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Deriving Temperature-dependent Material Models for Structural Steel using Artificial Intelligence

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ABSTRACT

Structural steel undergoes significant metallurgical and physio-chemical degradation under fire conditions. This degradation is often represented by temperature-dependent material models commonly adopted in fire codes and standards. A closer look into such models reveals few surprising, and to some extent, concerning facts. For instance, presentation of temperature-induced degradation in structural steel properties substantially varies across different fire codes. This not only causes inconsistences among researchers/practitioners with regard to carrying out fire resistance analysis, but also hinders ongoing standardization efforts. Further, and despite recent advancements in material science over the past few decades, code adopted temperature-dependent material models have not been updated nor revised. In order to promote a harmonized fire assessment methodology and to ensure realistic prediction of fire performance of steel structures, this paper utilizes Artificial Intelligence (AI) and machine learning tools to derive temperature-dependent thermal and mechanical material models for structural steel. The validity of the proposed models in predicting thermal and structural response of steel structures is demonstrated through number of case studies carried out using a highly nonlinear finite element model developed in ANSYS simulation environment.

Keywords: Fire; Artificial intelligence; Structural steel; Material model; Finite element analysis.

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1.0 INTRODUCTION

Structural steel is widely used in civil construction due to its ductility and high strength properties as well as ease of erection and sustainability [1, 2]. However, the high thermal conductivity and low specific heat of steel, when combined with the lower sectional mass (slenderness) associated with steel shapes, leads to rapid temperature rise in steel members once exposed to fire conditions. As the yield strength and stiffness properties of structural steel are highly sensitive to elevated temperatures, this rapid rise in temperature induces significant metallurgical changes to steel micro-structure which causes degradation in load carrying capacity under fire conditions [3]. As a result, steel structures exhibit lower fire resistance than structures made of other construction materials such as concrete [4, 5]. Concrete has better fire resistance properties due to its inert nature and slower loss of strength under elevated temperatures [5].

The adverse effects of fire on constituent materials, such as structural steel, can be represented by temperature-dependent material models. These models often comprise of simplified relations, expressions, charts, and/or material-based reduction factors which can be compiled from results of small scale material tests in which steel coupons are tested either under thermal (temperature) conditions or under simultaneous thermal and mechanical loading [6, 7]. Hence, two sets of material models are usually developed, "thermal" and "mechanical" models. The thermal models, which trace temperature rise and distribution within a steel section, include density, thermal conductivity, and specific heat properties. On the other hand, the mechanical properties, which contains yield strength, Young's modulus, and stress-strain curves, determine structural behavior of a fire exposed steel member. It should be noted that other material properties such as creep and thermal expansion are grouped under "deformational" models [6].

Deformational models determine the extent of deformations steel structures undergo once exposed to fire conditions.

Thu number of studies have presented temperature-dependent material models for structural steel, these models seem to vary significantly [7-11]. This variation can be mainly attributed to the lack of testing standards and guidance in 1960-1990's which led discrepancies in testing methods, loading/heating regimes, use of test facilities and equipment, sensitivity of sensors, data collection and processing techniques etc. Another factor that also seems to contribute to this diversification in material models, but is often neglected, is the fact that there exists distinct differences in metallurgical composition of structural steel in different regions of the world. Such differences arise due to variations in amount/type of supplementary minerals/additives, and also due to differences in fabrication/milling process.

In lieu of above discussion, a review of recent studies indicates that bulk of the fire engineering community seems to adopt temperature-dependent material models recommended by ASCE [12] and Eurocode 3 [13]. Although these models have been extensively used in number of research studies, such models continue to have few shortcomings [7, 14]. For a start, ASCE and Eurocode material relations implies that micro-structure and behavior of steel is independent of its origin, material composition, and fabrication process which is some scenarios may not be realistic. Further, these codal-promoted material models were arrived at and collected using vintage apparatus, which unlike modern testing equipment, provided researchers with limited set-ups, and relatively inferior measurements [15, 16]. Moreover, both ASCE and Eurocode 3 models have never been revised since their establishment which dates back to a few decades ago.

Perhaps one of the major concerns that continue to arise is the fact that there exists a large discrepancy in temperature-dependent material models between ASCE and Eurocode 3. This presents a major challenge to designers wishing to carryout fire resistance analysis on steel structures and also is a key issue that hiders standardization efforts. For example, if flexural capacity, M, of a W-shape section is to be evaluated at 450˚C, this capacity can be calculated by multiplying plastic section modulus, Z, by the yield strength of steel at 450˚C, $f_{y450^\circ C}$, such that; $M_{450^\circ C} = Z \times f_{y450^\circ C}$. The plastic section modulus of a steel section is a geometric feature that is not influenced by elevated temperature. On the contrary, the yield strength of structural steel is material-sensitive property. The yield strength at 450˚C can be estimated through a temperature-dependent reduction factor, $k_{450^\circ C}$, multiplied by the yield strength of steel at ambient condition (i.e. $f_{y450^\circ C} = k_{450^\circ C} \times f_{y20^\circ C}$).

According to ASCE and EC3 material models, the value of this temperature-dependent reduction factor at 450˚C ($k_{450^\circ C}$) equals to 0.63 and 0.88, respectively. Thus, the evaluated flexural capacity of a typical W-shaped steel section can, in theory, vary by 25%. Such large variation could lead to overestimating (or underestimating) flexural capacity and subsequently fire resistance (i.e. failure) of a fire exposed steel structural member. This variation in material models could potentially complicate fire resistance analysis and design especially when an engineer is required to check for complex load effects (ex: shear, buckling, moment-shear interaction) under fire conditions, select appropriate fire insulation type/thickness/rating, or carry out consulting services [17-19].

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In order to overcome some of the above discussed concerns, and in support of current effort to promote a more standardized procedure for fire resistance analysis and design, this paper presents a novel approach to derive temperature-dependent material properties of structural steel at elevated temperature utilizing machine learning and artificial intelligence (AI) techniques. More specifically, this study presents a brief review on high temperature properties of structural steel and development of an artificial AI model that can be used to develop simplified expressions for temperature-dependent thermal and mechanical material properties of structural steel. To ensure high model predictability, the developed AI model integrates data collected from number of fire codes and standards, as well as reports collected from various elevated temperature material tests published in the open literature. In essence, this paper hypothesizes that using AI and machine learning tools could potentially lead to developing a modern and unbiased temperature-dependent material models for structural steel that could pave the way towards developing universal constituent models for other construction materials. The validity of the proposed material models in predicting thermal and structural response of steel structures is demonstrated through number of case studies carried out in ANSYS [20].

2.0 TEMPERATURE-DEPENDENT MATERIAL PROPERTIES OF STRUCTURAL STEEL

The response of steel structures exposed to fire is generally governed by thermal and mechanical properties of structural steel material[†]. While thermal properties determine temperature rise, and propagation within a steel section, the mechanical properties govern degree

[†]It should be noted that there exist a third type of material properties, referred to as deformation properties, which determine the extent of deformations under fire conditions such as thermal expansion and creep. For brevity, deformational properties will not be discussed herein but the reader is encouraged to review following studies for additional information [6].

of temperature-induced loss in strength and stiffness and eventually the degrading load carrying capacity under fire conditions. Both thermal and mechanical properties vary with temperature and are highly influenced by material phase changes associated with temperature rise. This section provides a brief review of the thermal and mechanical properties of steel, together with available high-temperature constitutive models for structural steel.

2.1 Thermal properties

Thermal material properties are those that influence temperature rise and distribution in a steel member. These properties are density, thermal conductivity, specific heat, thermal expansion, and thermal diffusivity, and their behavior depends on the composition and characteristics of the constituent materials. From structural fire analysis point of view, density, thermal conductivity, and specific heat are of utmost importance [6, 7]. The density of structural steel, ρ (kg/m^3), is defined as the mass of a unit volume and often equals to 7850 kg/m^3. The thermal conductivity, K, determines temperature rise, as a result of heat flow, in a steel member. Carbon steels usually have thermal conductivity between 46–65 W/m.K [6]. On the other hand, the specific heat, C_ρ, is the characteristic that describes the amount of heat required to raise a unit mass of steel a unit temperature. The specific heat of structural steel may vary in the range of 420-435 J/kg.K at ambient conditions [6].

Since density of steel is assumed to be constant under fire conditions, then the two main thermal properties that influence temperature rise in structural steel are those referred to as thermal conductivity and specific heat [6]. Thu, there is limited test data on these properties, specifically under fire conditions, ASCE and Eurocode 3 recommend few relations to evaluate thermal properties of structural steel. These relations are presented in Eqs. 1-4.

Thermal conductivity (W/m.K.)

