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Please cite this paper as:
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AI-based Cognitive Framework for Evaluating Response of Concrete Structures in Extreme Conditions

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ABSTRACT

In order to highlight the potential of Artificial Intelligence (AI) in the field of engineering for extreme conditions, this study offers insights into developing an AI-based cognitive framework capable of accurately tracing response of concrete structures under elevated temperatures. This framework is utilized to derive simple expressions that allow evaluation of thermal and structural response of reinforced concrete (RC) beams and columns either; at a specific point in time or through tracing time-temperature/deformation history, for up to four hours of fire exposure. The developed AI-based framework successfully comprehends the naturally complex behavior of fire-exposed RC structural members and implicitly takes into account high temperature material properties of concrete and steel reinforcement, as well as associated phenomena; i.e. creep deformation and fire-induced spalling, and thus does not require input of temperature-dependent material properties nor need for distinct simulation/analysis software.

Keywords: Extreme conditions; Fire; Artificial intelligence; Concrete; Structural members.

1.0 INTRODUCTION

Concrete, an inert material, has superior properties which makes it well suited for use in extreme environments such as that associated with terrestrial (i.e. nuclear power plants) and extraterrestrial (i.e. lunar bases) applications where high temperatures and rapid temperature changes take place [1, 2]. Concrete maintains this superior behavior despite the fact that it undergoes a series of chemical and physio-mechanical changes that adversely affect its composition and nature. In some cases, these changes may alter key characteristics of concrete by

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developing cracks, inducing creep deformation or spalling (i.e. explosive reduction of cross-section driven by fire effects) [3]. As a result, predicting thermal and/or structural response of concrete structures concrete structural members/systems becomes a challenging task. This has been thoroughly documented over the past few decades [4-6].

Early research on tracing fire response of concrete structures started by examining the performance of structural members and assemblies in specially designed furnaces. In these fire tests, a concrete element is exposed to a pre-defined "standard" temperature-time curve such as that of the ASTM E119 [7] or ISO 834 [8]. In many instances, a tested element is loaded with a gravity loading corresponding to a portion of its sectional capacity i.e. 50% of that at ambient conditions. The fire-tested element could also be instrumented with thermocouples and deformation measuring devices to monitor its thermal and structural response during the fire. Once a fire test starts, the performance of the fire-tested element is closely monitored and documented. The fire test is terminated once the fire-weakened element exceeds a failure limit state, often when temperature at the unexposed side of the element or once deflection of element exceeds a predefined limit state. This point in time, when a structural element fails, is referred to as fire resistance.

Results from such fire tests were then compiled into tables, and then used to derive correlation equations that can estimate fire resistance of concrete elements (with features and conditions similar to those tested earlier). More recently, and due to the growing complexity of fire tests and lack of testing facilities, researchers and designers sought other means to evaluate fire response of concrete structures. With the advent of technological and computing advancement, the use of numerical techniques such as those associated with finite element (FE) analysis, has

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surged [10]. While such techniques provide a suitable and, in a way, clean/affordable prediction of fire response of concrete structures, the lack of proper validation and standardization of solution process (i.e. solving algorithms), required inputs (e.g. material properties, heat transfer boundaries etc.), as well as need for special software (which often require special licenses, certified expertise and demanding computing resources) continue to hinder the application and acceptance of numerical techniques [11].

From the vantage point of this work, most of the above challenges could be concurred through assimilating a new form of calculation techniques that leverages Artificial Intelligence (AI) to exploit relationships between key response parameters often linked with the fire problem or phenomenon. This is stems from the notion that AI has been widely used in a range of civil engineering sub-disciplines such as structural health monitoring [12], transportation [13], seismic and wind design [14], material sciences [15], yet has not been fully incorporated into structural fire engineering and fire safety applications.

The use of artificial neural networks (ANNs) was also specifically applied towards concrete structures primarily to predict sectional capacity and/or structural response. In one study, Sanad and Saka [16] investigated the use of ANNs to evaluate ultimate shear strength of reinforced-concrete deep beams by examining 111 data points. The outcome of this analysis shows that predictions from ANN can outperform that obtained from ACI codal provisions as well as Mau-Hsu method. Jadid and Fairbairn [17] also outlined an ANN-based framework to predict moment curvature of concrete beams under ambient conditions. This framework was shown to be easy to adopt and most importantly of high accuracy. Ahmadi-Nedushan [18] optimized instance-based learning approaches, compiled with generalized regression neural network and stepwise

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regressions, to predict the compressive strength of high performance concrete (HPC) given due consideration to mix proportion e.g. water to binder ratio, water/fly ash content among others. While Hadi [19] presented a comprehensive review on the application of ANNs into concrete structures, still, a thorough assessment of open literature shows that despite a handful of studies [20-25], the application of AI into structural fire engineering and fire safety continues to be lagging and did not reach its full potential yet.

In its simplest form, Chan et al. [21] developed an ANN able of quantifying magnitude of degradation in concrete strength under elevated temperatures (up to 1200°C). This ANN was developed using published experimental data points and was then applied to estimate the degradation in compressive strength property of concrete made of varying mix proportions and exposed to different environmental factors. It is worth noting that the maximum prediction error between the developed ANN and the experimental results was less than 15%.

Few researchers were able of developing AI models capable of predicting other aspects of fire response/behavior of concrete structures. For example, McKinney and Ali [22] developed a crude set of ANNs in order to qualitatively predict fire-induced spalling in concrete. These ANNs were first trained using actual observations from fire tests and then tested to validate their prediction capabilities. After 1500 training iterations, predictions obtained from these networks showed close agreement with that obtained from fire resistance tests and achieved a 0.5% error rate. Similarly, Lazarevska et al. [23] also trained a fuzzy-based neural network (FNN) as to evaluate expected time to failure (i.e. fire rating) of RC elements. These researchers also noted the suitability of FNNs especially in cases where there is virtually insufficient experimental and/or numerically data available on fire response of concrete columns.

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Naser et al. [20] was also able to predict thermal response in insulated FRP-retrofitted T-shaped reinforced concrete (RC) beams through a newly developed ANN. In this work, these researchers examined the effect of fire intensity, type of insulation material and thickness on temperature rise in insulated and strengthened FRP-RC beams. The results from the developed ANN were arranged into design charts/aids that can be used to select appropriate insulation material and thickness for FRP-RC beams expected to be subjected to standard or realistic (design) fires. These design aids could help in practical situations and provide an easy-to-pick insulation scheme for fire conditions similar to that to occur in buildings. The same research group was also able of utilizing ANNs and genetic algorithms to derive material models for various construction materials including high strength, high performance and fiber-reinforced concretes [24, 25]. In a separate work, Erdem [26] also trained an ANN to predict fire-caused loss experienced in flexural capacity of concrete slabs. The trained ANN can properly account for seven inputs, including concrete strength, reinforcement yield strength, effective depth of slab, and fire duration. Erdem [26] used 294 data points and reported how the developed ANN is able of achieving high prediction capabilities with a correlation coefficient of 99.775% and 99.750% for training and testing, respectively.

Unlike previously published works, this study seeks the development of a cognitive approach that is based on symbolic regression and genetic algorithms as to realize the complex thermal and structural behavior of RC structural members exposed to extreme temperatures (exceeding 1200°C). This framework has led to deriving simple expressions that are capable of evaluating temperature and deformation histories in a concrete member; at a specific point in time, or through tracing time-temperature/deformation history and up to four hours of exposure to a

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standard fire. These expressions are built to account for critical response parameters i.e. geometry of RC beams and columns, aggregate type used in concrete mix, steel reinforcement ratio, applied load level, thickness of concrete cover, fire exposure duration as well as compressive strength of concrete and yield strength of reinforcing steel. Furthermore, these expressions implicitly account for high temperature properties of concrete and reinforcing steel, as well as associated fire phenomena expected to occur in fire; such as creep and fire-induced spalling, and thus is not of need to collect or input of material properties nor acquiring special software for fire analysis.

In total, seven expressions were derived using the developed cognitive framework; two for evaluating thermal response (one for RC beams and one for RC columns) and five for evaluating structural response (one for RC beams and four for RC columns with varying aggregate types). The validity of the proposed simple expressions was cross-checked against fire-tested RC beams and columns collected from published works and open literature. The practical implications of integrating AI-based modeling, as well as applicability of extending derived expressions to RC beams and columns of various geometric properties, restraint conditions, and concrete strength classes is also discussed.

2.0 BEHAVIOR OF REINFORCED CONCRETE MEMBERS UNDER FIRE CONDITIONS

Before introducing the developed AI-based framework, a concise review of fire behavior of RC structural members is beneficial. This section highlights main mechanisms associated with thermal and structural behavior of RC beams and columns under fire conditions.

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When a RC member is exposed to fire conditions, cross-sectional temperature in this member slowly rises. This slow rise in temperature arises from the good thermal (insulating) properties of concrete. Due to the presence of moisture, low thermal conductivity and high specific heat of concrete, a significant amount of thermal energy is required before temperature in concrete starts to rise. Thus, a thermal gradient develops in which the temperature at the exposed surface of concrete is much higher than that at the level of embedded steel reinforcement or concrete core. Still, once the rising temperature reaches the depth (level) at which steel reinforcement is located, temperature in these reinforcement starts to rise as well. Since the area of steel reinforcement is very small as compared to that of whole cross-section, the temperature in reinforcing steel is practically assumed to be similar to that of the surrounding concrete; despite the fact that steel is a better conductor, with much higher conductivity and lower specific heat, than concrete.

With the advent rise in temperature, the mechanical properties (strength and modulus) of both concrete and steel reinforcement starts to degrade. This degradation; which is often assumed to vary according to specified material models prescribed in fire codes/standards (i.e. ASCE, Eurocode 2), triggers losses in sectional capacity (i.e. moment, shear, axial). While such temperature-induced degradation is slow, as it corresponds to the slow temperature rise in concrete, this degradation could be accelerated by few fire-induced effects such as spalling of concrete. Spalling is the loss of concrete chunks and can occur due to a number of factors including water vapor build-up, moisture migration, or development of thermal gradients. Spalling is mainly associated with high strength concrete and concretes of dense nature. An elaborate discussion on spalling is not provided herein for brevity but can be found elsewhere [27].

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While the mechanism of temperature rise in both RC beams and columns is similar, the structural response of these members significantly varies. In the case of the former, a simply supported RC beam will try to expand to accommodate thermal expansion facilitated by the rise in temperature arising from fire. Since the coefficient of thermal expansion of concrete is small, the expansion of the RC beam is often minimal. As the temperature further rises within the cross-section of the beam, additional layers of concrete, together with reinforcing steel rebars, slowly heat up causing the development of a gradient of thermal stresses as well as degradation to the strength and modulus properties of concrete and steel (where most losses occurring towards outer layers of concrete). With the continuous rise in temperature, combined with stresses developed from applied loading (e.g. uniformly distributed load (UDL) as shown in Fig. 1a), fire-induced property degradation causes the beam to crack, soften, and deflect. At this point, the beam is weakened due to the combined effects of thermal and gravity loads, experiences rapid rise in deflection, and becomes prone to failure.

