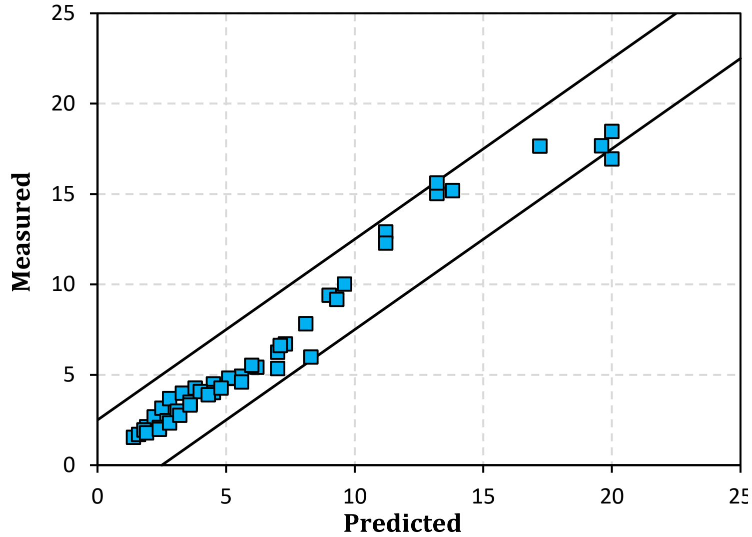
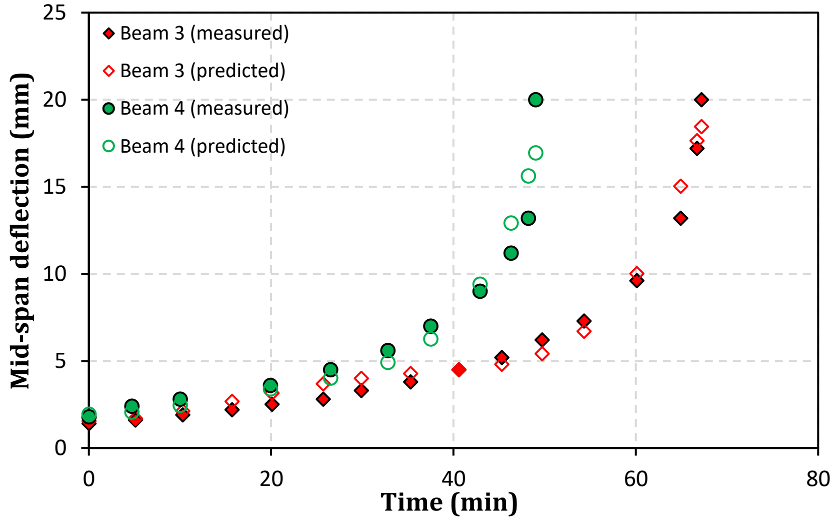