ASCE:

$$K = \begin{cases} -0.022T + 48 & \text{for } 20 \leq T \leq 900°\text{C} \\ 28.2 & \text{for } T > 900°\text{C} \end{cases} \quad (1)$$

Eurocode 3:

$$K = \begin{cases} 54 - 3.33 \times 10^{-2}T & \text{for } 20 \leq T \leq 800°\text{C} \\ 27.3 & \text{for } 800 < T \leq 1200°\text{C} \end{cases} \quad (2)$$

Specific heat (J/kg.K)

ASCE:

$$C = \begin{cases} (0.004T + 3.3) \times \frac{10^6}{\rho} & \text{for } T \leq 650°\text{C} \\ (0.068T + 38.3) \times \frac{10^6}{\rho} & \text{for } 650 < T \leq 725°\text{C} \\ (-0.086T + 73.35) \times \frac{10^6}{\rho} & \text{for } 725 < T \leq 800°\text{C} \\ 4.55 \times \frac{10^6}{\rho} & \text{for } T > 800°\text{C} \end{cases} \quad (3)$$

Eurocode 3:

$$C = \begin{cases} 425 + 7.73 \times 10^{-1}T - 1.69 \times 10^{-3}T^2 + 2.22 \times 10^{-6}T^3 & \text{for } 20 \leq T \leq 600°\text{C} \\ 666 + \frac{13002}{738-T} & \text{for } 600 < T \leq 735°\text{C} \\ 545 + \frac{17820}{T-731} & \text{for } 735 < T \leq 900°\text{C} \\ 650 & \text{for } 900 < T \leq 1200°\text{C} \end{cases} \quad (4)$$

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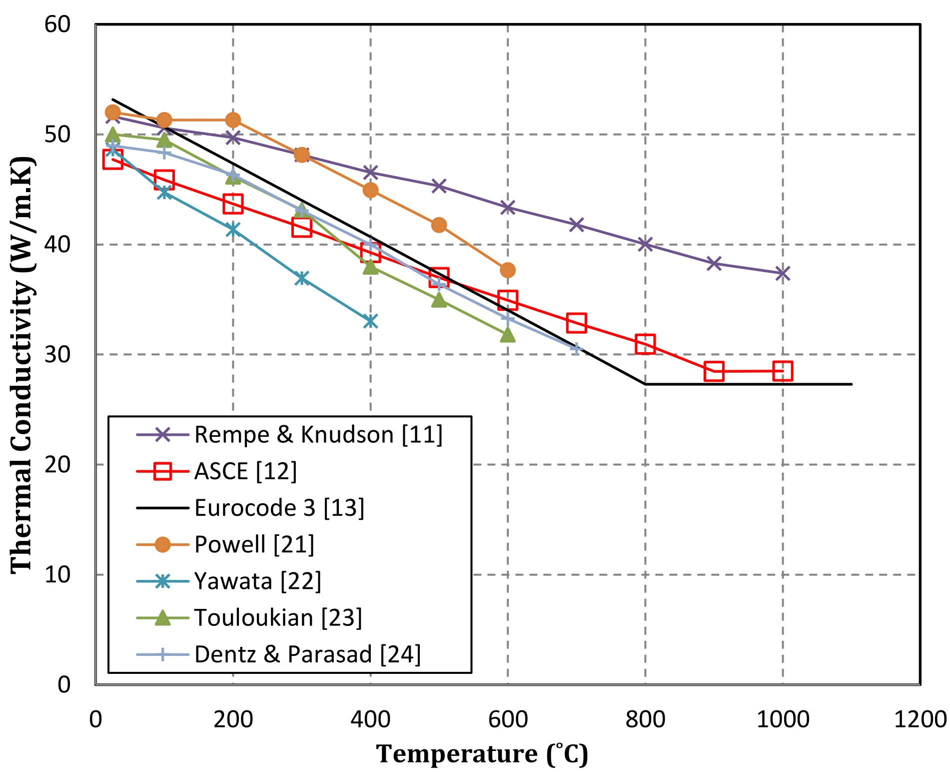
where,

ρ is the density of steel (kg/m^3)

T is the temperature in (°C)

Figures 1a and 1b present compiled plots of thermal conductivity and specific heat of structural steel as a function of temperature from various references. It can be seen from Fig. 1 that while the thermal conductivity of steel generally decreases with rise in temperature, the specific heat slightly increases with temperature rise until reaching a temperature of 700°C. After that, both ASCE and Eurocode 3 models show a large spike in specific heat at around 750°C due to absorption of considerable energy needed to enable transformation of steel from a face centered cubic to a body centered cubic structure. This transformation is needed to achieve a higher energy state at elevated temperature and stabilize steel micro-structure [7].



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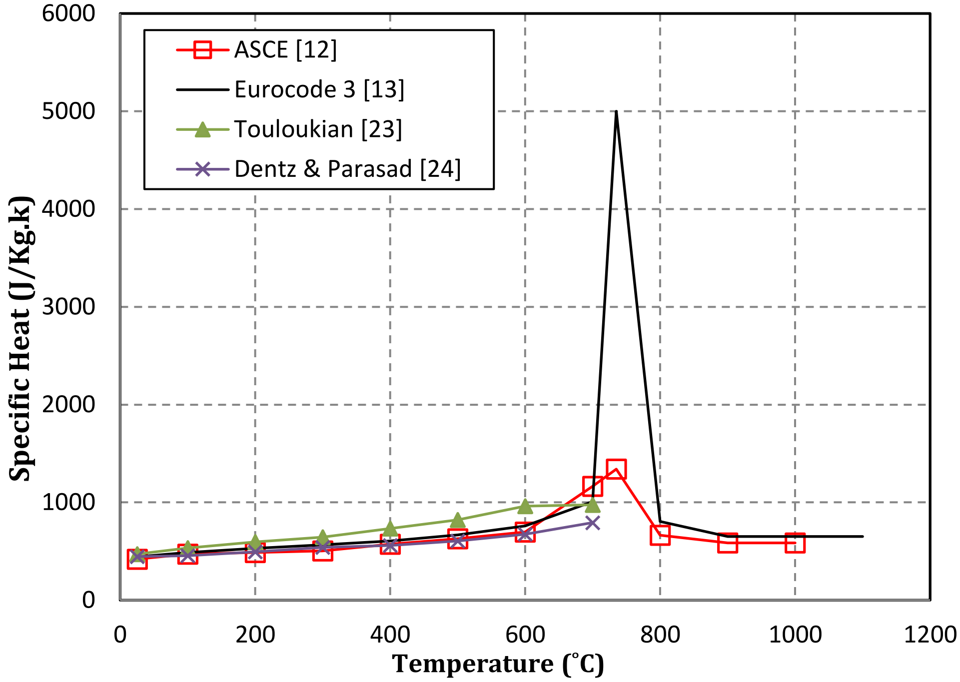
(a) Thermal conductivity



(b) Specific heat

Fig. 1 Thermal properties of structural steel as prescribed by fire codes and reported in different tests

Figure 1 also shows that there is a distinct variation in describing thermal properties (especially specific heat) between test data and codal models. This is attributed to the fact that most of compiled data points on specific heat originates from studies carried out on iron and non-structural steel alloys [7]. Further, data plotted in Fig. 1 shows that the maximum temperature reached in tests carried out by Powell [21], Yawata [22], Touloukain [23], as well as Dentz and Parasad [24] was below 750°C and does not capture full range of temperatures observed in actual fire conditions. In fact, a recent study has pointed out that more studies evaluated temperature-dependent mechanical properties of structural steel as oppose to temperature-dependent thermal properties [7].

2.2 Mechanical properties

The mechanical properties of structural steel comprise of yield strength, f_y (MPa), and modulus of elasticity (stiffness), E (GPa). These properties are often measured through tensile tests carried out on steel specimens (coupons). The high temperature tensile tests can be conducted in two[‡] different tests set-ups: steady-state and transient. In steady-state tests, a test coupon is heated to a specific temperature, while being allowed to expand freely. Once the target temperature is reached, the steel coupon is then subjected to linearly increasing tensile forces to measure its stress and strain response. Some of the factors that influence such test set-up are strain loading and heating rates. Due to the lack of a standard testing procedure, a large amount of test data was published without reporting information on strain rates [7, 14, 25]. Heating rate of steel also affects outcome of material tests depending on fire intensity and on presence of fre proofing materials. Generally, the heating rate of steel can vary between 3 and 7°C/min as well as 25 and 40°C/min, for protected and unprotected steel, respectively [7].

In transient-based material tests, a test specimen (i.e. steel coupon) is first subjected to a constant load and is then exposed to uniformly increasing temperatures. In this test procedure, temperature rise and strain development are recorded continuously under constant stress. Due to the fundamental differences in aforementioned test methods, there are large discrepancies in reported data and this resulted in variations of developed material constitutive models. Both ASCE and Eurocode 3 provide simplified relations for high-temperature reduction factors for mechanical properties of structural steel and these relations are shown in Eqs. 5-8.

[‡]A third test set-up can also be conducted in which properties are measured after exposing a steel coupon elevated temperature and cooling down to ambient conditions (i.e. through air or water cooling). A detailed discussion on this test procedure can be found elsewhere [6].

Yield strength

ASCE:

$$\frac{f_{y,T}}{f_y} = \begin{cases} 1.0 + \dfrac{T}{900\ln(\frac{T}{1750})} & \text{for } T \leq 600℃ \\ \dfrac{340-0.34T}{T-240} & \text{for } T > 600℃ \end{cases} \tag{5}$$

Eurocode 3:

$$\frac{f_{y,T}}{f_y} = \begin{Bmatrix} 1.0 & T < 100℃ \\ -1.933\times10^{-3}T + 1.193 & \text{for } 100 \leq T < 400℃ \\ -0.6\times10^{-3}T + 0.66 & \text{for } 400 \leq T < 500℃ \\ -1.8\times10^{-3}T + 1.26 & \text{for } 500 \leq T < 600℃ \\ -1.05\times10^{-3}T + 0.81 & \text{for } 600 \leq T < 700℃ \\ -2.5\times10^{-3}T + 0.25 & \text{for } 700 \leq T < 800℃ \\ -1.25\times10^{-3}T + 0.15 & \text{for } 800 \leq T < 1200℃ \end{Bmatrix} \tag{6}$$

Modulus of elasticity

ASCE:

$$\frac{E_{y,T}}{E_y} = \begin{cases} 1.0 + \dfrac{T}{2000\ln(\frac{T}{1100})} & \text{for } T \leq 600℃ \\ \dfrac{690-0.69T}{T-53.5} & \text{for } T > 600℃ \end{cases} \tag{7}$$

Eurocode 3:

$$\frac{E_{y,T}}{E_y} = \begin{Bmatrix} 1.0 & T < 100℃ \\ -1.0\times10^{-3}T + 1.1 & \text{for } 100 \leq T < 500℃ \\ -2.9\times10^{-3}T + 2.05 & \text{for } 500 \leq T < 600℃ \\ -1.8\times10^{-3}T + 1.39 & \text{for } 600 \leq T < 700℃ \\ -4.0\times10^{-3}T + 0.41 & \text{for } 700 \leq T < 800℃ \\ -2.25\times10^{-3}T + 0.27 & \text{for } 800 \leq T < 1200℃ \end{Bmatrix} \tag{8}$$

A comparison between ASCE and Eurocode 3 relations, together with others collected from open literature [26-33], is plotted in Figs. 2a and 2b, respectively, to represent temperature-dependent degradation in yield strength and modulus of elasticity. Similar to thermal properties, it can be seen from plotted data that there is large discrepancies in reported results on mechanical properties of structural steel. This variation can be primarily attributed to variations in applied heating rate and loading level. A review of these models shows that the rate of degradation and temperature at which mechanical properties start to degrade significantly vary. In general, the Eurocode model assumes slightly lower reduction in yield strength of steel as compared to the ASCE model. While the Eurocode assumes that yield strength of steel remains intact up to 400°C, the ASCE model estimates 30% loss in strength of at the same temperature. Overall, the degradation in yield strength of structural steel can be attributed to the increased probability of activating grain slip planes triggered by rise in temperature. On the other hand, Fig. 2b shows that both ASCE and Eurocode model presumes degradation in modulus of elasticity of steel to occur at relatively low temperature (i.e. 150°C). This is due to the fact that only a slight increase in temperature is needed to weaken interatomic bonds in the crystalline lattice and initiates dislocations.