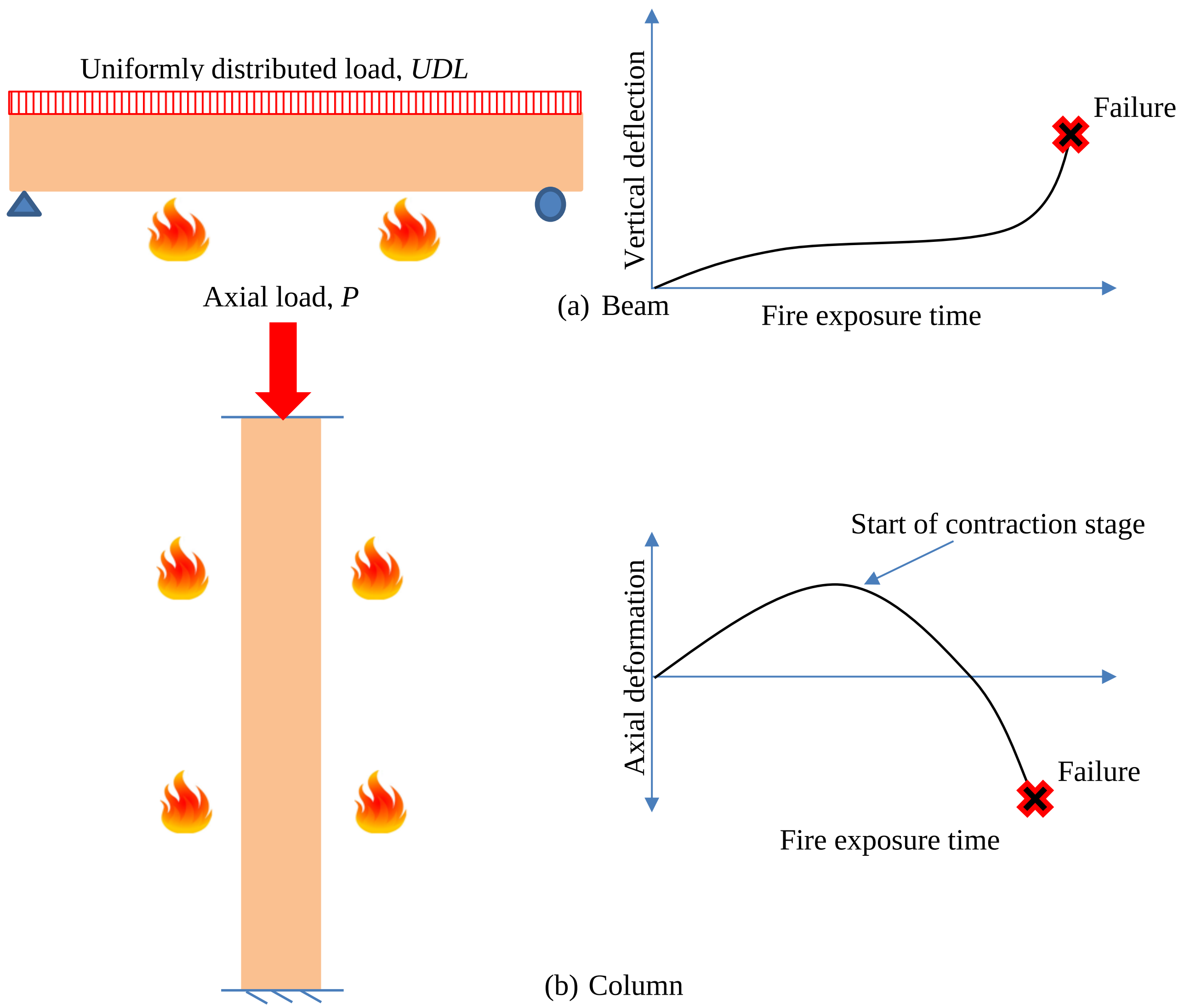

Fig. 1 Typical response of RC beams and columns under fire conditions

On the other hand, when a RC column is exposed to elevated temperatures, the column vertically expands as shown in Fig. 1b. Later on, and due to the rise in cross-sectional temperature and associated degradation in strength properties, the column starts to weaken. This corresponds to a contraction stage in which the axial deformation of the column decreases and shifts from an expansion-controlled (noted in the positive side of Fig. 1b) into a contraction-controlled (noted in the negative side of Fig. 1b). Eventually, with the increase of exposure duration which causes

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further losses in mechanical properties of concrete and reinforcing steel, the column buckles or crushes.

In any case, a RC beam or column fails once its sectional capacity (i.e. flexural for beams and axial for columns) falls below the level of applied loading (bending/shear for beams and axial force in columns).

3.0 ARTIFICAL INTELLIGENCE – BACKGROUND, RATIONALE, AND MODEL DEVELOPMENT

In contrast to statistical approaches, AI does not involve assumptions to start examining a phenomenon. Instead, AI is a specially designed computational technique that hopes to replicate human-like thinking/cognition ability to solve complex engineering problems that may not be appropriately solved in a timely manner using conventional methods or would require complex solvers or environments (software). AI is suitable for engineering scenarios in which there is a large amount of inputs (random variables), and there is an unclear (or unestablished) relationship between random variable and expected output(s) (results). In many instances, AI utilizes evolutionary algorithms that try to learn patterns concealed in random data points by means of systematic valuation. Once a pattern is discovered, this pattern turns into the main phase of solving the complex system by training and adaptive learning, or even probabilistic discovery of relevant patterns.

An AI-based cognitive framework (model) comprises of multiple layers and processing units (referred to as neurons). These neurons are assembled in visible and hidden layers to form a paradigm that resembles the human brain in which there is a continuous communication between

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neurons and layers (see Fig. 3). The input layer, comprises of random variables (predictors), is connected to hidden layers capable of establishing linear and/or non-linear models. From the other side, the hidden layers are also connected to the output layer that contains the outcome/target variable(s) of a given problem. From the perspective of this study, two phenomena are examined. The first being thermal response of RC beams and columns, and the second being structural response of the aforementioned elements/members under fire conditions.

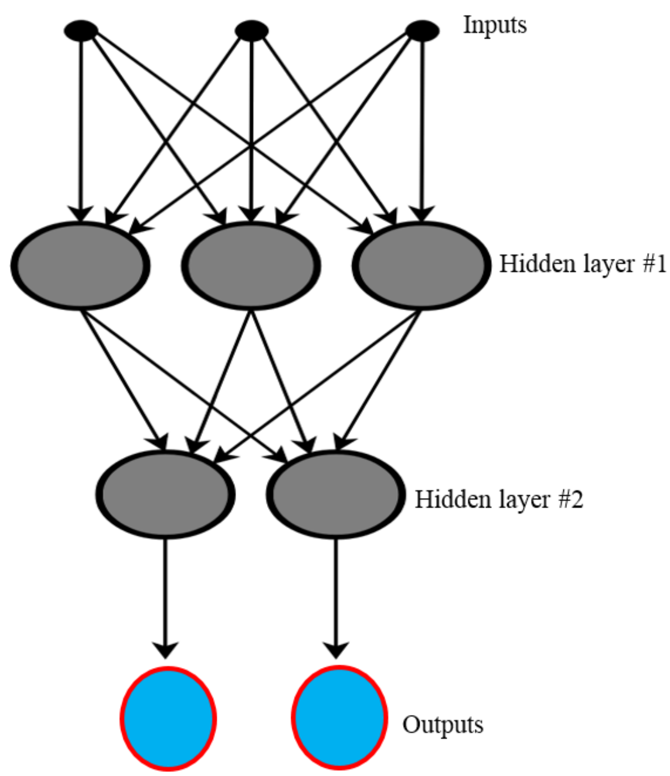

Fig. 2 Typical structure of an AI-based model

In the first (thermal) AI-based model, the geometric properties of RC beams and columns, together with fire exposure duration and temperature in concrete at steel reinforcement level are

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identified as input parameters. These parameters were first collected from published literature and then input into the AI-based model for analysis and training purposes. In the second (structural) AI-based model, the geometric and material properties of RC beams and columns including steel reinforcement ratio, concrete cover, compressive strength of concrete and yield strength of steel; as well as applied load level and aggregate type were identified as main parameters for analysis and then collected and also input into the AI-based model. Table 1 lists the selected input parameters in the case of thermal and structural analysis using the developed AI-based cognitive framework.

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Table 1 Selected input parameters for thr AI-based cognitive framework

Parameter/Case		Input parameters									Output parameters	
		Fire exposure time (*t*)	**Compressive strength of concrete (f_c)**	**Yield strength of steel (f_y)**	**Steel reinforcement ratio (ρ)**	**Load level (*P*)**	**Aggregate type (*A*)***	**Bottom cover to steel reinforcement (C_b)**	**Side cover to steel reinforcement (C_s)**	**Smaller width (dimension) of member (*b*)**	**Temperature (°C)**	**Mid-spam deflection/axial deformation (mm)**
Thermal response	**Beams**	√	-	-	-	-	-	√	√	-	√	-
	Columns	√	-	-	-	-	√	-	√	√	√	-
Structural response	**Beams**	√	√	√	√	√	-	√	-	-	-	√
	Columns	√	√	√	√	√	√	√	-	-	-	√

*Type of aggregate (carbonate vs siliceous) was shown to significantly affect thermal and structural performance of concrete columns much more than that in beams [28-48]. As a result, this input parameter was included in the case of RC columns but not in the case of RC beams.

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The aforementioned parameters (random variables) were selected through close examination of: 1) analyzing published fire tests and databases and examining which parameters were recognized to be of critical nature and to govern the fire response of RC beams and columns, and 2) common availability of such parameters between all reviewed studies. Critical parameters were also carefully selected in order to optimize size and complexity of AI-derived expressions, while capturing accurate behavior of RC structural members; in order to provide easy and simple-to-apply expressions that can be coded into spreadsheet and hence do not necessitate hefty calculations or special computer programs. The reasoning behind selecting most of previously identified critical parameters stems from engineering judgment, observations from fire tests and suggestions of previously published studies [28-47].

For example, temperature rise in steel rebars at any given point during fire exposure time in a RC beam is said to be a function of duration of fire exposure, t, bottom and side cover to steel reinforcement, C_b and C_s, respectively. Other parameters such as compressive strength of concrete or ratio of steel reinforcement do not contribute to temperature rise in a RC column exposed to fire and hence are neglected from inputting into the thermal-based AI analysis. For a particular RC beam, these parameters were first collected. As these parameters are temperature independent, they remain constant (fixed) throughout a fire exposure. Then, corresponding values of temperature rise at each point in fire exposure time (measured in time intervals of 1-5 min) as observed in the fire test, i.e. say 150°C at 60 minutes, 157°C at 65 minutes, were also collected and input into the AI-based model. This procedure was repeated for all beams selected to train the AI model. Using this procedure, thermal-based databases for RC beams and columns were developed.

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Through above procedure, the developed AI model can relate temperature rise in steel rebars to input parameters, t, C_b and C_s and then develops a simple expression that relates temperature rise to these three parameters; while implicitly accounting for thermal properties of concrete. This eliminates the need to input thermal properties in order to estimate temperature rise in a RC beam. In other words, since analyzed beams are made of normal strength concrete, and the thermal properties of this type of concrete can be assumed to be similar across different concrete mix batches, then the effect of thermal properties can be negated. A similar rationale was used in the case of other input parameters for RC columns as well as development of the structural-based AI models for RC beams and columns. It is worth noting that other factors such as stirrups spacing, load configuration and so forth, were maintained in the range of 10-20% of commonly reported values[*].