(s) Mid-span deflection in beams



(t) Validation against fire tests

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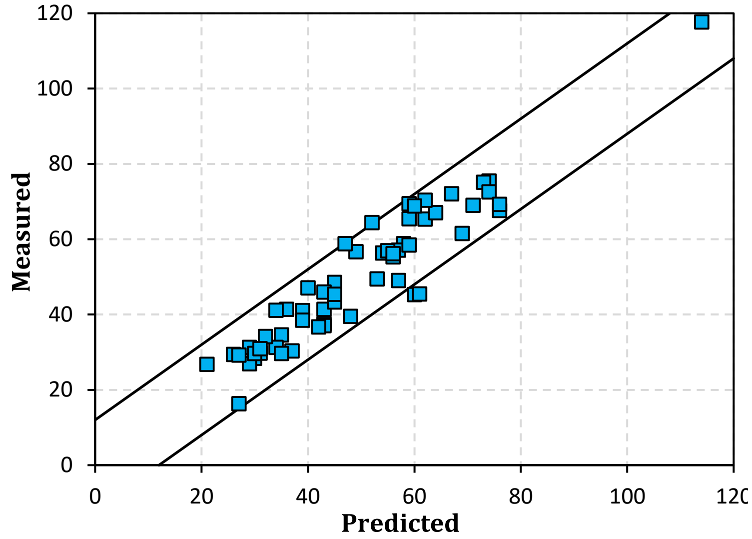
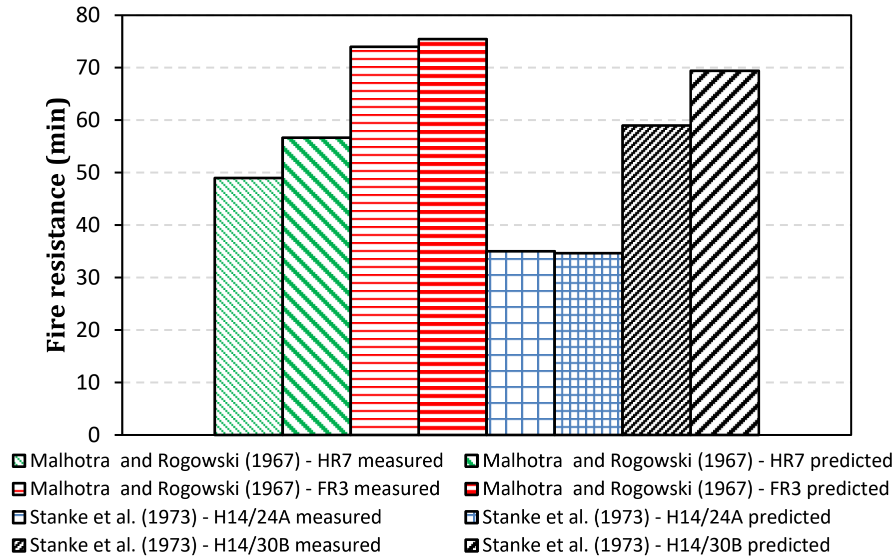


(u) Fire rating of columns



(v) Validation against fire tests

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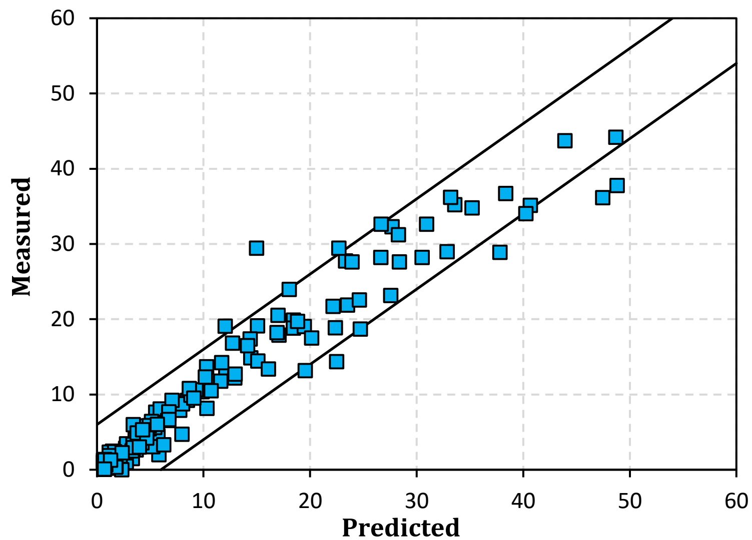
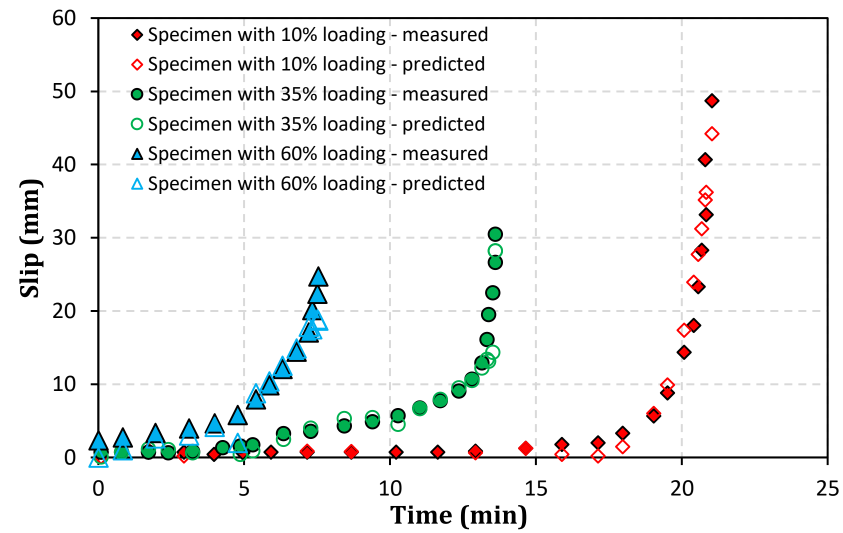