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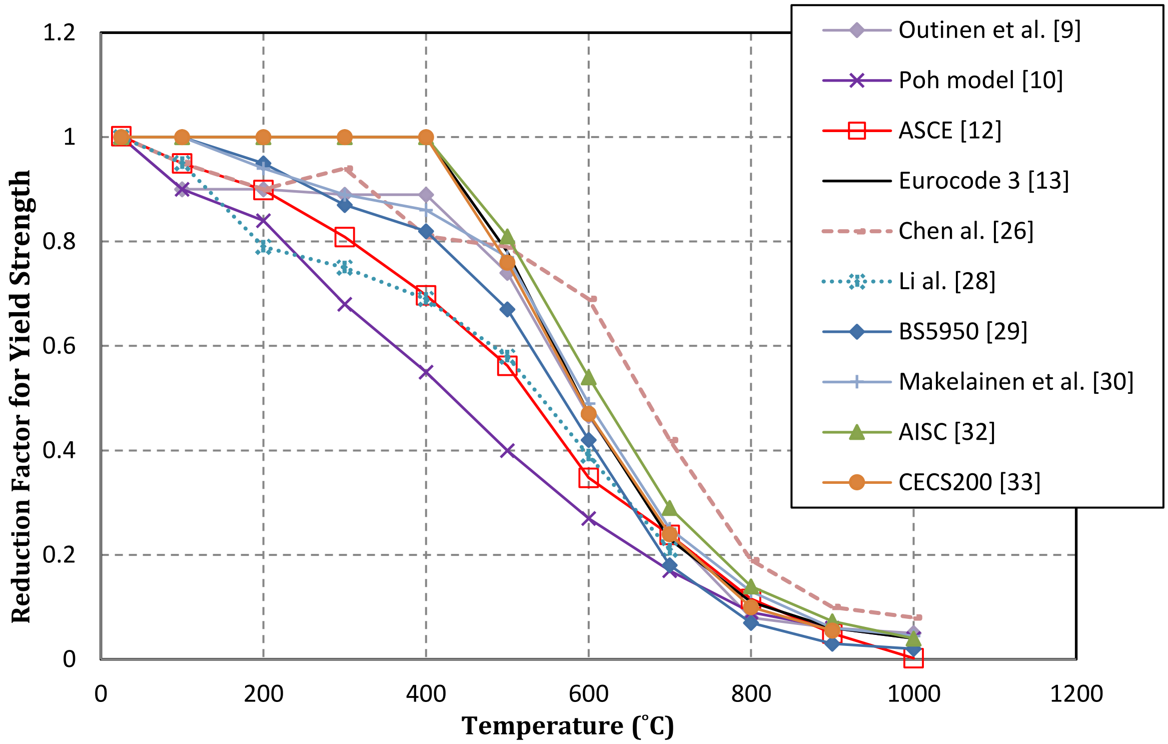
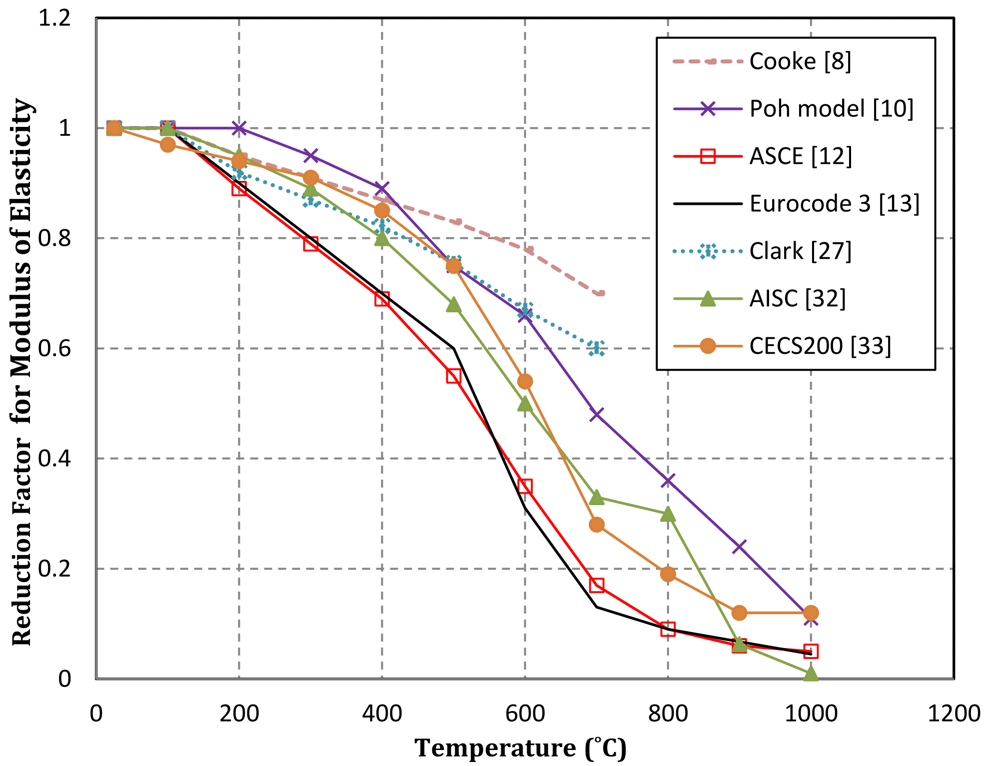


(a) Yield strength



(b) Modulus of elasticity

Fig. 2 Mechanical properties of structural steel as prescribed by fire codes and reported in different tests

3.0 BACKGROUND TO ARTIFICAL INTELLIGENCE

Unlike deterministic or statistical approaches, artificial intelligence (AI) does not rely on mathematical models nor require a certain set of assumptions to start an analysis. But rather, AI tires to mimic the cognition process of a human brain through what is commonly referred to as Artificial Neural Networks (ANNs). ANNs are computing techniques useful in scenarios where there are large amount of inputs (random variables), especially when the relationship between input data points and expected results (output(s)) is not well established. ANNs, a component of AI, are relatively crude systems that learn patterns hidden in random variables through systematic and repeated analysis of data. In order for an ANN to be successful, it needs to be able to comprehend the logic behind the associated random variables (i.e. material models) used in a given phenomenon (i.e. fire exposure).

In general, ANNs are built of multiple layers and neurons. These neurons, which represent the main processing units, are often arranged in number of hidden layers to form a network in which the connectivity and functioning of these layers (and neurons) are similar to that of the brain. The selected number of neurons (within each layer) largely depends on the complexity of describing a relationship between inputs and output(s) (results). In this study, a multilayer perception model, inspired by the structure of the human brain, with "feed-forward back-propagation and supervised learning" is used to develop an ANN. This model is best described by three layers as shown in Fig. 3. In this ANN, the input layer contains the independent variables (or predictors) and is connected to number of hidden layers with the ability to establish linear and/or non-linear models [34]. The hidden layers are also connected to the output layer comprising of target variable(s).

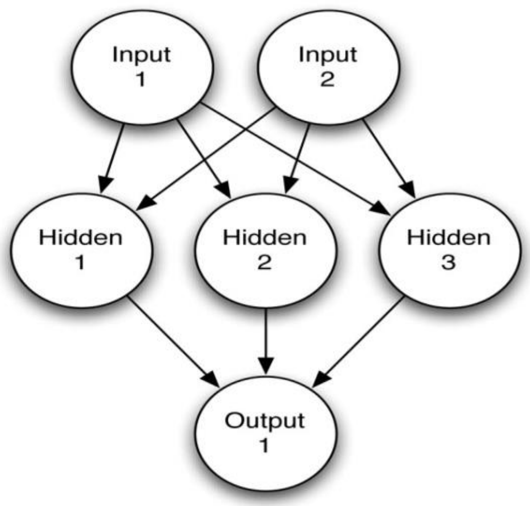


Fig. 3. Typical structure of an artificial neural network [34]

Once an ANN is developed, training of such ANN begins to solve a given phenomenon/problem. The ANN training starts by applying random values to weightage factors connecting input, hidden, and output layers. Then, input data points (i.e. temperature-dependent thermal and mechanical material models) are fed into the first input layer's nodes and are multiplied by the weightage factors. The result of this multiplication is used to activate a transfer function (such as logistic type etc.). Transformed output(s) from connected nodes are summed to yield predictions (i.e. AI-derived material properties). These predicted values are then compared to known values (i.e. code-adopted values or experimentally measured material properties). Upon comparison, the magnitude of error between predicted and measured values is calculated and, through a backward pass, is fed back into the network. Both forward and backward passes are repeated, while weightage factors are adjusted iteratively, until the predicted output(s) match those from experiments within an allowable level of confidence.