Owing to complexities with fire testing, availability of instrumentation (sensors) and equipment, and perhaps most of all, the unstandard styles in documenting results of fire experiments, few problems tend to arise. A common issue of particular interest to this work revolves around relative humidity of concrete, which is only reported in few tests. Thus, this parameter was not picked to be a critical input variable as to maintain unbiasness between other inputs. In the case where this variable is to be selected and input to the AI model, then data points associated with fire tests in which relative humidity of concrete is not reported were to: 1) be

[*] Selecting a few parameters as discussed herein is aimed to simplify the complexity arising in understanding the fire behavior of RC structures. The validity of selecting such parameters will be revisited in the following section where it will be shown that the adopted procedure still manages to capture the full spectrum of thermal and structural response of RC structures. It is worth noting that the developed framework has the potential to include ~10-20 independent (or dependent) input parameters. All that is needed is to collect information on such parameters.

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removed from the database which would reduce the overall number of input data points, or 2) be given "assumed" values which may risk prediction capability of the AI model. In other instances, a variable such as fire-induced spalling is often measured qualitatively (i.e., reported with terminology such as "minor" or "major" spalling) as instrumentations and methods to quantitative measure fire-induced spalling are still immature. Accounting for such a variable would introduce a new dimension to the AI model and this would require special treatment and technical manipulation. Few of the steps/solutions that can be applied to adapt such issues are briefly discussed towards the end of this study and will be thoroughly discussed in a future study specifically tailored towards overcoming these challenges.

4.0 DEVELOPMENT OF FIRE TEST DATABASES

The first step towards developing fire test databases to serve as training and testing data points is to carry out a comprehensive review of open literature to pinpoint suitable studies/reports in which RC beams and columns were tested under standard fire conditions. This section covers selected fire tests and further presents insights into the development of AI framework. Full details on collected tests, together with material properties and loading conditions in each test, is spared herein for brevity but can be found in their respective references. It is worth noting that the developed databases contain over 25500 data points and will made be available for use and download upon request.

4.1 Fire Tests carried out on RC beams

In one study, Palmieri et al. [28] carried out an experimental investigation to evaluate fire resistance of insulated RC beams retrofitted with near surface mounted (NSM) FRP rebars. Two

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of these beams, namely B0-F1 and B0-F2, were uninsulated, unstrengthened and were tested under the ISO 834 temperature-time curve. As a result, these two beams were deemed suitable for analysis in the study. The two beams had a height and width of 300 and 200 mm, respectively. The beams had a clear span of 3150 mm and were reinforced with tensile reinforcement consisting of 2 bars of a diameter of 16 mm. The compressive strength of concrete used in B0-F1 and B0-F2 was reported at 48 and 42 MPa, respectively. These beams were tested at the floor furnace at the WFRGent laboratory. A sample of the developed database for beam B0-F1, together with a RC column tested by Raut and Kodur, NSC-1, [29], is shown in Table 2.

Table 2 Sample database for RC beams and columns

Parameter/Case		**Fire exposure time (*t*)**	**Compressive strength of concrete (f_c)**	**Yield strength of steel (f_y)**	**Steel reinforcement ratio (ρ)**	**Load level (*P*)**	**Aggregate type (*A*) – 1 for carbonate, 2 for**	**Bottom cover to steel reinforcement (C_b)**	**Side cover to steel reinforcement (C_s)**	**Smaller width (dimension) of member**	**Temperature (°C)**	**Mid-span deflection/axial**
Beam, B0-F1, - Palmieri et al. [28]	**Thermal response**	0	-	-	-	-	-	30	25	-	25	-
		35	-	-	-	-	-	30	25	-	411	-
		..*	..	..	..	..	..	..	..	..	..	..
		85	-	-	-	-	-	30	25	-	692	-
	Structural response	0	48	570	0.0067	0.54	-	30	-	200	-	0
		35	48	570	0.0067	0.54	-	30	-	200	-	20
		..	..	..	..	..	..	..	..	..	..	..

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		85	48	570	0.0067	0.54	-	30	-	200	-	40.9
Column, NSC-1, - Raut and Kodur [29]	**Thermal response**	0	-	-	-	-	-	-	50	203	25	-
		9.3	-	-	-	-	-	-	50	203	43.06	-
		..	..	..	..	..	..	..	..	..	..	..
		120.4	-	-	-	-	-	-	50	203	507.2	-
	Structural response	0	51	450	0.0305	0.4	1	-	50	-	-	0
		29.6	51	450	0.0305	0.4	1	-	50	-	-	1.51
		..	..	..	..	..	..	..	..	..	..	..
		140.2	51	450	0.0305	0.4	1	-	50	-	-	5.15

*For values to be filled in.

Another fire-tested RC beam was that reported by Dotreppe and Franssen [30]. This beam was also of a rectangular (deep) cross section (600 × 200 mm) and was tested under ISO 834 fire exposure. The compressive strength of concrete and yield strength of steel reinforcement were 15 and 300 MPa, respectively. This beam was reinforced with three steel rebars (in the tension zone), each having a diameter of 22 mm. Dwaikat and Kodur [31] also tested number of RC beams made of normal and high strength concrete under standard and design fire conditions. Only those tested under standard fire conditions are of interest to this study. One beam, named B1, was simply supported and tested under ASTM E119 standard fire conditions and this beam was added to the developed database. This beam had a length of 3960-mm and was of rectangular cross section of 406 × 254 mm. The beam was made of concrete with a compressive strength reaching 58.2 MPa and had three 19 mm bars as tensile reinforcement. The yield strength of steel reinforcing bars was 420 MPa.

Rafi et al. [32] casted and tested one RC beam as part of their experimental work. This beam, BESS20-1, had a cross section of 200 × 120 mm and was made of a concrete with a compressive strength of 30.45 MPa. This beam was reinforced with two 10 mm diameter steel rebars with nominal yield strength of 530 MPa. It is worth noting that this beam was relatively shorter than some of the selected beam herein as it had a full span of 2000 mm. Choi and Shin [33] tested two RC beams made of normal strength concrete; N4 and N5, with cover to tensile reinforcement of 40 and 50 mm, respectively. The compressive strength used in these beams was 21 MPa. The beams were of rectangular shape 250 mm (width) × 400 mm (depth) and spanned 4700 mm. The beams were also reinforced with three rebars of 22 mm diameter of yield strength of 439 MPa. Two beams tested by Wu et al. [34], Beam I and Beam II, were used in the development of the fire test database. These beams had a cross section of 400 × 200 mm and were reinforced with three steel rebars, two of which were of 12 mm diameter and the third (middle) rebar was of 14 mm diameter. These rebars had a yield strength of 240 MPa. The measured compressive strength of concrete used in this study was 24.2 MPa. These beams were relatively long, reaching 5.4 m in span.

Data from other tests such as those carried out by Zhu et al. [35], Kodur and Yu [36], Blontrock et al. [37], Albuquerque et al. [38], Carlos et al. [39], Ellingwood and Lin [40], as well as Jiangto et al. [41] was also used as input into the developed AI database. These studies feature fire tests carried out on representative RC beams to that used in actual buildings, made of normal strength concrete, and subjected to standard fire conditions. These beams had rectangular cross

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sections of dimensions varying between small 200 × 120 mm and 600 × 200 mm, compressive strength of 15-60 MPa, yield strength of 240-593 MPa, tensile steel reinforcement ratio of 0.47-1.14%, span of 2000-6500 mm, applied loading of 30-60% of ambient capacity, and concrete cover of 20-50 mm. It can be seen that those tests cover a wide range of parameters often used in practical situations.

4.2 Fire Tests carried out on RC columns

Similarly, a number of studies examining fire response of RC columns under standard fire conditions were also complied to build a database for RC columns to be used in the AI-based framework. One notable study was carried out by Lie and Woollerton [42] at the National Research Council of Canada (NRCC) in order to update fire resistance ratings for RC columns in the National Building Code of Canada (NBCC). In this study, forty-one full size RC columns were exposed to fire. These tests varied factors such as shape and cross-sectional area of column, percentage of longitudinal reinforcing steel, concrete strength and mixture (type of aggregate), as well as load intensity. Overall, square, rectangular and circular concrete columns with varying dimensions (i.e. 305 × 305 mm, 203 × 203 mm, 355 mm diameter) were tested. All columns, except one, had a concrete cover thickness on 38 mm. On average, the compressive strength of concrete was 36 and 39 MPa, for carbonate and siliceous aggregate concretes. Steel reinforcement ratio as well as level of applied loading were varied between 2.19-3.97% as well as 0-90%, respectively. This is considered by far to be one of the most comprehensive tests carried out on fire resistance of normal strength RC columns.

In a separate study, Wu and Lie [43] tested seven RC columns, mainly made of siliceous aggregate, under the effect of ASTM E119 fire. All of these columns had a concrete compressive strength of 25 MPa. Five columns had a square cross-section (305 × 305 mm), and two were of rectangular cross-section (305 × 457 mm and 203 × 914 mm). The steel reinforcement ratio and applied loading were also varied between 1.39-2.53%, and 910-2218 kN, respectively. It should be noted that column No. 7 was subjected to an eccentric loading and as such was not used in the developed database.

Shah and Sharma [44] conducted fire resistance experiments on eight RC columns, six of which were made of carbonate-based normal strength concrete (f_c = 34 MPa) and two of high strength concrete (HSC). Eight steel rebars with 16 mm diameter were used as longitudinal reinforcement and were embedded behind 40 mm concrete cover. These rebars had a comparatively high yield strength of 569 MPa. Park et al [45] tested a number of large-scale columns made of two concrete types, normal strength (f_c = 60 MPa) and high strength (f_c = 100 MPa). All columns had dimensions of 500×500×3000 mm. The RC columns were reinforced with 16 rebars each having a diameter of 25 mm and yield strength of 400 MPa. The column of normal strength nature was included in the developed database. In a similar study, Kim et al. [46] tested ten columns of which were divided into five groups. Three groups were made of normal strength concrete (f_c = 40, 60 and 80 MPa) and two groups were made of high strength concrete (f_c = 80, and 100 MPa). These columns were subjected to 40% load level while being exposed to the ISO 834 fire exposure simultaneously.

Other studies were also used to supplement the developed database. These studies include fire tests carried out by Raut and Kodur [47] (see Table 2), and Kodur et al. [48]. In all of these

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tests, the compressive strength of concrete was in the range of 26.5-60 MPa, ratio of steel reinforcement varied between 1.22-4.38%, level of applied loading of 0.2-0.95% of axial capacity, and aggregate type (carbonate vs. siliceous). Unlike the case of RC beams, there were comparable amount of data on above mentioned types of aggregates and as such both types were used at individual input parameters.