(w) Slips in nailed connections



(x) Validation against fire tests

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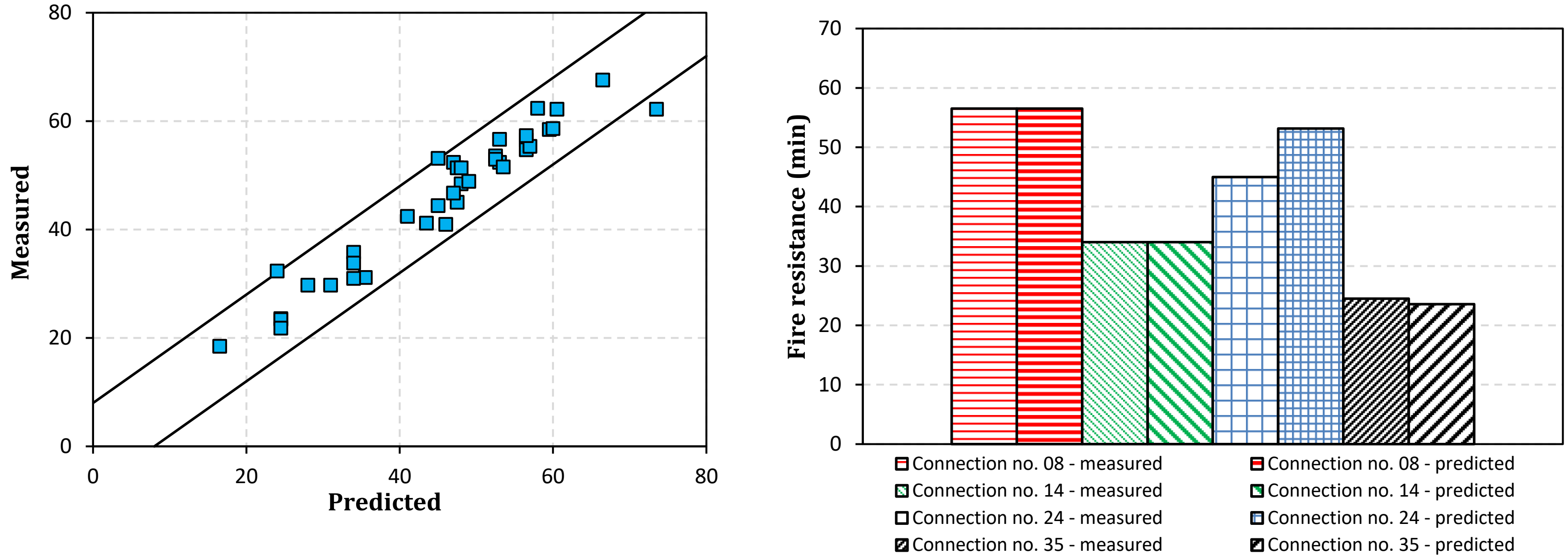

(y) Fire resistance of finger joints connections (z) Validation against fire tests

Fig. 7 Validation and performance of AI-derived expressions

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5.0 APPLICABILITY OF AI-DERIVED EXPRESSIONS TO NEW SCENARIOS

As discussed above, the derived expressions were validated against 30% of the input data points for the developed databases (as 70% of data points were used to train the AI-models). Due to the simplicity of tackled phenomena, this validation process carried out in Sec. 4.0 is expected to be suitable for expressions used to arrive at temperature-dependent material properties of timber. However, in the case of expressions derived to trace thermal and structural response of fire-exposed timber elements, an additional step was carried out herein to ensure proper validation of the AI-derived expressions. Thus, to further validate the predictability of the derived expressions, predictions obtained from these expressions were compared against data points measured in fire tests that were independently collected and were not included in the developed (training-based) databases. This further ratifies the validity and adaptability of the derived expressions in new scenarios to which they have not been exposed to earlier.