AI and ANNs have proven to be useful techniques in different domains including structural fire engineering [35-42]. In an earlier study, the author was able to successfully predict fire resistance of insulated reinforced concrete (RC) T-beams strengthened with Carbon Fiber Reinforced Polymers (CFRPs) laminates using an ANN [35]. The developed ANN was also predominantly used to study effect of various fire scenarios (intensity), as well as insulation materials and thicknesses on the response of CFRP-strengthened RC beams. The outcome of this study was used to develop number of charts and design aids for selecting required insulation material and thickness to arrive at appropriate rating for fire-insulated CFRP-strengthened RC beams subjected to standard and/or design fire scenarios.

Similarly, Xu et al. [36] also developed an ANN that can accurately predict temperature rise of tubular steel trusses exposed to fire. In their study, these researchers used a three-layer back-propagation ANN architecture to account for several input parameters such as steel tube diameter, wall thickness, diameter–thickness and the level of applied loading. Xu et al. reported a good correlation between temperature predictions obtained through ANN and that carried out by finite element analysis using ABAQUS. In a separate study, Hozjan et al. [37] specifically developed an ANN to study the structural behavior of steel frames under fire conditions. This ANN was used to help in formulating stress-strain curves of steel coupons at elevated temperatures.

Zhao [38] presented degradation in flexural capacity for steel beams at fire conditions using a hybrid ANN that also uses genetic algorithms to search for optimum number of hidden neurons. The developed ANN utilizes sigmoid and radial basis function neurons in hidden layers and was found to effectively capture the relationship between the input data points. In a related study, Erdem [39] used ANNs to predict degrading moment capacity of RC slabs exposed to fire. The developed ANN accounted for number of parameters such as strength of the concrete, effective depth, area of tension reinforcement, and fire exposure time. Erdem concluded that the developed ANN can predict fire resistance of RC slab with high accuracy. Lazarevska et al. [40] used results of numerical analysis as input to a newly developed ANN capable of predicting fire resistance of fire-exposed RC columns. These researchers applied a forward propagation model consisting of one input layer, one hidden layer (with different number of neurons varying between 2 to 10 neurons), and one output layer.

Al-Jabri and Al-Alawi [41] also developed an ANN model that can predict the behaviour of semi-rigid flexible end-plates and flush end-plate joints under fire conditions. This ANN took into account seventeen parameters representing degree of applied loading, geometrical and mechanical properties of the joints as well as temperature rise in the joints. In total, these researchers evaluated more than 250 experimental cases with high accuracy (R^2 = 97%). In order to predict fire-induced spalling of high strength concrete columns under fire conditions, McKinney and Ali [42] developed two supervised ANNs. The inputs for these ANNs were spalling degree, load level, furnace temperature, restraint (boundary) conditions, and failure time. The ANN were trained using the resilient propagation algorithm and showed close comparison to actual observations (collected from fire tests). It can be seen from the above review that AI and ANN tools can be a useful tool in carrying out fire analysis and design for complex problems.

4.0 ARTIFICAL INTELLIGENCE MODEL DEVELOPMENT, VALIDATION, AND DERIVED EXPRESSIONS

In this study, collected data points in terms of different values for material properties of structural steel were used as input into the developed ANN. These data points were obtained from codal-adopted models (ASCE, Eurocode 3, BS5950 etc.), as well as those reported by experimental studies [12, 13, 21-24, 26-33]. For example, the input data points for reduction factors of yield strength as a function of elevated temperatures were complied, for each corresponding temperature i.e. 25, 100, .., 1000°C, from material model recommended by ASCE, Eurocode 3, as well as other models shown in Fig. 2a. Out of all complied data points, 70% of the collected data is used to train the ANN and the remaining 30% were used to validate and test the performance of the developed ANN as recommended in NeuroShell software [43]. As the collected data used in developing the ANN was gathered from several resources; no specific source was used as a reference (or benchmark) such that it does not influence ANN unbiasedness. It should be noted that the thermal material properties investigated herein are thermal conductivity and specific heat[§]. On the other hand, mechanical properties of interest are yield strength and stiffness properties of structural steel.

The successfully trained ANN was used to predict unbiased and improved thermal and mechanical temperature-dependent material expressions. Figure 4 shows that predictions from ANN lie within the range of the collected data. The developed ANN also managed to achieve a close match with the data selected for "testing and validation" as can be seen in Table 1. The

[§] The thermal expansion of steel linearly increases with rise in temperature. Both ASCE and Eurocode 3, together with other studies [7, 14], provide similar material models to represent behavior of expansion of steel at elevated temperature. Due to the high similarity between these models, the thermal expansion of structural steel was not examined.

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coefficient of determination (R^2) for this ANN is 99.8, 90.1, 99.5, 98.3% for thermal conductivity, specific heat, yield strength, and stiffness properties, respectively.

Table 1 Coefficient of determination (R^2) for different material properties obtained from developed ANN

Material property	**Coefficient of determination (R^2)**	**Ave. error**
Thermal conductivity	0.998	0.296
Specific heat	0.901	0.510
Yield strength	0.983	0.031
Modulus of elasticity	0.995	0.014

In addition to the value of coefficient of determination (R^2), the performance (accuracy) of the ANN was also determined based on and how well the predicted data lies on the 45-degree line (within a ±10% bound). While Table 1 lists coefficient of determination (R^2) for the different material properties/reduction factors, Figs. 4a-d further illustrates the accuracy of the developed ANN. It can be seen that the data points in Fig. 4 lie within a ±10% bound. It is safe to conclude that the developed ANN can be used, with confidence, to develop temperature dependent material models and associated expressions. Thus, the validated ANN was used to arrive at expressions for thermal and mechanical material models for structural steel.

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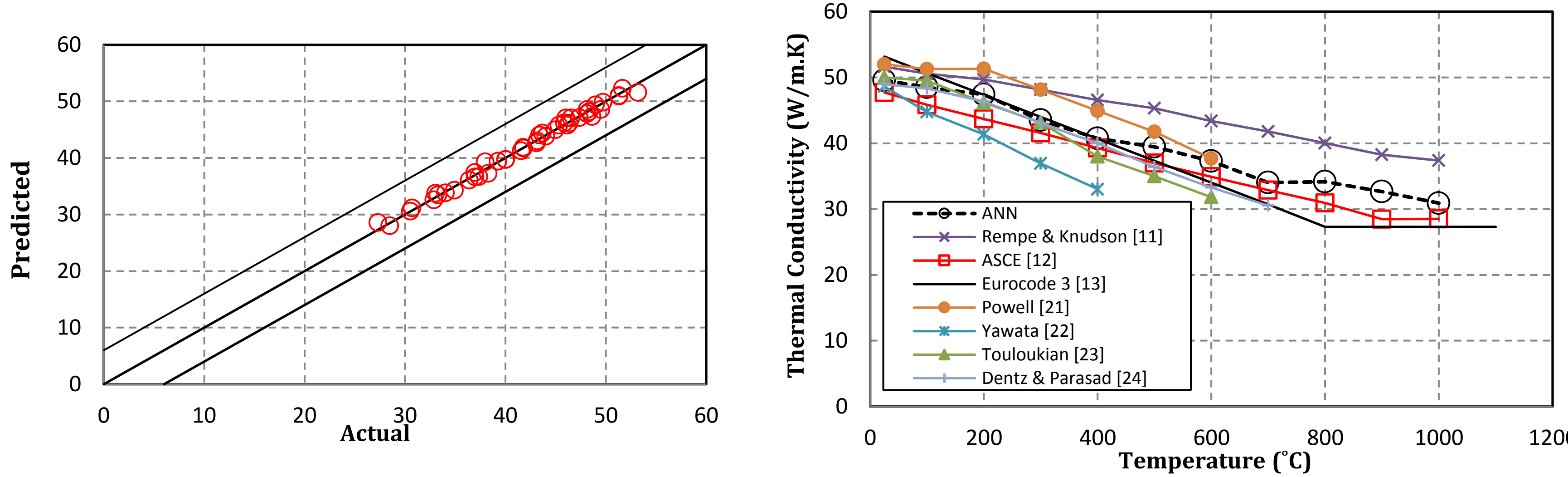
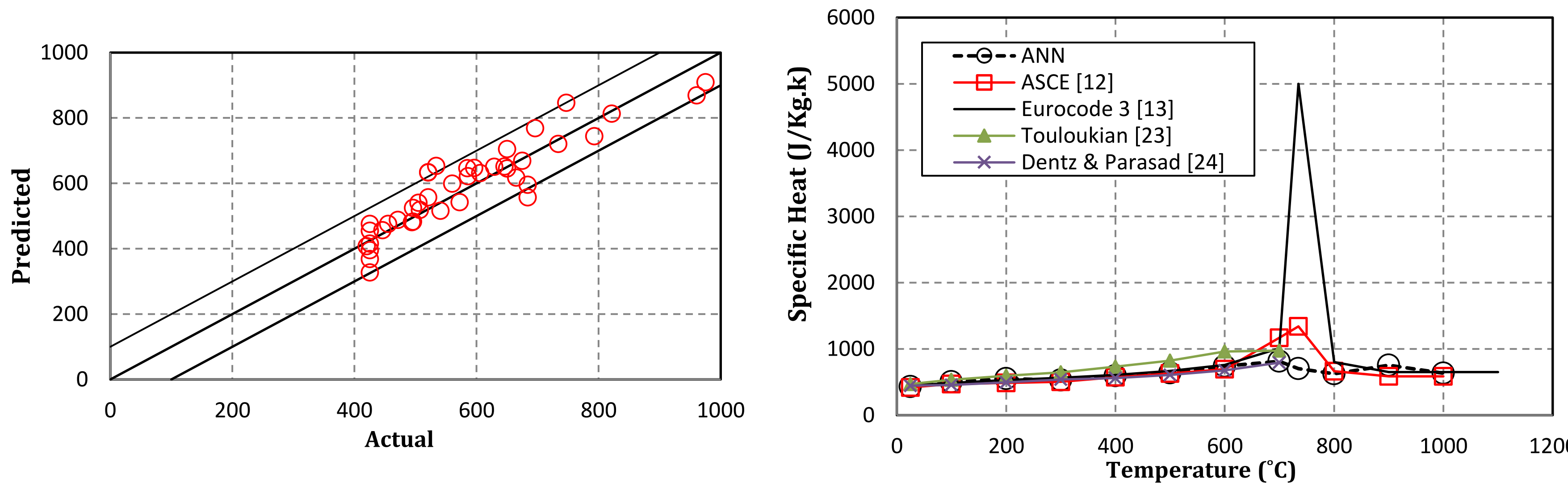