5.0 PERFORMANCE AND VALIDATION OF AI-BASED DERIVED EXPRESSIONS

Upon completion of collecting the above databases, these databases were input into the AI environment; developed by Searson [48]. In this software, candidate expressions are derived through symbolic regression to arrive at a relation between thermal and structural-based input parameters, i.e. fire exposure time (t), compressive strength of concrete (f_c) etc. Each relation encompasses a number of operators i.e. +, - and/or, mathematical functions (sin, cos..). The compiled input parameters were first randomly assembled to remove any specific reference/layout in order not to influence the AI-based model. In total, 70% of the data points is used to train the cognitive framework while the other 30% was used to validate and test the AI-derived expressions [15, 48]. The derived expressions are tested using a fitness function that establishes the difference between AI-predicted predicted and measured values in experiments (e.g. temperature in rebars or deformation). The derived expressions, as well as their fitness metrics i.e. coefficient of determination (R^2), correlation coefficient (R), and mean average error (MAE) are listed in Table 3. In addition, Fig. 3. plots validation (performance) of those expressions against measured data points[†].

[†] The reader is encouraged to review two numerical examples provided in the appendix illustrating proper use proposed expressions.

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Table 3 AI derived expressions to evaluate fire response of RC beams and columns

Case		Derived expressions	R^2	R	MAE
Thermal response	Beams	$T = 0.0169tC_b + + \frac{182.64t}{C_s} + t\sin(5.21C_b) - 6.43 - 0.0098t^2$	95.1	97.5	24.6°C
	Columns	$T = 0.0922b + 0.332t\,A + 0.331t\,C_b - 11.677t - 15.125A - 0.0086t^2$	94.5	97.2	27.6°C
Structural response	Beams[*]	$\Delta = 36.2\,exp(0.023t)\cos(\sin(23040\,P))\cos(\sin(2.28\times10^{-8}\,P)) - 0.206C_b - 9.28\sin(f_y) - 12.59\exp(0.0236t) + 4.5 + 0.105t + 2.299\times10^{-6}t^{f_c\rho\,P}$	95.6	97.8	4.8 mm
	Columns[**]	$\Delta = 0.085t + 0.0081t\sinh(\sinh\left(\operatorname{atanh}\left(\sin(0.265f_c)\cos\left(\operatorname{acosh}\left(\frac{P}{\rho}\right)\right)\right)\right) - 0.039t\,A - 0.000421t^2 - 0.0599t\,A\cos\left(\operatorname{acosh}\left(\frac{P}{\rho}\right)\right) - 0.0001f_y$	87.6	94.2	0.91 mm

[*]In some instances, this expression might unexpectedly give relatively high values for initial deflection. In this case, all that is needed is to normalize this deflection through subtraction.

[**]Additional expressions were also derived for RC columns. These expressions are to be used for RC columns made of:

1. Carbonate aggregate concrete: $\Delta = 0.043t + 0.0063t\tan{f_c}^2 - 4.701\times10^{-8}P\frac{t^3}{\rho} - 0.0053t\,tan{f_c}^2\cos\left(tan\,{f_c}^2\right) - 0.000085f_y$ (with R^2 = 94.03, R = 96.98, and MAE = 0.53 mm)
2. Siliceous aggregate concrete: $\Delta = 2.499t\,\rho + \frac{0.0057tf_c - 0.307t\,P}{100\rho^2} - P\,\operatorname{asinh}(Psin(-0.325f_c)\sinh(1.52\times10^{-6}Pt) - 1.52\times10^{-6}t^3 - 0.00009f_y$ (with R^2 = 89.4, R = 94.5, and MAE =0.89 mm)

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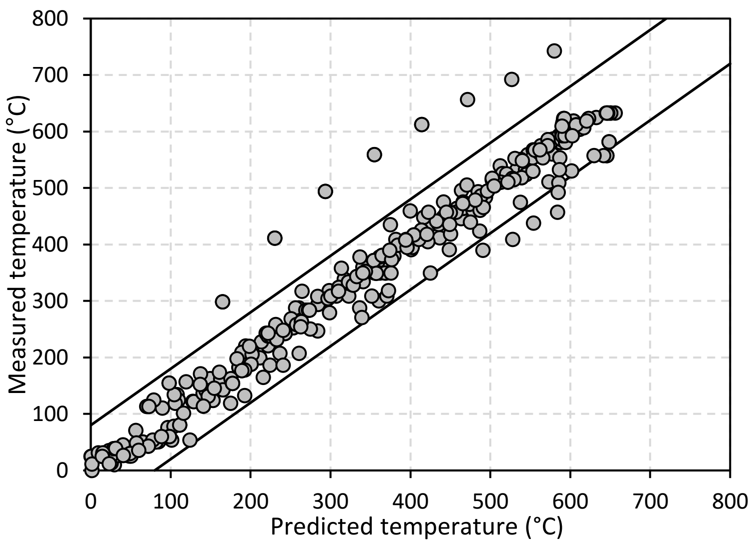
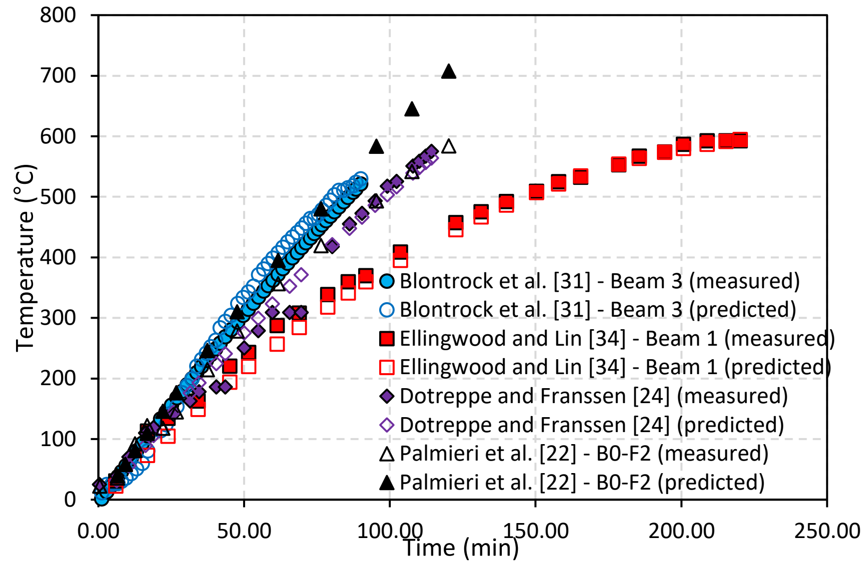


(a) Temperature in rebars (beams)



(b) Validation against fire tests

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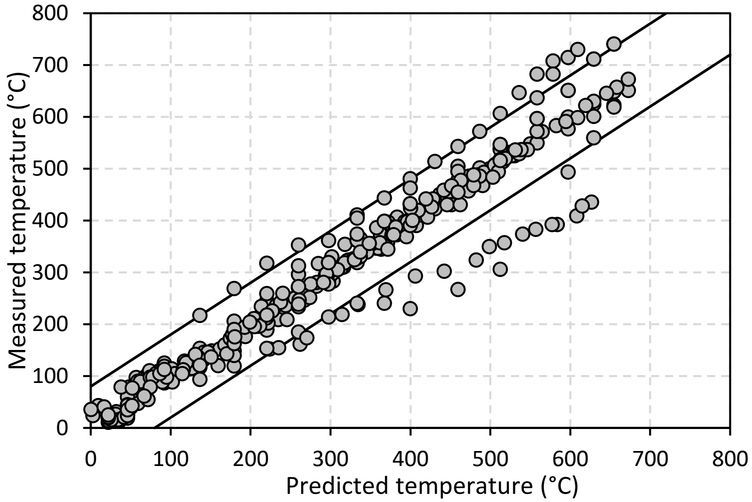
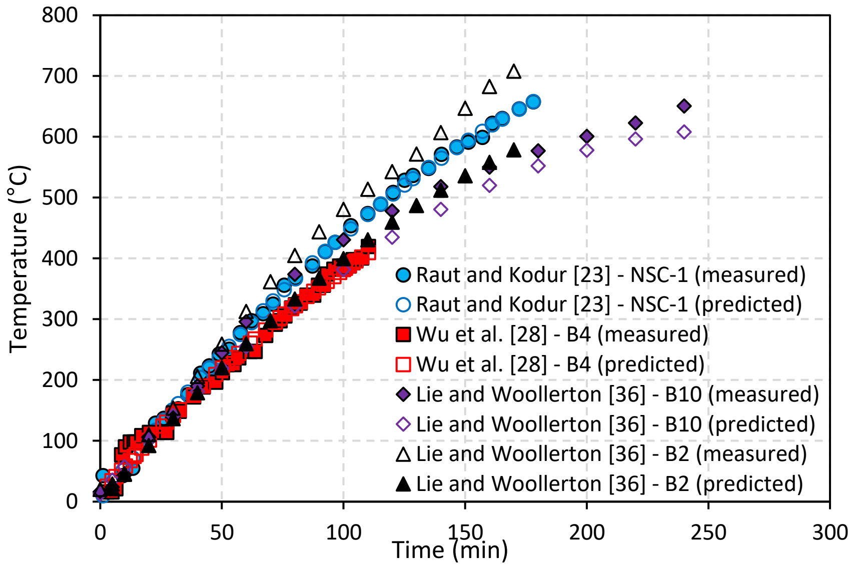


(c) Temperature in rebars (columns)



(d) Validation against fire tests

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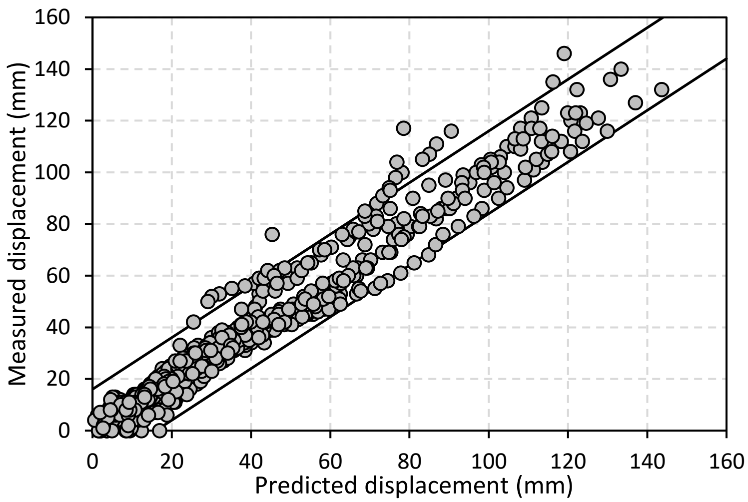
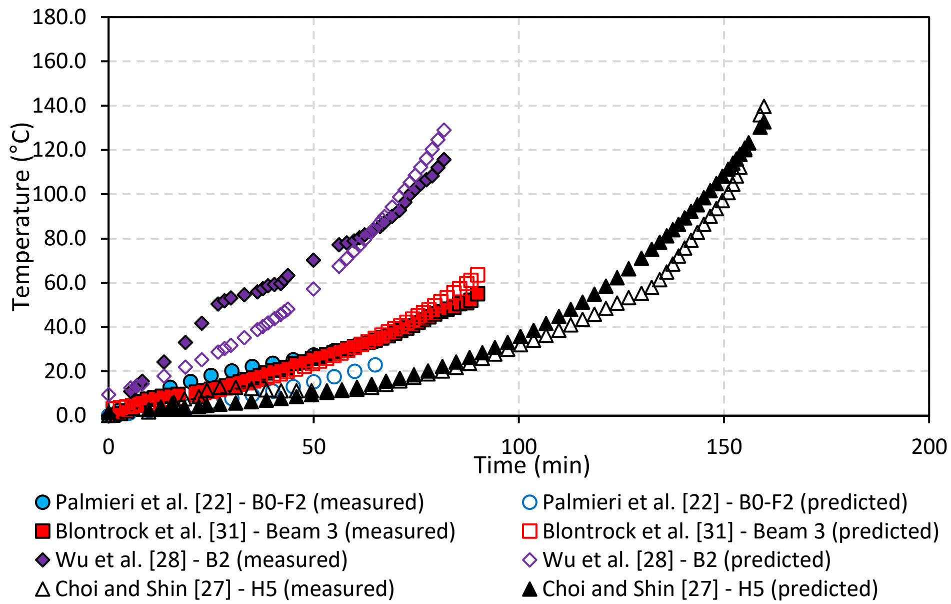


