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Concrete under Fire: An Assessment through Intelligent Pattern Recognition

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ABSTRACT

Concrete, a naturally resilient material, often undergoes a series of physio-chemical degradations once exposed to extreme environments (e.g. elevated temperatures). Under such conditions, not only concrete weakens but also becomes vulnerable to fire-induced spalling; a complex and exceptionally random phenomenon. Despite serious efforts carried out over the past few years, we continue to be short of developing a methodical procedure that enables accurate assessment of concrete under elevated temperatures with due consideration to fire-induced spalling. Unlike traditional works, this study aims at investigating fire behavior of concrete through a modern perspective. In this study, a number of intelligent pattern recognition (IPR) techniques that capitalize on artificial intelligence (AI) are applied to derive expressions able of accurately trace the response of normal and high strength as well as high performance concretes under elevated temperatures. These expressions take into account geometric, material, and specific features of structural components in order to examine fire response as well as to predict occurrence of fire-induced spalling in concrete structures. These expressions were developed through rigorous and data-driven analysis of actual fire tests and were derived to implicitly account for physio-chemical transformations in concrete and as such do not require collection/input of temperature-dependent material properties nor special analysis/simulation. This study also features the development of an IPR-based database and fire assessment software that can be used to examine

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fire performance of concrete members and be regularly updated as to continually improve the accuracy of the proposed expressions.

Keywords: Concrete; Fire; Spalling; Pattern recognition; Artificial intelligence.

1.0 INTRODUCTION

Due to the unique properties of concrete, this material has been successfully implemented in ambient and extreme working conditions (i.e. nuclear power plants) [1,2]. Concrete, together with its derivatives, is perhaps one of the only building materials that do not require special treatment/proofing when utilized in applications associated with elevated temperatures or rapid temperature changes [3]. The exceptional behavior of concrete under elevated temperatures can be attributed to a combination of its inert thermal properties (i.e. low thermal conductivity and high specific heat capacity) as well as slow degradation in mechanical and deformational properties (i.e. strength, modulus etc.) [4]. As a result, not only concrete maintains its integrity under extended exposure to elevated temperatures but can also promptly recover a large portion of its original strength post exposure to such trauma [5]. This is especially true for traditional concretes [6].

In the case where modern (i.e. high strength/performance) concretes are exposed to elevated temperatures, such an extreme loading may adversely affect the very nature of these materials. Such concretes are especially tailored to maximize its packing density and to incorporate novel additives etc. as to improve essential properties and performance under ambient conditions [7]. In the event that high strength/performance concrete is subjected to fire, the dense nature of this concrete; accompanied with its inherently low permeability, water/cement ratio, and capillary voids, promotes fire-induced spalling [8]. In fact, a number of researchers has pointed out that the higher the complexity of concrete mix (i.e. compressive strength), the more vulnerable the concrete becomes to spalling, and the more intense this phenomenon turns out to be [9].

Fire-induced spalling can be defined as the breakout of chunks occurring when concrete is exposed to fire conditions [5]. The occurrence of spalling can jeopardize the integrity of concrete structures on a number of fronts. For example, fire-induced spalling abruptly slims overall cross sectional size and hence reduces available sectional capacity in a concrete member. This reduction in sectional size is: 1) unaccounted for in the design process, 2) not uniform across the span of the member, 3) reduces bond strength at the concrete-steel interface (in reinforced concrete (RC) members), 4) exposes steel reinforcement as well as internal concrete layers to elevated temperatures; causing thermal shocks (due to the rapid and sudden rise in temperature) and thereby accelerates the rate of strength and modulus deterioration leading to additional losses in sectional capacity, and 5) leads to local instability which may trigger progressive collapse [10]. While the deterioration of strength in constituent materials can slowly reduce fire resistance of a concrete structural member over fire exposure time, failure through abrupt damage or instability can be much more pronounce, sudden and drastic as duly noted in recent investigations [11].

The above discussion infers that fire-induced spalling complicates fire assessment of newly designed and existing concrete structures as well. In effect, a cross examination of published works reveals that an accurate fire analysis and design such as that to predict thermal and structural response of concrete structures may not be truly realized without given due consideration to the fire-induced spalling phenomenon [12,13]. While it is true that currently adopted fire codes and standards provide tabulated listings and assessment methods to assign fire resistance ratings to concrete members, it is interesting and equally concerning to note that these listings/assessment methods were developed based on fire tests that were: 1) conducted under standard fire conditions – often argued to be of different characteristics (i.e. heating rate/duration) and not representative

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of actual fire conditions [14], 2) carried out in 1960-1990s – on concretes of much simple microstructure and features than that used nowadays and as such have not been validated against modern concretes, and 3) and do not necessarily account for fire-induced spalling nor provide authoritative solutions to mitigate such phenomenon [15]. This represents one of the main motivations behind this work.