(a) Thermal conductivity



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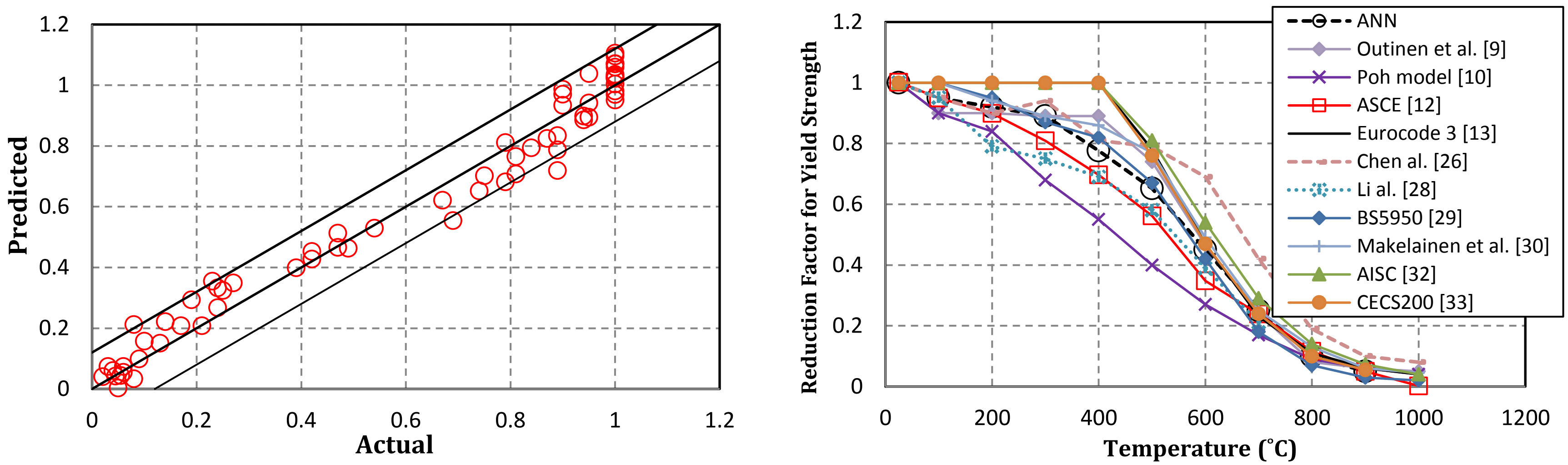
(b) Specific heat



(c) Yield strength

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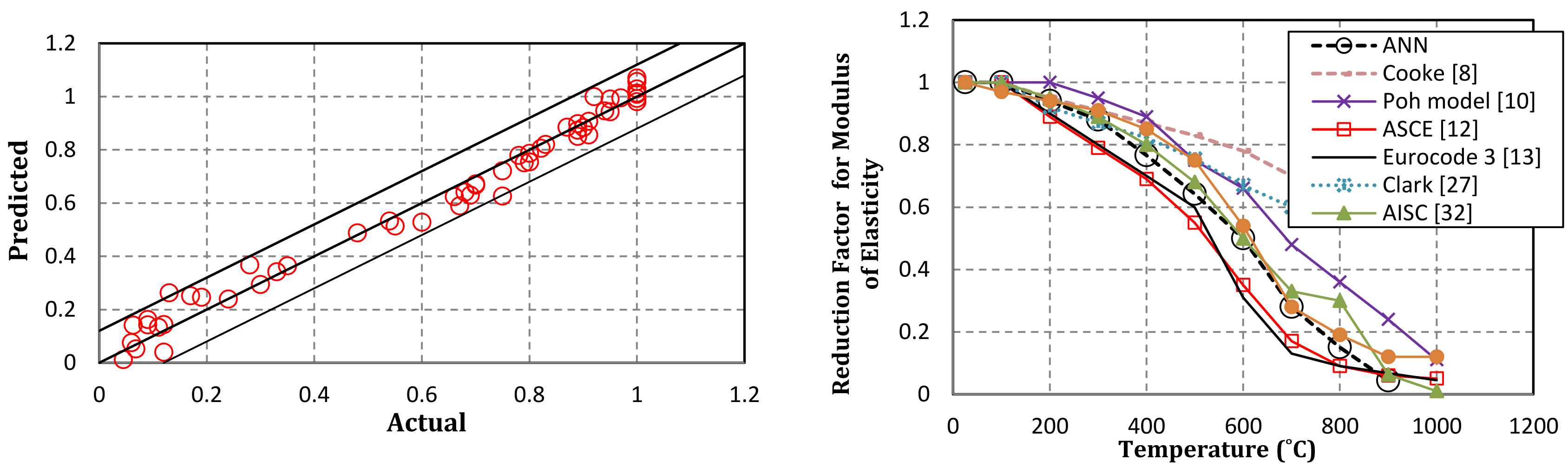


(d) Modulus of elasticity

Fig. 4 Accuracy of the developed ANN accuracy for material properties and reduction factors of steel material

ANN predictions are used to derive nonlinear symbolic expressions, and this was carried out using a genetic algorithm software known as Eureqa Formulize [44]. In Eureqa, candidate solutions are encoded with terminal nodes corresponding to constants and variables that best describe the phenomenon on hand. These candidate solutions can be joined through encoded mathematical functions (i.e. building blocks) such as addition (+), multiplication (×), trigonometric functions (sin, cos..) etc. the best solution is then obtained once a fitness function is optimized. The fitness function is usually governed by the difference (absolute or squared) between values predicted by a candidate solution and those measured through experiments, with parsimony corrections to favor compact expressions. In this study two expressions are derived for each property; a simple and more a complex expression. These expressions, together with their coefficient of determination (R^2) as obtained from Eureqa software, are listed in Table 2.

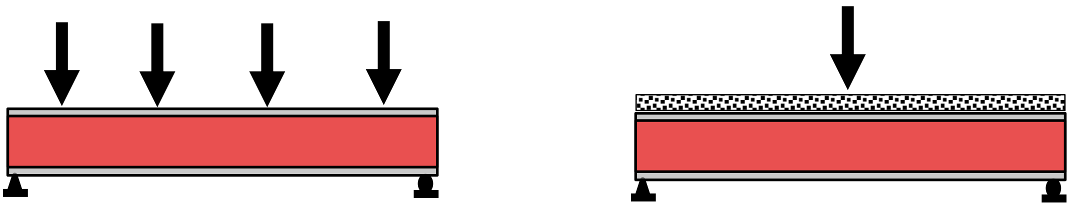
Table 2 Derived equation for temperature-dependent material properties

Material property	**Derived expression**	**R^2**
Thermal conductivity (W/m.K)	$50.04 + 0.019T$	97.6
	$49.62 + 1.55e^{-7}T^3 - 7.09e^{-11}T^4 - 0.000103T^2$	99.2
Specific heat (J/Kg.K)	$379.6 + 0.64T + 52.17\cos(0.0012TT^2) - 3.69e^{-10} - 10T^4$	93.5
	$266.81 + T + 215.72cos(0.0012T^2) + 0.00076T^2cos(0.0012T^2) - 6.61e^{-7}T^3 - 0.72Tcos(0.0012T^2)$	98.6
Reduction factor for yield strength	$1.00 - 1.4e^{-6}T^2$	96.4
	$0.99 - 4.11e^{-12}T^4 - 4.99e^{-9}T^3$	99.6
Reduction factor for modulus of elasticity	$1.19 - 0.0013T$	95.4
	$1.06 - 0.000434T - 8.51e^{-7}T^2$	99.5

5.0 DEVELOPMENT OF FINITE ELEMENT MODEL

In order to further validate the proposed the AI-derived material models and examine their ability to predict thermal and structural response of steel structures, these models were input into a newly developed three-dimensional finite element (FE) model capable to conducting transient thermal-stress analysis. This developed FE model, developed in ANSYS, takes into account geometric and material nonlinearities, and temperature-dependent material properties. This model is specifically designed to have the same geometric and material features of the three fire-tested beams (two steel beams and one composite beam) [45, 46].

The steel beams 1 and 2 were tested by Wainman and Kirby [45] and these beams were made of Grade 400 MPa steel. Beams 1 and 2 were of UB305×165, and UB406×178 shapes, respectively. On the other hand, the third beam comprised of a composite steel beam made of W24×62 standard hot-rolled section, fabricated from Grade 345 MPa steel, and was tested by Aziz et al. [46]. The concrete slab, cast along the full length of the steel beam, was made of normal strength concrete of compressive strength of 45 MPa and had a depth and width of 140 and 815 mm, respectively. Figure 5 shows boundary conditions and loading set-up in these beams.



(a) Steel beams (tested by Wainman and Kirby [45])

(b) Composite beam (tested by Aziz et al. [46])

Fig. 5 Boundary conditions and loading set-up used in selected beams for analysis

Each beam is first discretized with thermal elements readily available in ANSYS to investigate its thermal response. These elements are SHELL131, SOLID70, LINK33, and SURF152. SHELL131 is a layered shell element used to simulate steel beam and has in-plane (and through thickness) conduction capability. SOLID70 is a cubic element used to discretize the concrete slab in the composite beam. LINK33 is a uniaxial element that can conduct heat between its nodes and is used to simulate steel reinforcement. SURF152 is overlaid on top of SHELL131 and SOLID70 elements to simulate transfer of heat from fire (flames) to the beams in order to obtain nodal temperature. Once the thermal analysis is completed and nodal temperatures are generated, these temperatures are used as input into the structural model.