(a) Deflection of RC beams



(b) Validation against fire tests

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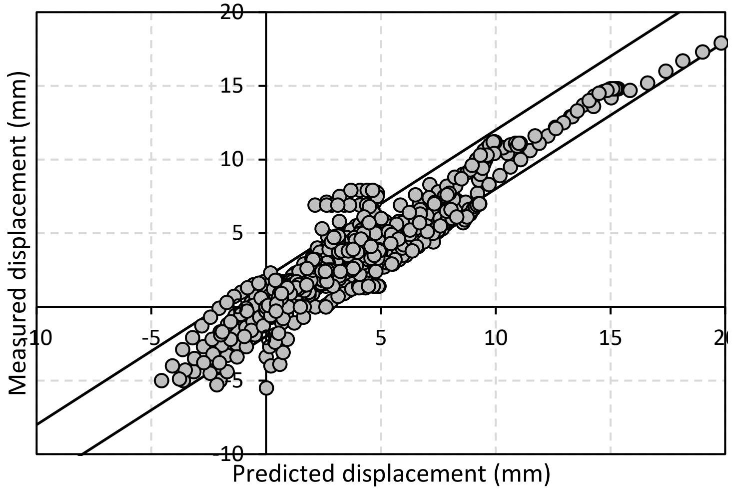
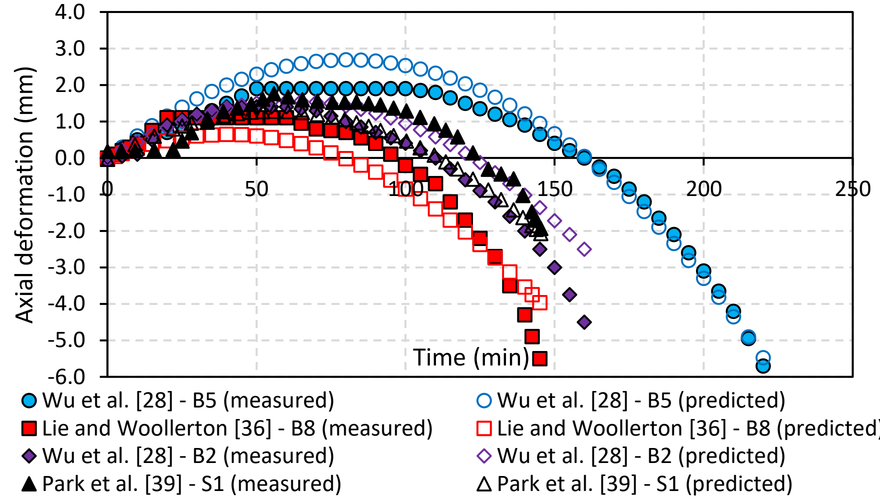


(c) Axial deformation of RC columns



(d) Validation against fire tests

Fig. 3 Validation of the AI-derived expressions

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It can be seen from above table as well as Fig. 3 that there is an adequate correlation between predicted and measured data points where the bulk of the predicted data points fall within the ±10 bounds. Both R^2 and R exceeds 94% for all expressions, except for that R^2 = 87.6 in the case of the general expression associated with predicting axial deformation of RC columns under fire conditions. This is due to the complexity arising from the unique behavior of RC columns under fire conditions i.e. expansion in the early stages of fire followed by contraction, possible creep, spalling, and sudden failure as discussed in Sec. 2.0. Given the fact that this expression traces the temperature-deformation history in terms of few millimeters and after a closer examination to Fig. 3 (specifically to Fig. 3d), which shows that derived expressions are of good accuracy, it is then believed that these expressions can be conveniently used to trace both thermal and structural response of RC beams and columns.

Still, few attempts were made to improve the prediction ability of this general expression. These attempts noted the sensitivity of the AI-model to the type of aggregate used in the RC columns. As a result, two additional expressions were specifically derived; one for carbonate aggregate concrete (with R^2 = 94.03, R = 96.98, and MAE = 0.53 mm), and the other is for siliceous aggregate concrete (with R^2 = 89.4, R = 94.48, and MAE = 0.89 mm). The two expressions have much improved prediction capability and could be used in lieu of the more general expression discussed above. By examining Fig. 4, it can be inferred that the AI-derived expression for carbonate aggregate concrete seems to better capture the structural response of RC columns made of carbonate aggregate under fire conditions, when compared to the expression for RC columns of siliceous aggregate. This is a reflection of the fact that minor spalling was reported in few RC columns used in the databases (despite being carried out on RC columns made of normal strength concrete (of siliceous aggregate)). Still, it can be safe to conclude that the developed AI framework and derived expressions can be used, with

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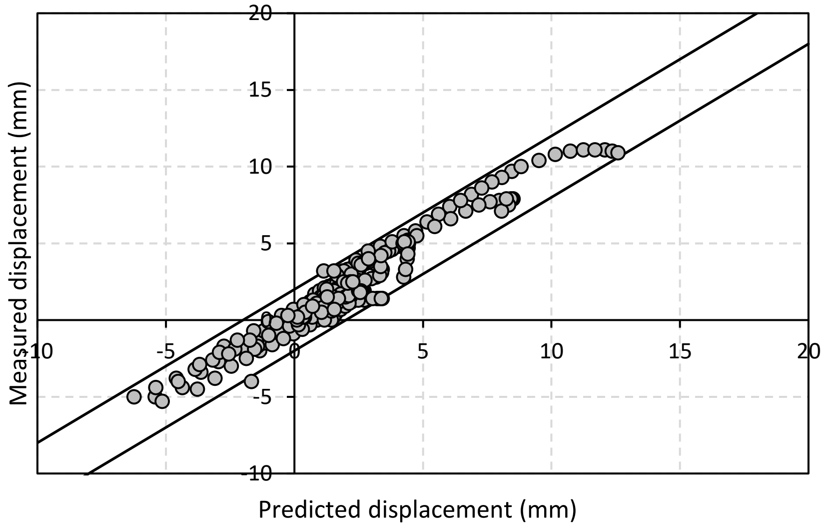
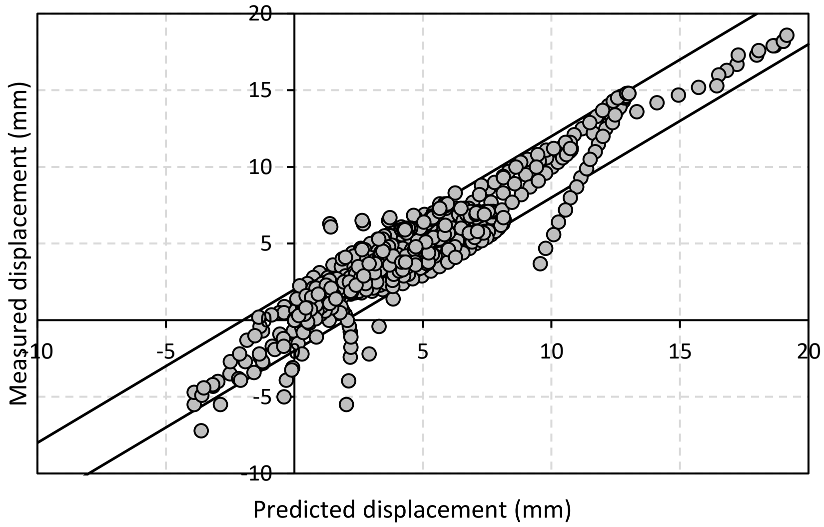
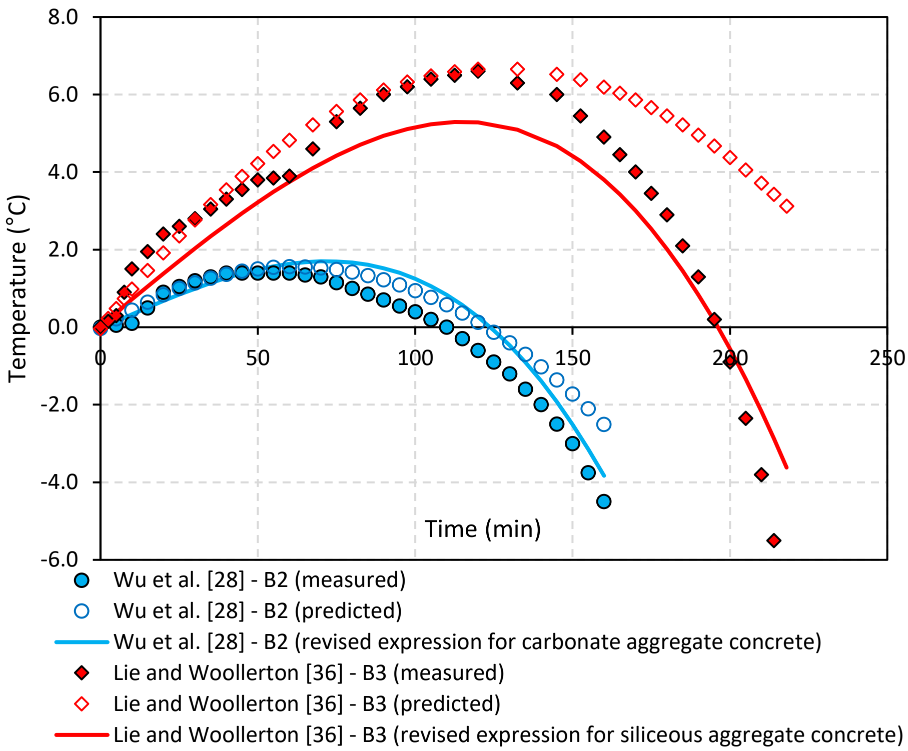
confidence, to safely predict temperature-time and temperature-deformation history of RC beams and columns with similar features to those described towards the end of Secs. 4.1 and 4.2.



(a) Carbonate aggregate concrete



(b) Siliceous aggregate concrete



(c) Comparison between accuracy of derived expressions

Fig. 4 Validation of AI-derived expressions for carbonate and siliceous aggregate concrete

Through simple mathematical manipulation, the derived models can be arranged to arrive at an expected failure time as adopted in number of fire standards, i.e. when a critical temperature is reached (e.g. T_{crit} = 593°C for steel rebars) or maximum mid-span deflection is exceeded ($\Delta > \Delta_{max} = L_c/400d$) where L_c and d are span and depth of a RC beam, respectively.