The validity of the proposed expressions for tracing temperature rise in floor assemblies was examined by predicting thermal response of three floors tested by Sultan et al. [62] and were not part of the training process discussed in Sec. 4. These floors were assembly 18, 13 and 5 which had no insulation, rock fiber insulation and glass fiber insulation, respectively. In the case of timber beams, Beam 6 was a glulam beam tested by Fahrni et al. [63] and was not included in the developed database for training, and hence was selected to cross-check the validity of the AI-derived expression in predicting mid-span deflection of beams. This beam has a height of 217 mm, charring rate of 0.7 mm/min, and was subjected to an applied loading of 30% of its room temperature capacity.

Further, some of the columns that were tested by Malhotra and Rogowski [64] and well as Stanke et al. [65] were kept outside the developed databases. These columns were then used to examine the prediction capability of the proposed expression to evaluate fire resistance of

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timber columns. These columns, i.e. CP16, FU1, H20A, R27C, vary in geometric features, specific gravity, compressive strength of wood, and level of applied loading. Similarly, fire resistance rating of four finger-jointed connections (no. 3, 9, 31, and 39), as well as two nailed connections (loaded with 15% and 45% of initial capacity) were also examined as these connections were not part of the training procedure. The applicability of the derived expressions in capturing fire response of these timber members, which were not part of the training-based databases, is plotted in Fig. 8.

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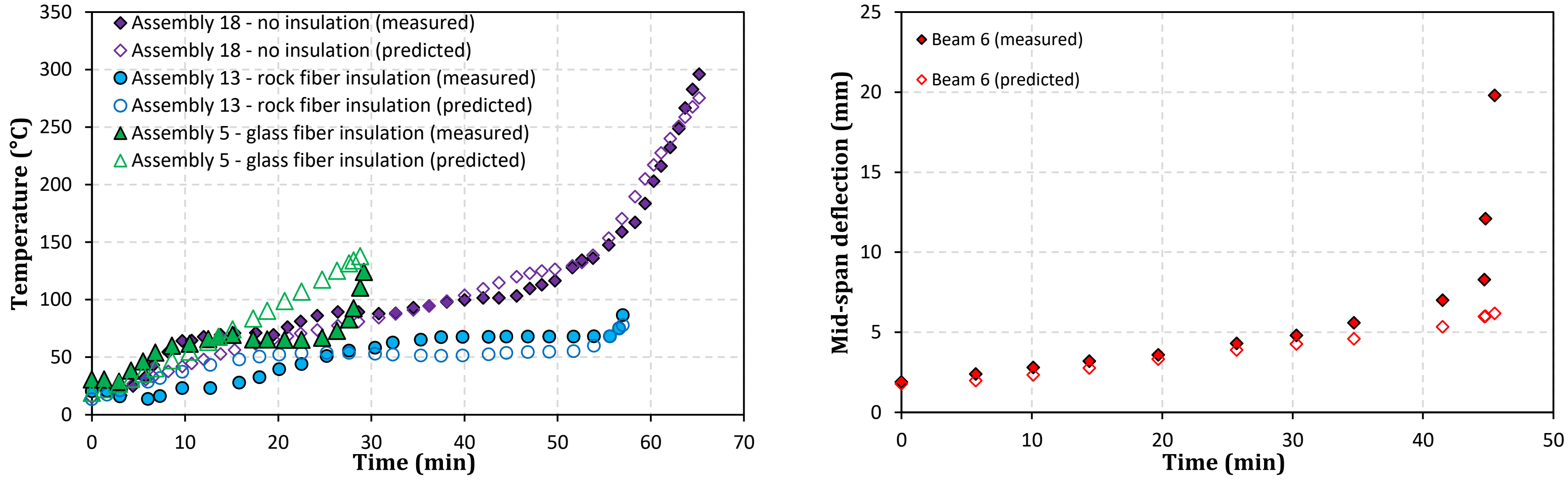