To carry out the structural analysis, steel and composite beams are re-discretized with suitable structural elements, namely SHELL181, SOLID65, LINK8, and BEAM188. SHELL181 is a shell element specifically formulated to discretize thin plates (flanges and web) as those present in steel beams. SOLID65 is used to discretize concrete slab since it is capable of accounting cracking and crushing of concrete. LINK8 is used to simulate steel reinforcement embedded in concrete slab while BEAM188 is used to simulate shear studs at the interface between steel beam top flange and concrete slab.

In order to account for composite action developed between concrete slab and steel girder, nonlinear surface-to-surface CONTA174 and TARGE170 elements are used. This contact pair can be adjusted to simulate fully and partially bonded (i.e. slip-enabled) composite action between the concrete slab and steel beam. It should be noted that default settings with regard to numerical convergence, thermal and structural loading etc. were selected to minimize any numerical biasness. Further details on discretization and simulation techniques can be found elsewhere [17-19, 47, 48].

In order to effectively trace the fire response of beams 1-3, high-temperature material properties were input into the developed FE model. The selected material models for structural steel comprise of those recommended by ASCE [12], Eurocode 3 [13], Poh [10] (for structural analysis only), and proposed models derived in Sec. 4. In order to maintain subjectivity, the material properties of concrete, reinforcing steel, and shear studs were assumed to remain similar to that at ambient conditions and recommended by Eurocode 2

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[49] as temperature rise in concrete slab in beam 3 was much below 150°C [46]. The validity of this assumption is examined in Sec. 6.1.

Both structural and reinforcing steel were simulated using multilinear stress-strain relationships that incorporate Von-Mises plasticity and hardening criterion. On the other hand, Williams and Warnke [50] constitutive material model, which takes into account spread of plasticity in both compression and tension regimes, was used to simulate concrete material. Furthermore, crack development of concrete is assumed to follow a trilinear model in which the tensile strength of concrete is taken as $0.62\sqrt{(f'_c)}$; where f'_c is the compressive strength of concrete. In this model, once concrete reaches its tensile strength, cracking occurs via introducing a tensile stiffness multiplier of 0.6 to simulate a sudden drop in concrete stiffness of about 60% of the initial tensile strength [50].

The failure in the selected three can occur due to exceeding flexural, shear, thermal (limiting temperature), and/or deflection limit states. Hence, at each time step, flexural and shear capacity are evaluated though integrating internal bending and shear stresses across critical section (i.e. mid-span of beams). Once these stresses are summed (integrated), generated stresses are used to calculate associated moment and shear capacity of beam and are compared against bending and shear effects arising from applied loading level. Once the moment and/or shear capacity falls below level of applied loading, the beams are said to fail.

In order to account for deflection limit state, once mid-span deflection of beams exceeds a deflection of $L^2/400d$ or rate of deflection reaches $L^2/9000d$, where L and d are the span and depth of the structural member, respectively, the structural member is also said to attain failure [51].

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6.0 CASE STUDIES

The main aim of this paper is to derive a uniform and up-to-date presentation of temperature-dependent material models for structural steel at elevated temperatures. Such models were presented in Sec. 4 and their applicability is examined herein through three numerical case studies carried out to investigate temperature evolution, mid-span deflection, and temperature-induced flexural capacity degradation response in beams 1-3 described above. The objective of these case studies is not to examine failure of analyzed beams but rather to examine the accuracy of the proposed thermal and structural material models (i.e. in terms of closeness to measured thermal and structural data points) against models adopted by common fire codes and standards (i.e. ASCE and Eurocode 3) as well as other researchers (eg. Poh [10]). In each case study, selected beams were analyzed using material models from ASCE, Eurocode, and AI-derived models and thus these beams are referred to as ASCE, Eurocode, and AI, respectively.

6.1 Thermal effects

Results from finite element simulations, plotted in Fig. 6, show that temperatures in steel beams 1 and 2 rise rapidly due to relatively low specific heat and high conductivity of structural steel. In the case of the composite beam, temperature in steel section also rises at a much rapid pace than that in concrete due to the heat-sink effect of concrete slab; facilitated by higher heat capacity and lower thermal conductivity of concrete. Towards the end of fire exposure, average temperature in web and lower (bottom) flange was in the range of 700-850°C, however temperature in shear studs and mid-depth of concrete slab remained well below 150°C which concur with the decision to use ambient temperature material properties for concrete, shear studs, and steel reinforcement.

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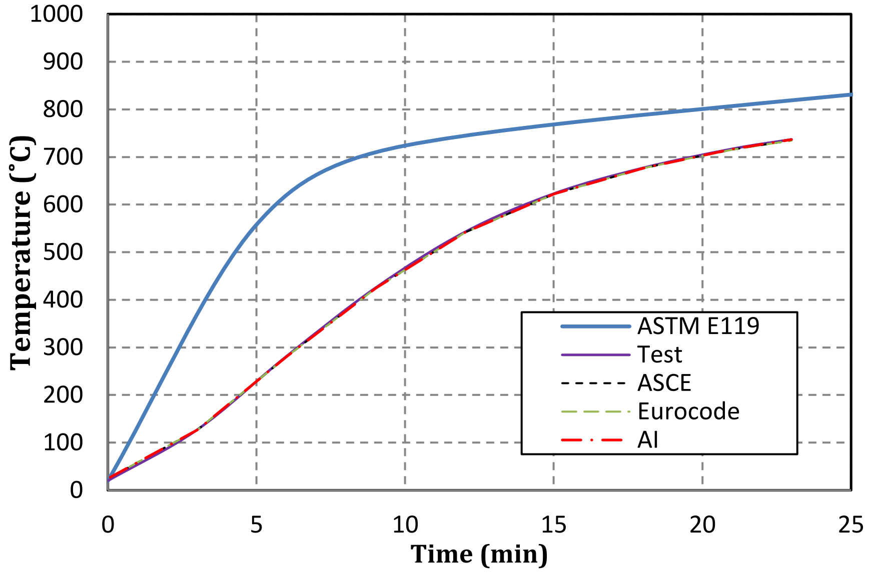
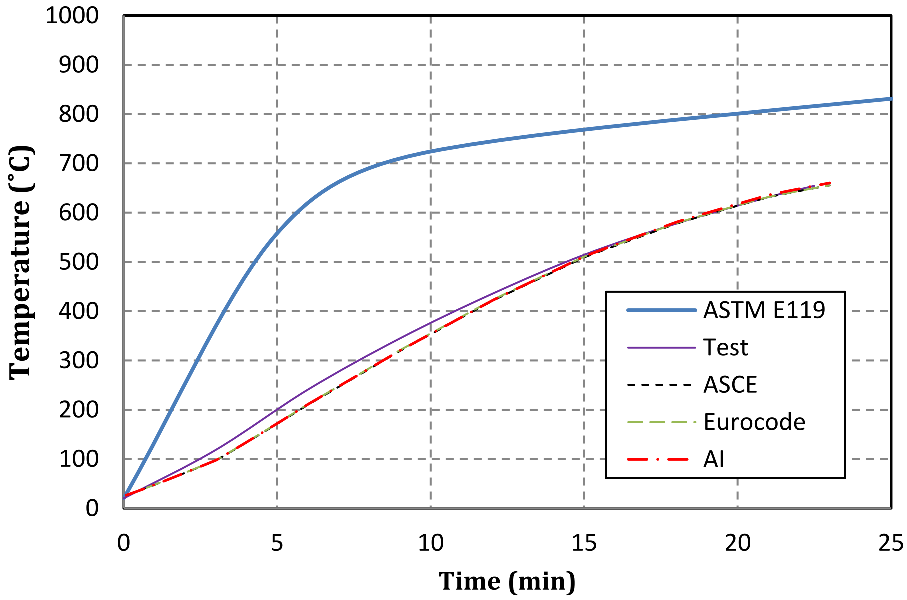
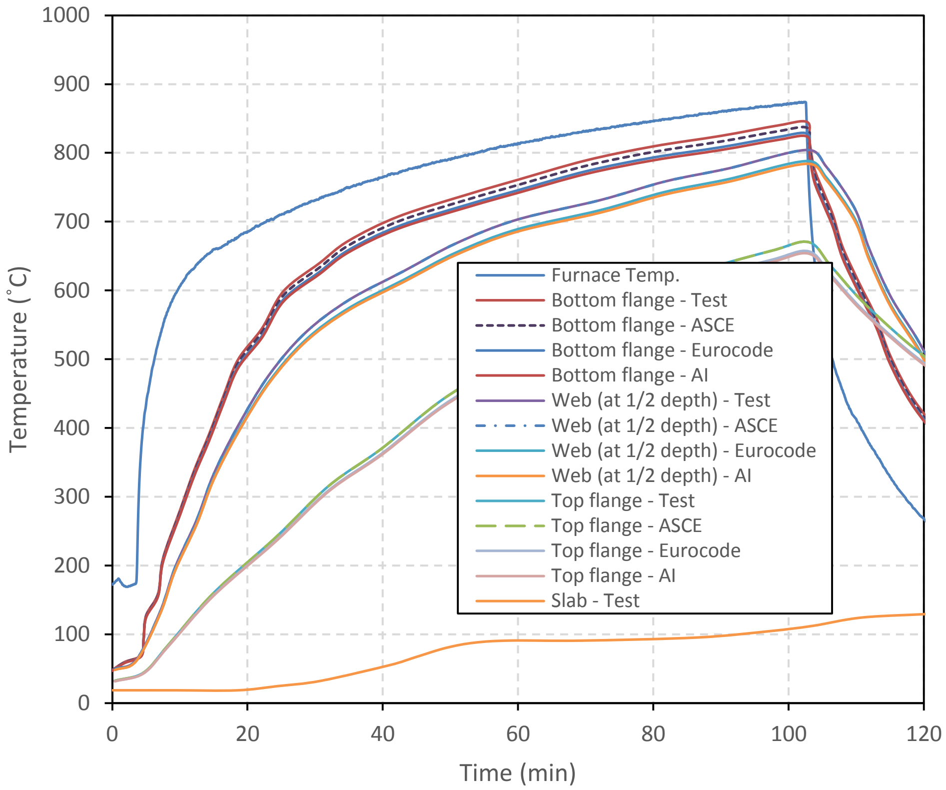


(a) UB406×178



(b) UB305×165



(c) W24×62

Fig. 6 Predicted and measured temperatures in the steel and composite beams

Figure 6 shows applied temperature-time curve (ASTM E119) and the resulting temperatures in beam as measured in the fire tests carried out by Wainman and Kirby [45] and Aziz et al. [46] as well as predicted using Eurocode, ASCE and AI-derived thermal material models. Overall, it can be seen that the variation in the predicted and measured temperatures are minor. This observation agrees with findings in other studies carried out by Kodur et al. [7] and Khorasani et al. [14]. Plotted results also show that predicted temperatures using ASCE and AI-derived models seem to be slightly higher than that predicted using Eurocode model; specifically at temperatures between 700-750°C. This can be attributed to the fact that values for specific heat of structural steel predicted by ASCE and AI is lower than that from Eurocode at that particular temperature.