6.0 EXTENSION OF AI-DERIVED EXPRESSIONS TO NEW SCENARIOS

Figures 3 and 4 show the validity of the proposed expressions when examined against 30% of the data points that were part of the developed databases. To further validate the predictability of the derived expressions in new scenarios to which they have not been seen before, these expressions were tested to examine the fire response of new RC beams and

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columns that were not part of the developed databases. At the time of this study, these scenarios include different cross-sectional sizes, restraint conditions, and type of concrete class.

6.1 RC beams

In one study Carlos et al. [39] demonstrated the outcome of bending-dominant fire tests carried out on RC beams strengthened with carbon fibre reinforced polymer (CFRP) laminates. As part of this study, one beam made of compressive strength of 30.1 MPa, and with a rectangular cross section of 300 × 150 mm was not strengthened but tested under four-point bending and fire conditions (ISO 834). This beam, referred to as RC, was reinforced with two rebars of 10 mm diameter having a yield strength of 500 MPa. Another study from the same research group was conducted by Albuquerque et al. [38]. This study examined the fire response of slightly smaller beams (250 × 100 mm) with varying restraint conditions.

In a separate study, Ahmed and Kodur [49] also tested a similar RC beam, B01, under standard ASTM E119 fire conditions. This beam was of 254 mm width and 406 mm depth with a span of 3960 mm. The RC beam was reinforced with three no. 6 rebars (of Grade 60) and was subjected to a load level of 55%. Jiangtao et al. [41] also tested seventeen CFRP-strengthened RC beams and similar to Carlos et al. [39], one of these beams, T0, was unstrengthened and uninsulated. This beam was exposed to the ISO 834 fire exposure. The selected beam was 200 mm in width, 300 mm in depth and 2600 mm in span. The compressive of the concrete used in this beam was 43.2 MPa and this beam was reinforced with two rebars of 12 mm diameter. The yield strength of the rebars was reported at 414 MPa.

The validity of the proposed expressions in tracing fire response of these RC beams; that were not part of the training stage, is shown in Fig. 5. This figure shows how the derived expressions managed to effectively trace both thermal and structural behavior of these beams. While the AI-model was developed for RC beams with simply supported boundary conditions,

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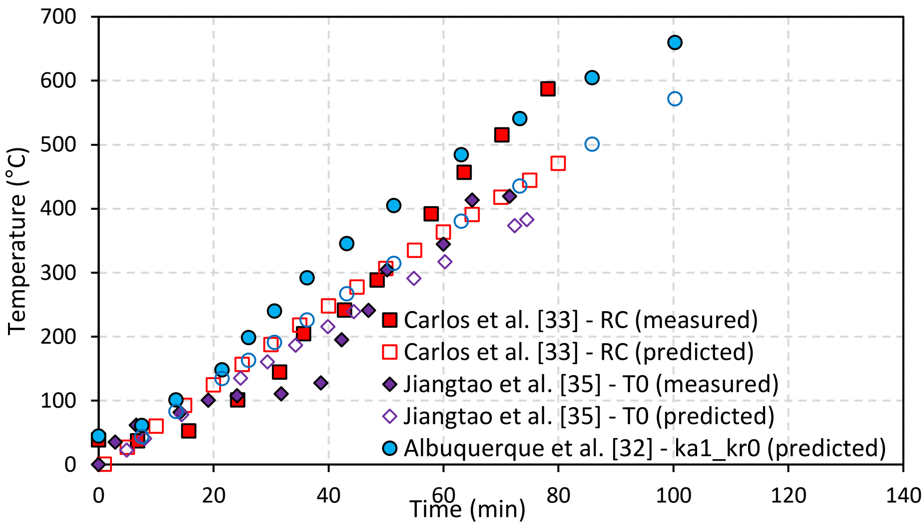
its performance in predicting structural response of RC beams with axial restraints was briefly examined. As expected, the derived expression seems to better capture the deformation history of simply supported beams but poorly captures the structural response of RC beams with axial restraints (and fire-tested by Albuquerque et al. [38]). This shows that the effect of restraint conditions is significant and requires to be explicitly included into the AI-model. Still, it is worth noting that the AI-derived expressions still manage to accurately capture thermal response of beams with varying restraint conditions (see Fig. 5a).



(a) Thermal response

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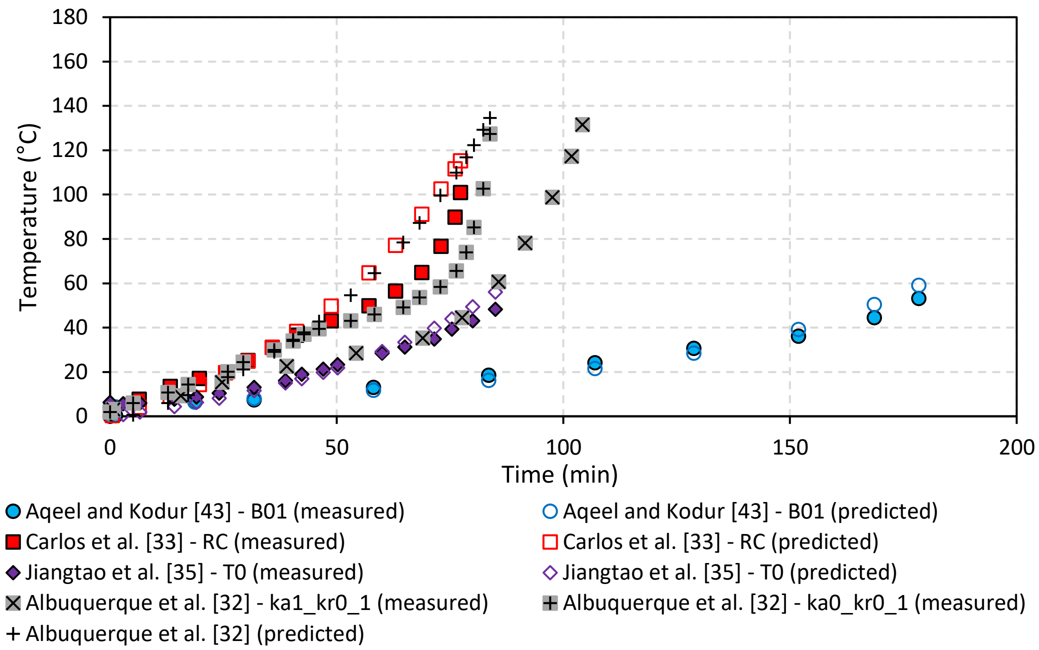

(b) Structural response

Fig. 5 Applicability of derived expressions in tracing fire response of RC beams

6.2 RC columns

Similarly, the applicability of AI-derived expressions in predicting thermal and structural response of RC columns in scenarios that were not part of the validation process was also investigated. In this process, the effect of cross-sectional shape (circular vs L-shaped vs T-shaped vs rectangular (mini-wall)), columns of varying boundary conditions (fixed-hinged), as well as those made of high strength concrete (f_c > 83 MPa) were examined.

In the study commissioned by the NRC and carried out by Lie and Woollerton [42], out of the 40+ columns, two RC columns were made of circular shape of a diameter of 355 mm and one of rectangular shape (mini-wall column of 914 × 203 mm). The thermal response (i.e. temperature rise in steel rebars) of circular columns, B11 and B12 of the second series as well as mini-wall (B6 of the third series), is plotted in Fig. 6a. It can be seen that although this expression was primarily derived using concrete columns of square cross-section, this expression still manages to capture the thermal response of these two circular columns. In a

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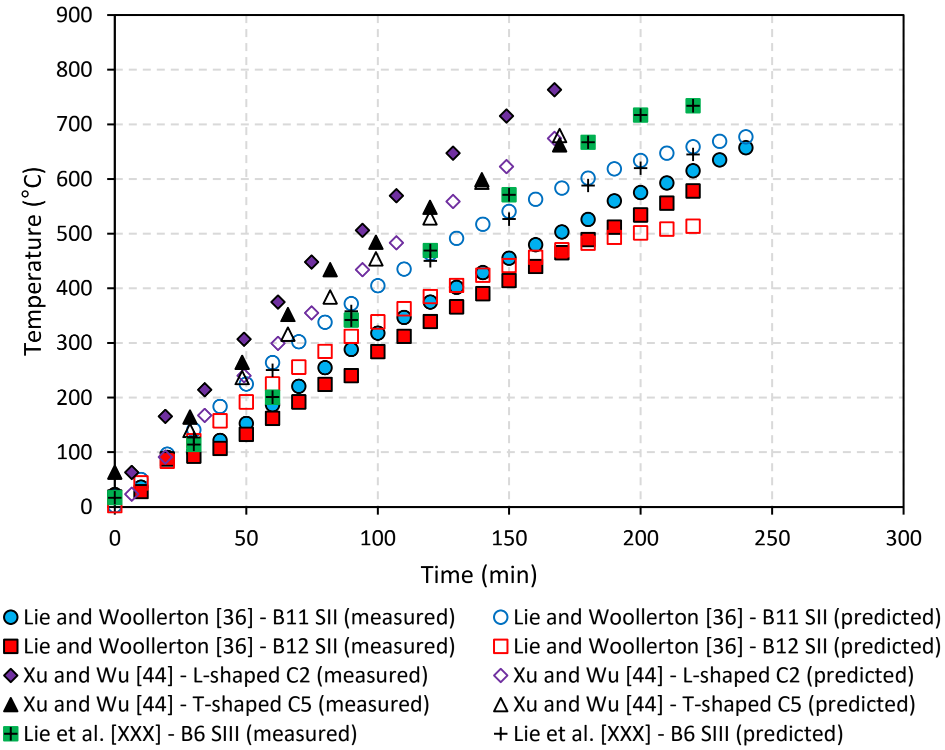
similar manner, this expression was also successful in tracing thermal response of two RC columns tested by Xu and Wu [50] as part of a unique experimental program aimed at evaluating fire resistance of RC columns with L- and T-cross sections. These columns were of a relatively larger cross-sections (equivalent to 500 × 500 mm), made of siliceous aggregate concrete and were tested under ISO 834 fire scenario.