(a) Timber floors (b) Timber beams

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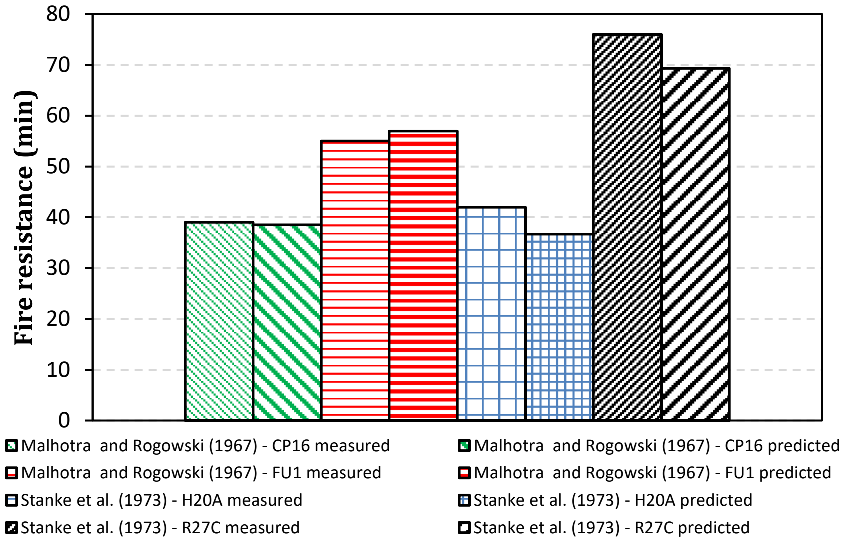
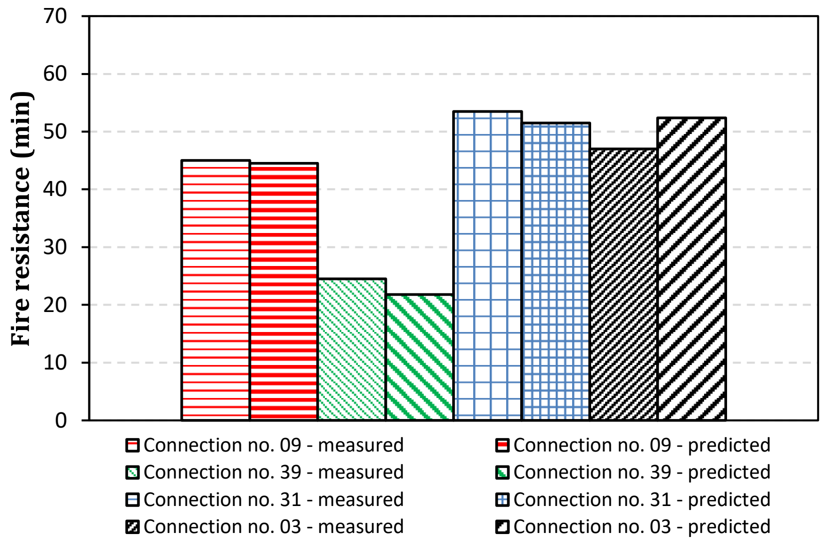


(c) Timber columns



(d) Finger-jointed connections

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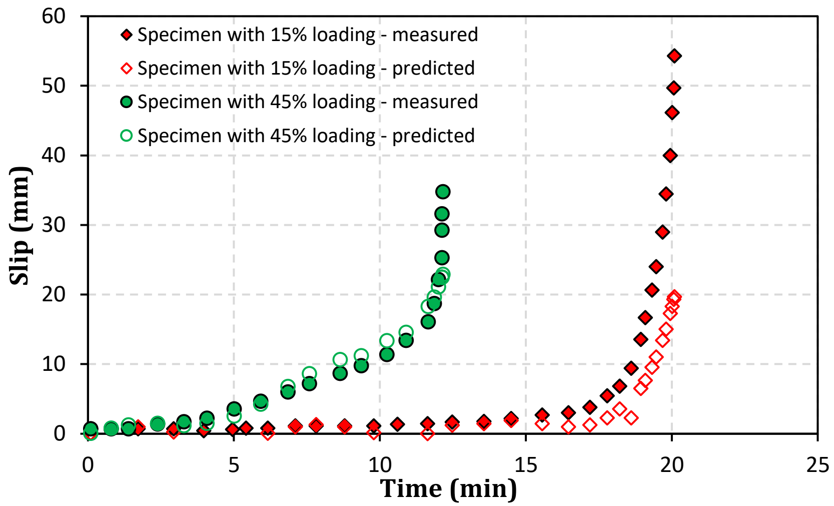

(e) Nailed connections

Fig. 8 Cross-checking to validate AI-derived expressions using structural members/components that were not part of the training procedure

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It can be seen that the derived expressions managed to successfully capture the thermal and structural response of most timber elements and components. The derived expressions appear to accurately trace the thermal response of floor assemblies without insulation and that insulated with rock fiber insulation. The expression also captures the thermal response of the third assembly (insulated with glass fiber), despite over-predicting temperature rise between 15 and 25 minutes of exposure to standard fire. The AI-expression in the case of timber beams captures the mid-span deflection of Beam 6 up to failure. The proposed expressions to evaluate fire resistance of columns and finger-jointed connections seem to have good correlation as well. In a similar manner, the slip response of nailed connections (loaded with 15% and 45%) was also accurately captured till failure (in spite of predicting lower slips towards the end of fire exposure).