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6.2 Structural effects

A coupled thermal-structural analysis was carried out to investigate mid-span deflection, and temperature-induced flexural capacity degradation response in beams 1-3. In order to eliminate variations due to minor differences in thermal properties (as observed from Sec. 6.1), temperatures measured in fire tests were directly applied to the beams to carry out the coupled thermal-structural analysis. For each beam, four analysis cases were considered and in each case material models from ASCE, Eurocode, and Poh were used independently and then compared to that predicted by proposed (AI-derived) material models.

Figure 7 shows the time-history of mid-span deflection in selected beams (1-3) as a function of fire exposure time. This figure clearly shows that mid-span deflection in these beams can be grouped into three distinct stages. The mid-span deflection increases linearly when the temperatures in steel section reaches about 300°C during the initial stage of fire. The deflection at this stage is influenced by development of significant thermal gradients and associated thermal stresses along the beam. The rate of mid-span deflection further increases between 7 min and 20 min in beams 1 and 2 and 10 min and 25 min in beam 3 due to rapid degradation of strength and stiffness properties of the steel as sectional temperatures exceed 500°C. While beams 1 and 2 fail at approximately same point in time (i.e. 22 minutes), the composite beam fails after 40 min, when flange and web temperature exceeds 750°C leading to spread of plasticity at mid-span.

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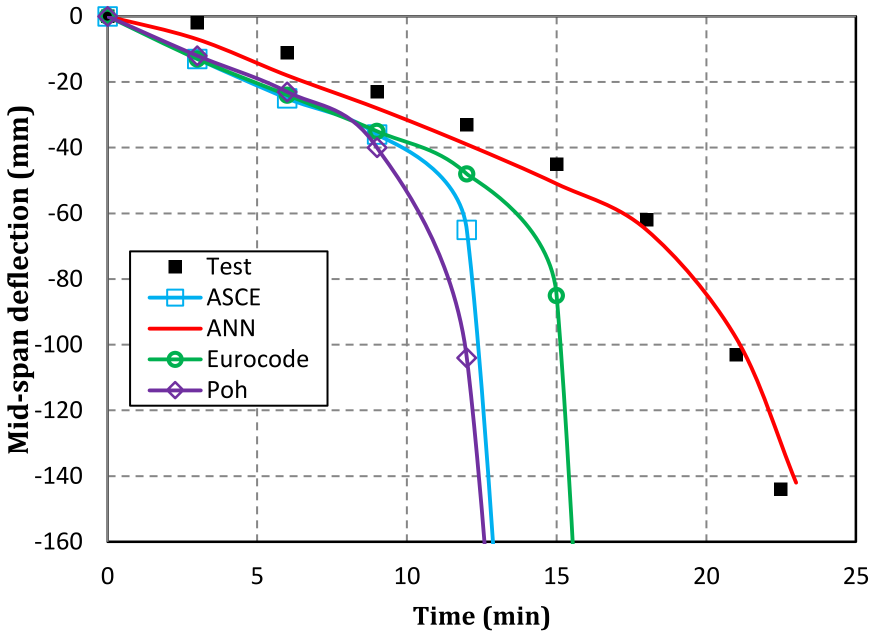
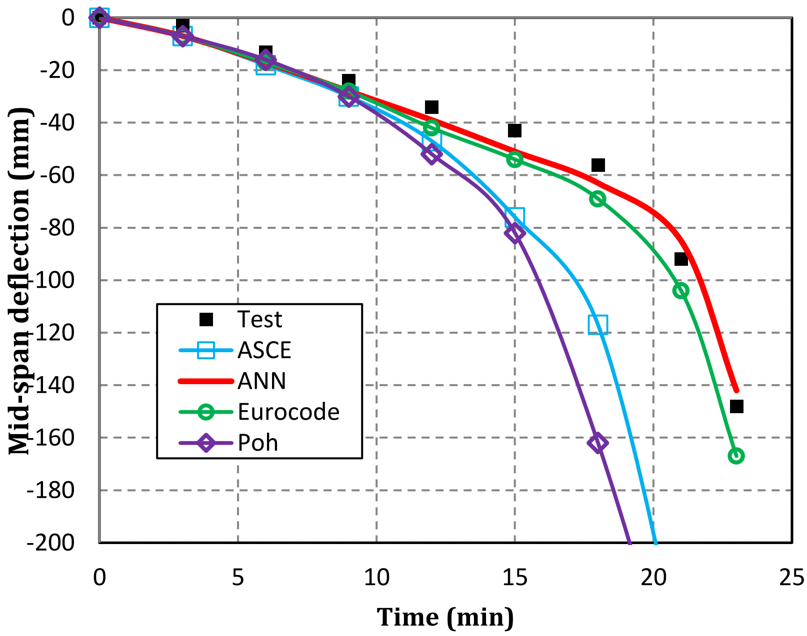


(a) UB305×165



(b) UB406×178

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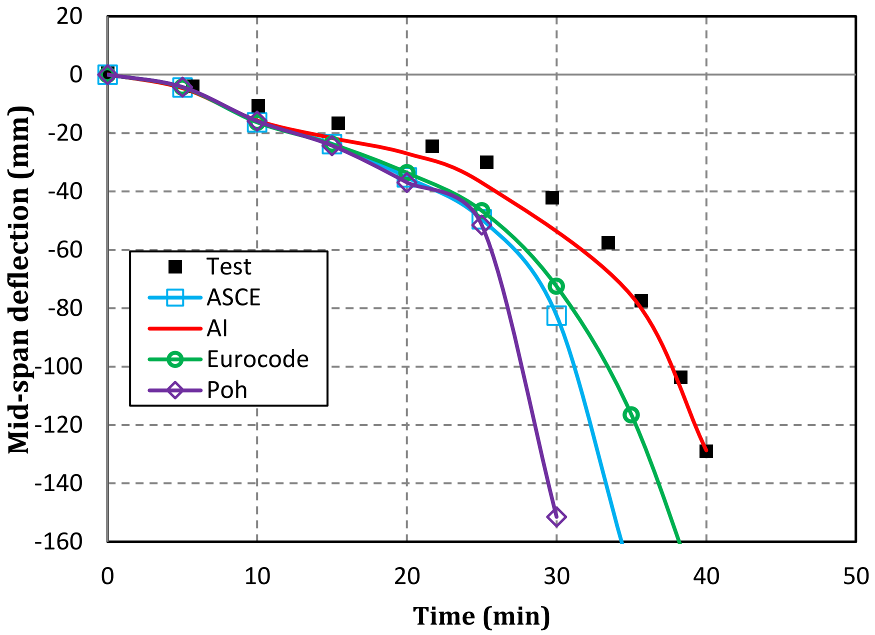

(c) W24×62

Fig. 7 Comparison between mid-span deflections of selected beams using different material models

Results plotted in Fig. 7 show that the predicted mid-span deflection using ASCE, Eurocode 3, and Poh models does not quite match with the measured mid-span deflection. This is unlike predictions from AI-derived models which seem to achieve a better correlation with measured data. This can be attributed to the fundamental differences in constitutive material models. For example, degradation in yield strength, as per Eurocode 3, starts in steel at 400°C while Poh (and ASCE) material model assumes that yield strength starts to degrade at relatively lower temperatures (i.e. slightly greater than 100°C). Therefore, with the rise of steel temperature, plastic deformations achieved much faster using Poh model as oppose to that observed in Eurocode 3 or AI models. Overall, using Poh (or ASCE) material model leads to earlier yielding of steel and correspondingly shorter fire resistance as compared to Eurocode 3 or AI models.

It should be noted that at higher temperatures (of more than 500°C), other factors, such as creep and strain hardening start to influence structural response of steel structures.

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Both of these factors are accounted for in the AI-derived material models because the developed ANN used input data points obtained from tests that accounted for such effects. This explains why numerical predictions with input properties using ASCE, Eurocode, and Poh was not fully successful in capturing measured mid-span deflection of analyzed beams. While creep effect is partially accounted for in Eurocode 3, and AI-derived models, this effect is not included in ASCE constitutive material model. Similarly, effect of strain hardening, which is ignored in both ASCE and Eurocode 3, was accounted for in Poh [10] used to develop the aforementioned ANN. It is clear that both creep and strain hardening effects are required to capture steel behavior under high temperature as can be seen in Fig. 7.

In order to further demonstrate applicability of AI-derived material models, the variation in degrading flexural capacity in beams 1-3 is analyzed as a function of fire exposure and is plotted in Fig. 8. This flexural capacity was obtained by extending room temperature design expression ($M=f_y \times Z$) to fire conditions by incorporating temperature-induced degradation in yield strength [17]. It can be seen from plotted data points that the variation in degradation of moment capacity follows presented in various material models and as such, there is a significant variation between different models, specifically in temperature range of 100-700°C. As shown in Fig. 8, the degraded flexural capacity obtained using reduction factors arrived at using AI lies in between those predicted by ASCE, Eurocode 3, and Poh models. This is expected as the developed ANN employs multiple material models for degradation of steel material yield strength.