(a) Effect of different cross-sectional shapes

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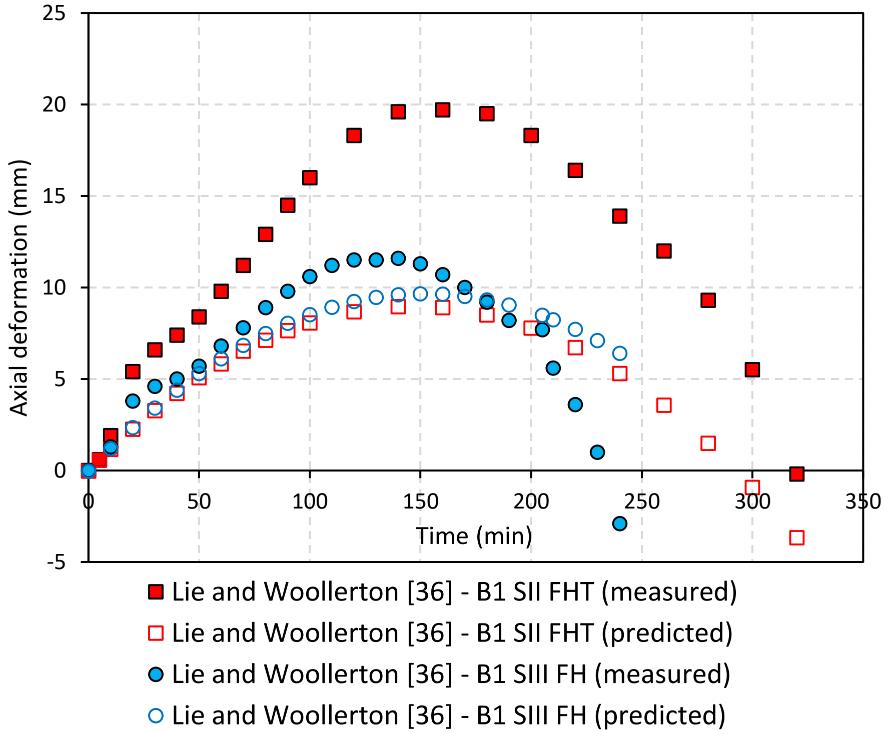
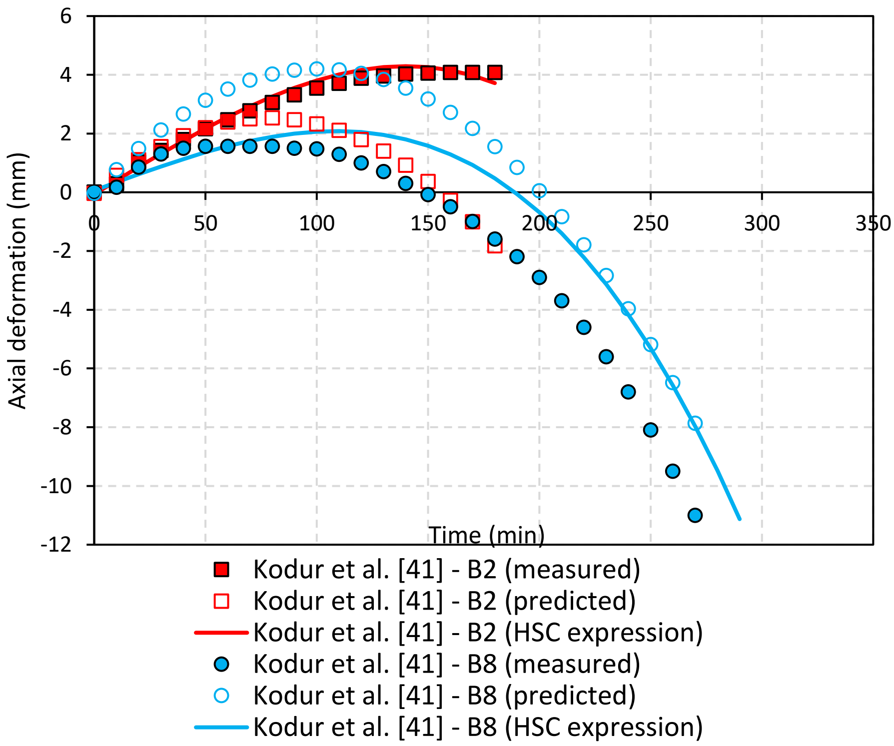


(b) Effect of restraint conditions



(c) Effect of high strength concrete

Fig. 6 Evaluation of applicability of AI-derived expressions in predicting thermal and structural response of RC columns

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Lie and Woollerton [42] also tested two RC columns, B1 of series II and B2 of series III, with fixed-hinge with free translation restraint conditions and fixed-hinged boundary conditions. The two columns were employed to assess the applicability of the derived general expression. As can be seen in Fig. 6b, the AI model seems to capture the main elements of structural response of the column with fixed-hinged restraint conditions but not the one with fixed-hinge with free translation restraint conditions. The additional allowance of translation was not properly captured, as expected, as the AI-derived expressions was mainly developed using data points from RC columns with fixed-fixed conditions. On a similar note, the derived expression was also unable of capturing the structural response of RC columns with unique cross-sections as in those tested by Xu and Wu [50] (data plots for these columns are not shown in Fig. 6b).

The applicability of the derived expression in predicting structural fire response of RC columns made of high strength concrete (HSC) with a compressive strength exceeding 83 MPa was also investigated. Since very few fire tests were carried out on RC columns made of HSC, two RC columns, B2 and B8, were selected from a study carried out by Kodur et al. [47]. These columns had similar geometric configuration to those tested by Lie and Woollerton [42] and were made of concrete with a compressive strength of 126 and 119.7 MPa, respectively. An examination of measured and predicted response as plotted in Fig. 6c shows that the AI-derived expression manages to better capture the structural response of these columns within the first hour of the fire after which predicted response seem to vary. In essence, HSC columns, such as the ones tested by Kodur et al. [47], are very vulnerable to fire-induced spalling. The occurrence of spalling simply changes fundamental aspects of fire response of RC columns as

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spalling significantly reduces cross-sectional size and expose internal reinforcement to direct temperature rise, both of have adverse effects on fire performance of HSC RC columns.

The derived expression listed in Table 3 was then slightly modified to account for higher compressive strength of concrete in columns made of HSC. The revised expression, which implicitly accounts for tendency of HSC to fire-induced spalling, seem to have better prediction capability. This expression, which is suitable for carbonate and siliceous aggregate concrete, is given as:

$$\Delta = 1.855 + 0.034t + 0.0309t\sin(-1.07.89f_c) + 0.00894t\sin(1.529f_c) + \sin(221.67\frac{\rho\, P}{A}) - 0.023f_c - 7.91\times10^{-7}t^3 + 0.000093f_y \quad \text{Eq. 1}$$

The statistical metrics of this expression are: R^2 = 96.12, R = 98.0, and MAE = 0.51 mm. The predicted axial deformation using above expression in the case of columns made of HSC is plotted in Fig. 6c. This expression is still being calibrated and will be further improved upon and discussed in a companion study.

In general, the degree of precision in predictions obtained from AI-derived expressions is higher against RC beams and columns with common features with the specimens used in training/developing the AI model. Further discussion on suitability of derived expressions in above scenarios as well as additional cases is presented in the following section.

7.0 PRACTICAL IMPLICATIONS, CHALLENGES, AND FUTURE RESEARCH

This study presents a concept that capitalizes on the fact that artificial intelligence (AI) and machine learning techniques seem to be rapidly evolving and this favors utilizing such methods into engineering applications. In this optimistic view, one must realize that the simplicity of AI-derived or AI-developed approaches does not come easily. As such, some of the challenges and limitations of utilizing AI into practical solutions and applications need to be highlighted. For a start, the prediction capability of an AI-model largely depends on the

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number of observed/measured input data points. From the point of view of the study, it is without a doubt that available/useful information on fire tests is limited, keeping in mind the large margin of variability and the fact that very few tests were carried out with duplicated specimens. This has been illustrated in few cases presented in this study, notably those associated with RC beams made of HSC, RC beams and columns with varying restraint boundary conditions and tendency to fire-induced spalling. In general, having few (or limited/useful) data points limits development of properly trained AI-models/expressions with accurate prediction capabilities.

On a similar note, the bulk of the 40+ RC columns tested by Lie and Woollerton [42] as well as Kodur et al. [47] were reinforced with steel rebars with a yield strength of 414 and 400 MPa, respectively. If all of these specimens were to be input into the developed databases, then steel grade, as a random variable, may deem to be an insignificant input parameter. This is because the AI framework can recognize that most of these specimens share the same steel grade and as a result would shy from further examining such a factor (i.e. by normalizing its effects and neglecting its contribution to a derived expression – in a similar manner to that of temperature-dependent material properties). In order to overcome this issue, only handful of specimens were used from the aforementioned experimental programs. This discussion clearly infers that having limited experimental works (documented observations) seem to be a key challenge that may limit full utilization of AI into structural fire engineering and fire safety problems.

The author hopes that upcoming experimental (as well as numerical) works will lead to developing much improved and intelligent cognitive frameworks. Next generation AI-based models are expected to accommodate common and advanced construction materials, complex geometries, different fire exposures (e.g. travelling/realistic fire), complicated phenomena (e.g.

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debonding, restraint conditions) etc. Similar to these derived in this study, future AI models can also evaluate fire response of structural members at an arbitrary point in time or through an iterative (step-by-step) procedure. Such models can come in handy in future infrastructure, such as those of cognitive and autonomous abilities [51].

8.0 CONCLUSIONS

This work fosters artificial intelligence as a modern assessment tool into structural fire engineering and fire safety applications. This study highlights the development of a cognitive framework capable of predicting thermal and structural response of fire-exposed RC beams and columns as well as sheds light into some of the limitation and key challenges associated with incorporating AI into fire engineering and safety. The following key items could also be drawn from the results of this work:

- There is an urgent demand to cultivate simple and automated assessment methods to improve current state of structural fire engineering. Such methods can be developed using AI.
- The derived AI-based expressions, together with cognitive framework used to derive these expressions, are able to accurately predict thermal and structural response of RC beams and columns under fire conditions.
- A few challenges continue to limit integrating AI-based approaches to fire problems, i.e. limited fire tests, and some of these challenges are expected to be overcame through collaborative works and interdisciplinary efforts.

9.0 Conflict(s) of interest

The author declares no potential conflict(s) of interest with respect to the research, authorship, and/or publication of this article.

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This is a preprint draft. The published article can be found at: https://doi.org/10.1016/j.engappai.2019.03.004

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11.0 APPENDIX

Two examples illustrating application of AI-derived expressions to evaluate fire response of a typical RC beam and RC column is listed herein.

11.1 Example - RC beam

In one study Blontrock et al. [37] tested a beam, Beam 3, under ISO 834 fire exposure. This beam was of height of 300 mm, width of 200 mm and a span of 3150 mm. The tensile reinforcement consists of 2 bars of 16 mm diameter (ρ = 0.0067). The compressive strength of the siliceous-based concrete used in this beam was 59.47 MPa. The concrete cover to steel reinforcement was 25 mm. The beam was subjected to a loading equivalent to 46% of its ultimate flexural capacity. The input parameters were collected from the experimental study and are listed into Table A.1.