Overall, and as one would expect, the level of accuracy of predictions obtained from AI-derived expressions, for thermal and structural response of timber members, is much higher in cases obtained from the developed databases and share common features and are of close proximity to the specimens used in training/developing the AI models. More advanced expressions with higher extrapolating capabilities are currently being developed and will be presented in future studies.

6.0 PRACTICAL IMPLICATIONS AND FUTURE RESEARCH NEEDS

With the rapid rise of technology, especially with regard to developing algorithms and efficient computing systems, it is a matter of time before AI is utilized to understand fire engineering phenomena. Results of this work clearly demonstrates the merit for utilizing AI/machine learning into developing contemporary design tools that could modernize the field of structural fire engineering and fire safety. One of the best qualities of AI modeling is that it can account for large number of variables at once, a feature not available in fire testing or traditional simulations [69-71]. Unlike fire testing or advanced simulations/calculation methods, AI modeling is quick, quite affordable and can be carried out with minimum supervision. For example, instead of developing a complex 3D thermo-structural FE model to predict mid-span deflection of a glulam beam (which may not fully account for specific phenomenon such as charring), all that is needed is to apply the AI-derived expression presented in Table 6 without the need to supply any temperature-dependent material properties, software licensing or development of complex models.

From the point of view of this study, the reader should realize that the simplicity of AI modeling does not come easily. For example, the accuracy and prediction capability of an AI model primarily depends on the number of observed/measured input data points. In a similar analogy, increasing the number of input data points to an optimal degree would work similarly to reducing the size of element (mesh) or size of time-step (iteration) in a finite element model. While this is often accompanied with a noticeable improvement in accuracy of predicted results, this often comes with a significant increase in computational time and resources in the case of advanced simulations (and not in AI modeling). Thus, a balance between accuracy and computational resources needs to be realized. Establishing such a balance, specifically tailored towards structural fire engineering and fire safety problems, is a key challenge that requires further investigation.

From this field’s perspective, the amount of available fire tests is limited, with even fewer tests carried out with duplicated specimens, specimens with comparable features/properties, or tested under similar conditions [72]. This appears to be another key challenge associated with AI modeling when it comes to structural fire engineering and fire safety applications. In order to overcome some of the aforementioned challenges, our community needs to work together to compile results of previous tests, to plan for new fire

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tests, as well as to generate databases similar to the ones developed here. These tests are to be designed taking into account that results of such tests would be used in AI-based modeling, training, and validation. A unique feature of AI-based models is that they are flexible enough to learn from their past mistakes and to improve overtime; once additional data points are available. As a result, the proposed tests can be undertaken in stages during which different versions of AI-based models and expressions can be developed. Another solution would be to develop validated FE models that can be used to generate raw input data points to be used in AI-models and databases. This option was not applied in this study but is hoped to be examined in a future work as well as by fellow researchers.

It is anticipated that future experimental and numerical efforts may lead to developing state-of-the-art AI-based models within the next 5-15 years. Due to the limited fire tests, the presented expressions in this preliminary study are only applicable to certain configurations and fire conditions. Future AI-models are expected to accommodate different construction materials (i.e. timber, steel, concrete etc.), more complex cross-sections, various fire conditions (i.e. travelling fire, realistic fire, design fire etc.), account for interaction of structural members (e.g. composite assemblies, system level analysis etc.), varying restraint conditions, as well as complex phenomena (viz. charring in timber, fire-induced spalling and creep in construction materials etc.). While this study promotes AI modeling as a modern technology to carry out fire resistance evaluation, this technology is best used in conjunction with traditional fire resistance evaluation methods at least for the time being.