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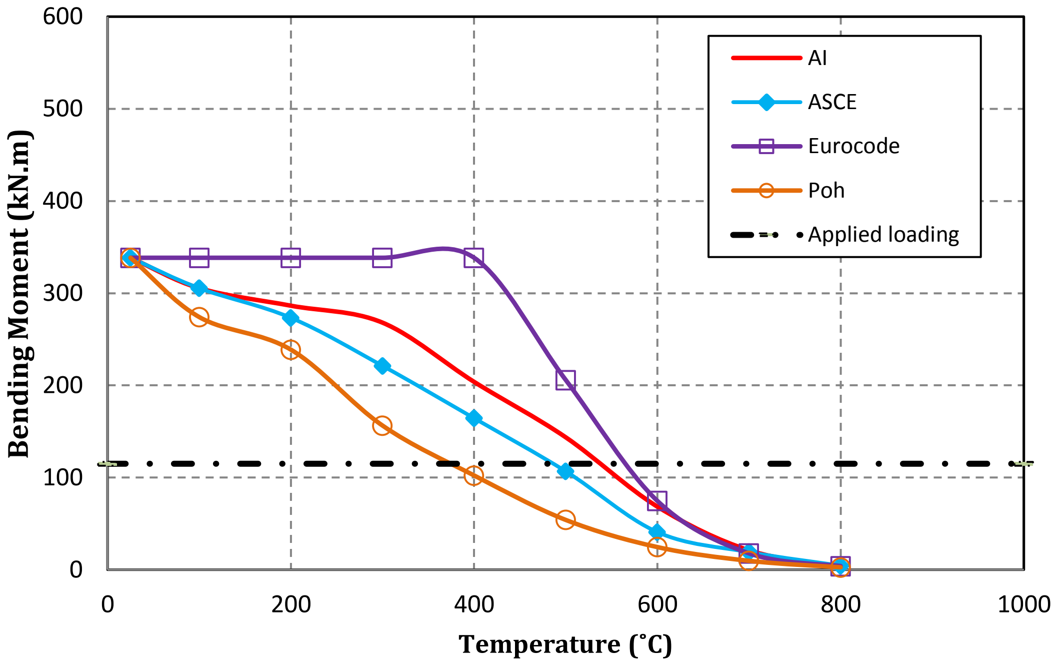
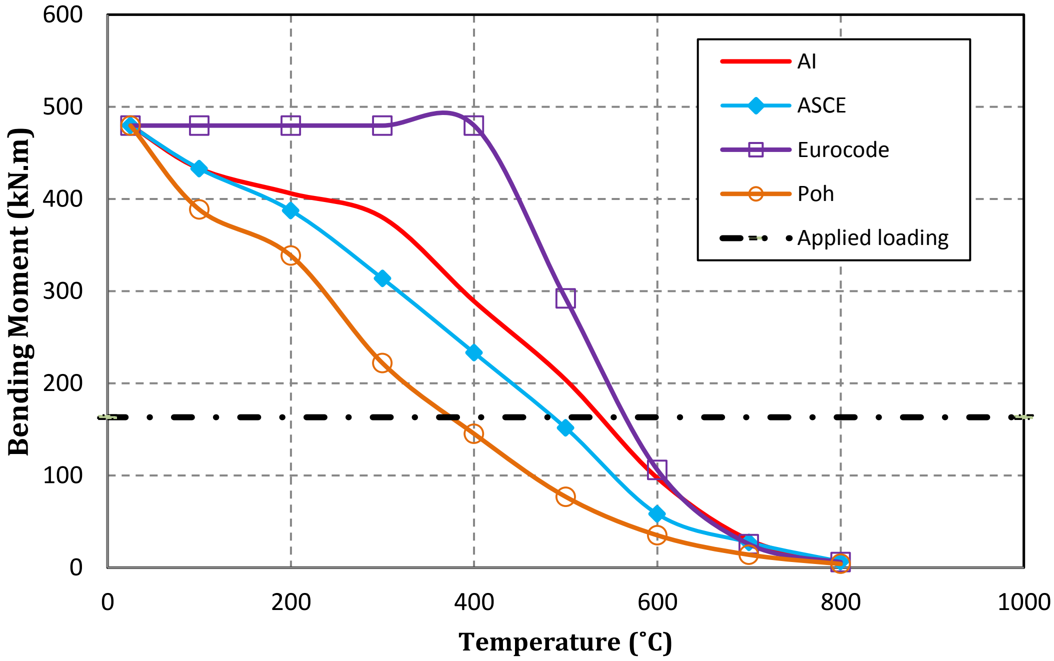


(a) UB305×165×54 (under 35% loading)



(b) UB406×178×60 (under 35% loading)

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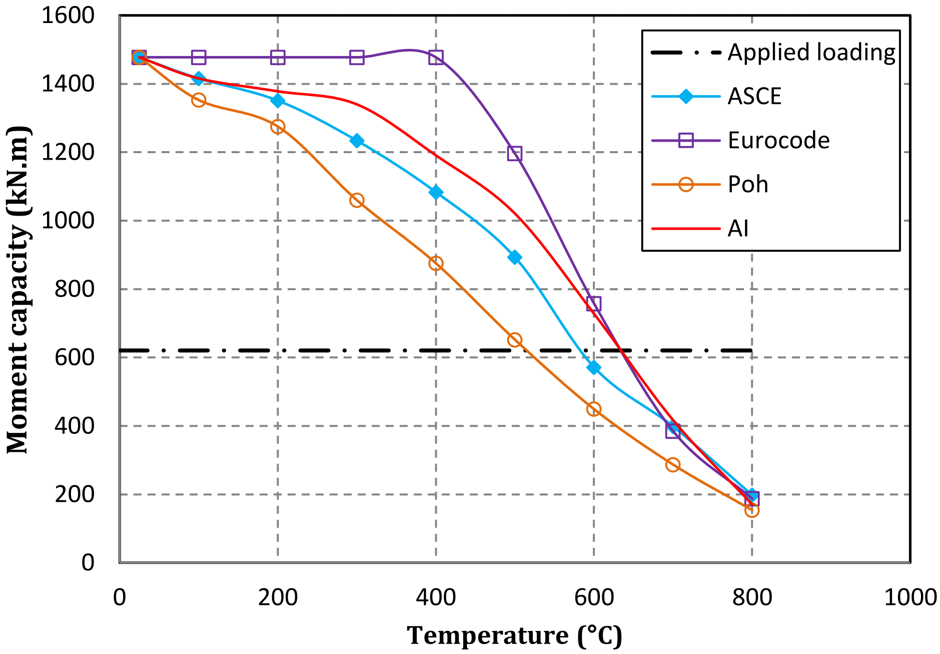

(c) W24×62 (under 45% loading)

Fig. 8 Comparison of flexural capacity with elevated temperature as obtained from AI prediction as well as different material models

Since failure in this beam, under fire conditions, occurs when the applied loading exceeds the available flexural capacity, the failure of fire-exposed beams can be obtained numerically by tracing response of degrading moment capacity. For example, Fig. 8 shows that all material models predict that applied loading on beam UB305×165 produces a bending moment of 340 kN.m at ambient conditions. In this particular beam, the degrading moment capacity falls below level of applied bending moment (calculated as 35% of ambient temperature flexural capacity [45]) at 375, 510, 545, 550 and 570˚C according to Poh, ASCE, AI, and Eurocode 3 material models (see Fig. 8a). This variation in material models can influence predictions of structural response and mislead designers and engineers. As a result, design decisions with regard to use of insulation material, thickness and type of insulation, and/or selection of larger sections becomes critical and would require further verifications either through seeking expert opinion or via experimental testing which is expensive, time consuming, and requires specialized facilities.

7.0 PRACTICAL IMPLICATIONS

The presented case studies in Sec. 6 illustrate how variation in material properties can significantly affect outcome of fire resistance analysis. In fire safety practice, researchers and practitioners seek optimum and safe designs that satisfy structure functionality and codal requirements. Such designs are often arrived at through iterative fire resistance analysis procedure (i.e. FE simulation etc.). In most practical (design) scenarios, the behavior of a steel member (or structure for that matter) might not be known from past experience/previous fire tests. As such, predictions from fire resistance analysis are received with caution. This is a classical scenario where designers and engineers face difficulties in making critical design-oriented decisions. In fact, unless a thorough material testing is conducted to measure different material properties for each structural member, and the outcome of such tests is used as inputs to numerically predict response of steel structures, then an optimum and safe design might not be achieved nor verified.

The predictability of currently adopted fire resistance models is often associated with arriving at over- (or in some cases under-designed) structural members. If a structural member is over-designed, concerns regarding cost and sustainability might arise. On the other hand, if a member is under-designed, pre-mature failure and violation of safety requirements could occur. Since fire-related sectional capacity evaluation and numerical modeling largely depend on material properties input parameters, the use of a uniform and up-to-date representation of material properties at elevated temperatures can be of a great aid to both researchers and designers/practitioners. The drive to achieve such material models could be regarded as the first step towards a more globally uninform design approach for fire actions.

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While this study is concerned with deriving material models for structural steel using AI techniques, future studies will extend this approach to derive constitutive material models for other construction materials such as concrete, masonry, and wood. It should be noted that a similar approach to the one presented herein could be applied to arrive at more robust material models using larger volume of input models and utilizing other AI optimization techniques such as Particle Swarm Optimization, Ant Colony Optimization, and Tabu Search etc.

8.0 CONCLUSIONS

This paper presents a framework to derive temperature-dependent thermal and mechanical material properties of structural steel using AI methods, specifically Artificial Neural Networks (ANNs) and Genetic Algorithms (GAs). The applied techniques utilize experimental data as well as material models adopted by current fire codes and standards to ensure uniformity and unbiasedness. The following conclusions could be also drawn from the results of this investigation:

- Variation of material properties at elevated temperature significantly varies depending on the constitutive material model used/adopted in fire codes.
- The need to develop a uniform and up-to-date representation of material properties at elevated temperatures can significantly enhance the current state of structural fire design.
- It is possible to use AI techniques to derive unbiased material models that could serve as a benchmark for more robust models.

9.0 ACKNOWLEDGMENT

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