Table A.1 Input parameters as obtained from Blontrock et al. [37]

Parameter/Case	**Compressive strength of concrete (f_c)**	**Yield strength of steel (f_y)**	**Steel reinforcement ratio (ρ)**	**Load level (P)**	**Aggregate type (A) – siliceous (A = 2)**	**Bottom cover to steel reinforcement (C_b)**	**Side cover to steel reinforcement (C_s)**
Thermal response	-	-	-	-	2	25	25
Structural response	59.47	591	0.0067	0.46	-	25	-

Thermal response:

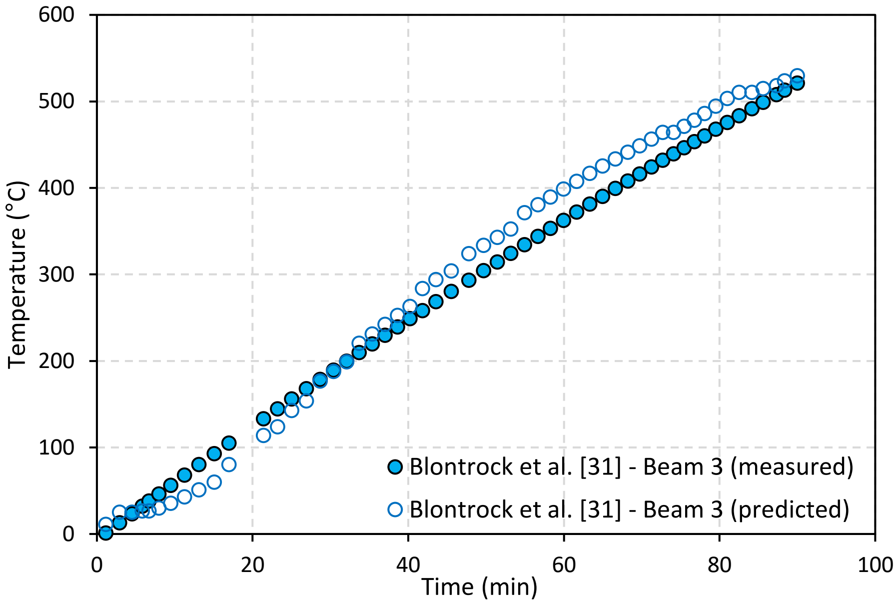
Temperature rise in steel rebars at any point in time (say 45.5 min) can be evaluate using the following expression:

$$T = 0.0169tC_b + \frac{182.64t}{C_s} + t\sin(5.21C_b) - 6.43 - 0.0098t^2$$

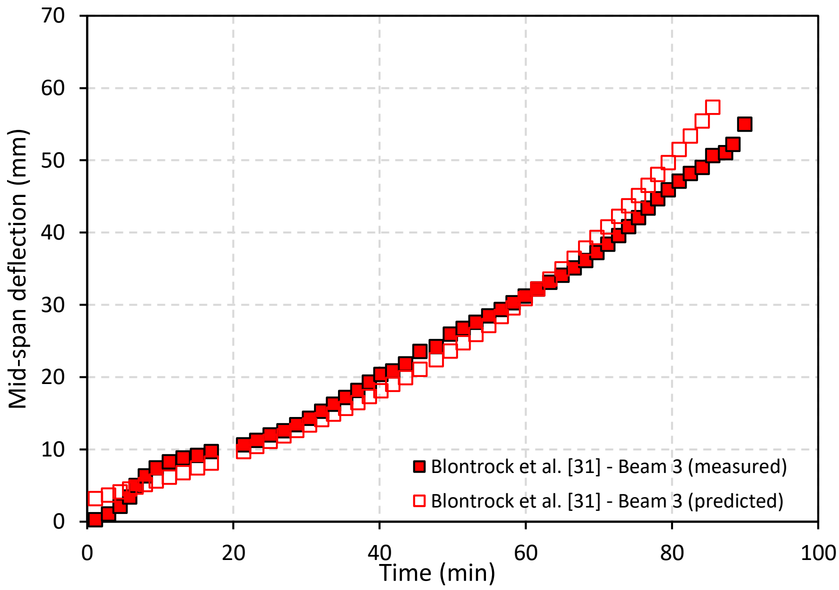
Such that:

$T = 0.0169 \times 45.5 \times 25 + \frac{182.64 \times 45.5}{25} + 45.5 \times \sin(5.21 \times 25) - 6.43 - 0.0098 \times 45.5^2 = 280.4\ ℃$, which is within 7.9% of measured value (304.3°C).

The same expression can be applied in an iterative manner to evaluate temperature rise in rebars throughout the whole fire. A comparison between measured and predicted results is shown in Fig. A.1a.



(a) Thermal response



(b) Structural response

This is a preprint draft. The published article can be found at: https://doi.org/10.1016/j.engappai.2019.03.004

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Fig. A.1 Comparison of thermal and structural response in Beam 3 tested by Blontrock et al. [37]

Structural response:

The structural response (mid-span deflection) of the same beam can also be evaluated at any given temperature (say 53 minutes) using the following expression:

$$\Delta = 36.2\, exp(0.023t)\cos(\sin(23040\, P))\cos(\sin(2.28\times10^{-8}\, P)) - 0.206C_b - 9.28\sin(f_y) - 12.59\exp(0.0236t) + 4.5 + 0.105t + 2.299\times10^{-6}t^{f_c\rho\, P}$$

Such that:

$$\Delta = 36.2\, exp(0.023\times53)\cos(\sin(23040\ \times0.46))\cos(\sin(2.28\times10^{-8}\times0.46)) - 0.206\times25 - 9.28\sin(591) - 12.59\exp(0.0236\times53) + 4.5 + 0.105\times53 + 2.299\times10^{-6}\times53^{(59.47\times0.0067\times0.46)} =$$

$25.9\ mm$, which is within 6% of measured deflection (27.6 mm)

The same procedure can also be applied in an iterative manner to evaluate rise in mid-span deflection. A comparison between measured and predicted results in shown in Fig. 10.Ab.

11.2 Example - RC column

In a similar manner to example 10.1, thermal and structural response of RC column, B2, tested by Wu et al. [34] can also be evaluated. This column was of a square cross section (300 × 300 mm) and was made of carbonate aggregate concrete. The concrete cover thickness to reinforcing steel was 48 mm. This reinforcement was of Grade 340 MPa and the compressive strength of concrete measured at 29 MPa. The input parameters were collected from the experimental study and input into Table A.2.

Table A.2 Input parameters as obtained from Wu et al. [34]

This is a preprint draft. The published article can be found at: https://doi.org/10.1016/j.engappai.2019.03.004

Please cite this paper as:
Naser M.Z. (2019). "AI-based cognitive framework for evaluating response of concrete structures in extreme conditions." Engineering Applications of Artificial Intelligence. Vol. 81, pp. 437-449. (https://doi.org/10.1016/j.engappai.2019.03.004).

Parameter/Case	**Compressive strength of concrete (f_c)**	**Yield strength of steel (f_y)**	**Steel reinforcement ratio (ρ)**	**Load level (P)**	**Aggregate type (A) – carbonate (A = 1)**	**Bottom cover to steel reinforcement (C_b)**	**Side cover to steel reinforcement (C_s)**	**Width of member (b)**
Thermal response	-	-	-	-	1	-	48	300
Structural response	29	340	0.0169	0.84	1	-	-	-

Thermal response:

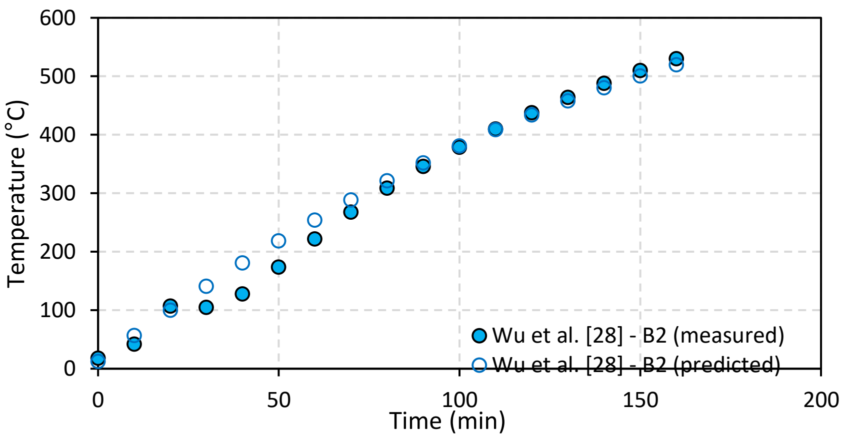
Temperature rise in steel rebars at any point in time (say 140 min) can be evaluate using the following AI-derived expression:

$$T = 0.0922b + 0.332t\,A + 0.331t\,C_b - 11.677t - 15.125A - 0.0086t^2$$

thus,

$$T = 0.0922 \times 300 + 0.332 \times 140 \;\times 1 + 0.331 \times 140 \;\times 48 - 11.677 \times 140 - 15.125 \times 1 - 0.0086 \times 140^2 = 480.4°\text{C}$$, which is with 2% of measured temperature (488°C).

The same procedure can be carried out in an iterative (step-by-step approach) to evaluated temperature rise in rebars. A comparison between measured and predicted results in shown in Fig. A.2.



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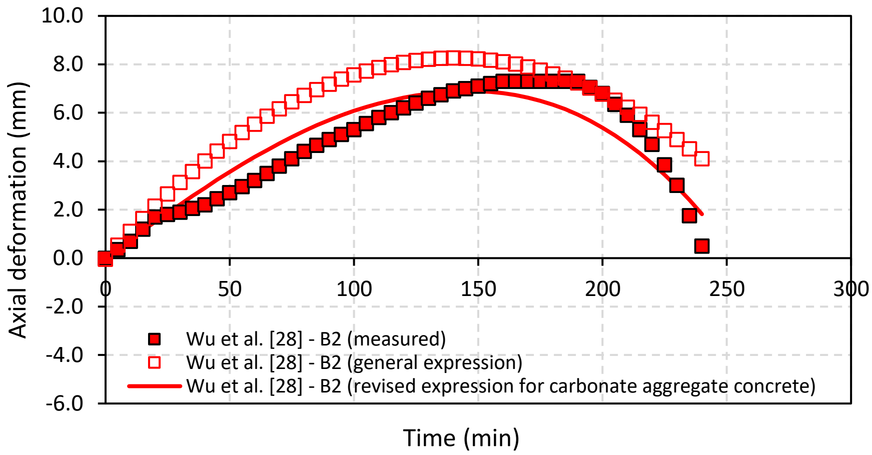
(a) Thermal response



(b) Structural response

Fig. A.2 Comparison of thermal and structural response in column B2 tested by Wu et al. [34]

Structural response:

The structural response (axial deformation) of this column can also be evaluated towards the end of the fire experiment (at 125 minutes) using the following expressions:

General expression:

$$\Delta = 0.085t + 0.0081t\sinh(\sinh\left(\text{atanh}\left(\sin(0.265f_c)\cos\left(\text{acosh}\left(\frac{P}{\rho}\right)\right)\right)\right) - 0.039t\,A - 0.000421t^2 - 0.0599t\,A\cos\left(\text{acosh}\left(\frac{P}{\rho}\right)\right) - 0.0001f_y$$

$$\Delta = 0.085\times125 + 0.0081\times125\times\sinh(\sinh\left(\text{atanh}\left(\sin(0.265\times29)\cos\left(\text{acosh}\left(\frac{0.84}{0.0169}\right)\right)\right)\right) - 0.039\times125\times1 - 0.000421\times125^2 - 0.0599\times125\times1\times\cos\left(\text{acosh}\left(\frac{0.84}{0.0169}\right)\right) - 0.0001\times340 = -0.13\,mm$$

Revised expression for carbonate aggregate concrete:

$$\Delta = 0.043t + 0.0063t\tan f_c{}^2 - 4.701\times10^{-8}P\frac{t^3}{\rho} - 0.0053t\,tan f_c{}^2\cos\left(tan\ f_c{}^2\right) - 0.000085f_y$$

$$\Delta = 0.043\times125 + 0.0063t\tan 29_c{}^2 - 4.701\times10^{-8}\times84\times\frac{125^3}{0.0169} - 0.0053\times125\ tan\times 125^2\cos(tan\ 125^2) - 0.000085\times340 = -0.08\,mm.$$

Predictions from both of these expressions are within 0.82 mm when compared to the measured axial deformation of -0.9 mm.