7.0 CONCLUSIONS

This paper promotes integrating principles of artificial intelligence into structural fire engineering applications. More specifically, this study presents a view into development of AI-derived expressions capable of accurately predicting both thermal and mechanical/structural response of timber at the material and elemental level. These expressions were explicitly derived with due consideration to temperature-dependent material properties as well as associated fire phenomena; such as charring and creep, and as such do not require input of such properties nor special computing platform/software. The following conclusions could also be drawn from the results of this investigation:

- There is a need to develop simple and modern approaches in order to improve current state of fire resistance evaluation, analysis and design. These approaches can conveniently be derived through principles of AI.
- The derived AI-based expressions are able of accurately predicting thermal and structural response of timber at material and member level.
- A number of challenges continue to hinder full utilization of AI-based approaches, such as limited population of fire tests, as well as guidance on to using AI technologies etc. Some of these challenges can be overcome through collaborative work and between researchers and interdisciplinary efforts.

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8.0 NOMENCLATURE

A	Adhesive type
B	Column breadth (mm)
C	Number of layers in ceiling finish
Ch	Charring depth (mm)
C_ρ	Specific heat (kJ/kg.K)
D	Column depth (mm)
E	Young's modulus (MPa)
f_c	Compressive strength (MPa)
FR	Fire resistance (min)
f_t	Tensile strength (MPa)
f_v	Shear strength (MPa)
H	Height of beam (mm)
I	Type of insulation used in cavity
k	Thermal conductivity (W/m.K)
k_{th}	Thickness of sub-floor (mm)
P	Load level (%)
RF	Reduction factor for material property
S_G	Specific gravity of timber
t	Fire exposure duration (min)
W	Width of finger-joint connection (mm)
β	Charring rate (mm/min)
Δ	Mid-span deflection (mm)
δ	Slip in nailed connection (mm)
ρ	Density (kg/m^3)

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10.0 APPENDIX

This appendix illustrates two examples with full procedure into applying the AI-derived expressions as to evaluate thermal and structural response of timber elements subjected to standard fire conditions.

10.1 Example 1 – Temperature rise in a timber floor assembly

In order to evaluate temperature rise in a timber floor assembly, such as that tested by Sultan et al. [62] and shown in Fig. 5, the following parameters were collected from assembly no. 18 of the same study and are listed herein:

Point in time, t = 30.8 min.

Number of layers in ceiling finish, C = 2

Sub-floor thickness, k_{th} = 15.5 mm

Uninsulated assembly, I = 0

Temperature rise at a point in time (say 30.8 min) can be evaluate using the following AI-derived expression:

$$T = 11.2 + \frac{k_{th} + 0.255t^2}{CI + C} + \frac{0.047\cosh(0.133t\sin(-0.091t))}{\operatorname{asin}(\sin(17.8k_{th}))} - 27\sin(-0.091t)$$

Such that:

$$T = 11.2 + \frac{(15.5)+0.255(30.8)^2}{2(0)+2} + \frac{0.047\cosh(0.133(30.8)\sin(-0.091(30.8)))}{\operatorname{asin}(\sin(17.8(15.5)))} - 27\sin\big(-0.091(30.8)\big) = 84.5°\text{C},$$

which is within 4.1% of the measured value (88°C).

The same expression can also be used in an iterative procedure to evaluate temperature rise throughout fire exposure. A comparison between measured and predicted results is shown in Fig. 8a.

10.2 Example 2 – Fire resistance in a timber column

In order to evaluate fire resistance rating of a timber column similar to that tested by Malhotra and Rogowski [64], column CP16 is selected for analysis. This column has the following features:

Depth, D = 142 mm

Breadth, B = 381 mm

Specific gravity, S_G = 0.38

Compressive strength, f_c = 22 MPa

Level of applied loading, P = 23%

Fire resistance of this column can be evaluated using the following AI-derived expression:

$$FR = 44.18 + 19.67\ln(f_c) + 0.0073DBS_G - \sin(0.7DBS_G)\,\mathrm{asinh}(0.0073DBS_G) - 60.36 - 327.95S_G - 19.67\ln(P) - 0.0022DB - 1.1\times10^{-9}(DB)^2$$

Such that:

$FR = 44.18 + 19.67\ln(22) + 0.0073(142\times381\times0.38) - \sin(0.7\times142\times381\times 0.38)\,\mathrm{asinh}\big(0.0073(142\times381\times0.38)\big) - 60.36 - 327.95(0.38) - 19.67\ln(0.23) - 0.0022(142\times381) - 1.1\times10^{-9}(142\times381)^2 = 38.5\,min$ ≈ 39 min (measured in the fire test carried out by Malhotra and Rogowski [64]).