The second motivation of this work is the fact that fire-induced spalling is a complex and often described to be more of a random phenomenon with a multitude of dimensions and governing factors [8,14]. Thus, understanding such a phenomenon could perhaps be better realized through a modern perspective; one that utilizes a revolutionary paradigm. In this data-driven perspective, intelligent pattern recognition (IPR) techniques, which capitalizes on the notion that artificial intelligence (AI), can be utilized to recognize patterns and assess highly complex phenomena, is applied. While traditional soft computing methods have been primarily used to optimize concrete mix designs [16,17], a review of published works shows that only one study has been carried out to examine fire-induced spalling of concrete through neural networks (NN) [18]. In this particular study, McKinney and Ali [18] developed a simple NN to classify fire-induced spalling phenomenon in small-scale concrete columns. Unfortunately, this early attempt only incorporated a primitive NN algorithm supplemented with limited number of observations obtained from one particular mix, was only applicable to qualitatively classify spalling and did not develop tools nor expressions to predict fire-induced spalling.

With the advent advancements in simulation and computer sciences, this study applies a combination of novel IPR techniques, i.e. deep learning (DL) and genetic programing (GP), together with multi-linear regression (MLR), to derive expressions able of accurately predicting occurrence of fire-induced spalling as well as fire resistance of RC columns made of different types of mixes including (normal strength, high strength and high performance concretes). In addition, the derived expressions can also be applied to RC members with varying cross sectional sizes, concrete compressive strength, concrete cover in addition to being subjected to concentric or eccentric loading of various magnitudes. Furthermore, the IPR-based expressions implicitly account for temperature-dependent material properties of concrete and reinforcing steel, and as such do not require input of such properties nor special simulation/analysis procedure. In total, seven expressions were derived; four for evaluating fire-induced spalling of concrete and three for evaluating fire resistance of RC columns. The validity of these expressions was examined against actual fire-tested RC columns collected from various fire tests. This study also features the development of a universal IPR-based database as well as a dedicated fire assessment software that can be freely shared among interested researchers to be regularly tested and updated as to continually improve the accuracy of the proposed IPR frameworks.

2.0 FACTORS GOVERNING FIRE BEHAVIOR OF CONCRETE STRUCTURES

When fire breaks out in a RC structure, temperature in a structural member (say a column) starts to slowly rise due to the low thermal conductivity and high specific heat of concrete. In the early stages of fire, a thermal gradient develops in which the temperature at the exterior faces of this concrete column is hotter than that at internal layers. With the continuous exposure to elevated temperatures, this thermal gradient reduces as internal layers also start to heat up. This rise in temperature adversely affects strength and modulus properties of both concrete and steel reinforcement and causes degradation. Since the bulk of the RC column comprises of concrete, the overall temperature-induced degradation is of slow rate as the mechanical properties of concrete degrades slowly. However, this degradation could be accelerated by fire-induced effects such as cracking, or most notably spalling.

Of interest to this study is fire-induced spalling. This spalling can be broadly grouped under two classes; explosive spalling and corner spalling [5]. The first type of spalling occurs with a distinct violence and often during the early stages of fire exposure [5,19]. On the other hand, corner spalling mainly occurs gradually and along exposed surface and corners of edged members (i.e. rectangular or square RC columns/beams) due to unrestrained thermal expansion in the transverse direction. The effects of this type of spalling is often minor and cosmetic [20].

In any case, fire-induced spalling in concrete can be explained through two main mechanisms: 1) pore pressure development and moisture migration of free and physically or chemically bound water; especially once concrete reaches a temperature in the range of 250-420°C [8,9,19,21], and 2) due to the development of a thermal gradient and a parallel stress gradient that breaks concrete once reaches material failure limit (Bažant and Kaplan [22], Ulm et al. [23]). Unfortunately, the above mechanisms are often used in a “if it fits, then it makes sense” manner to explain occurrence of fire-induced spalling in concrete as notable studies point out that there is enough experimental evidence to verify the validity of above mechanisms, as well as to contradict their rationales [19,24–27]. A more detailed and up-to-date discussion on conflicts between spalling mechanisms and observations from fire tests with regard to this phenomenon can be found elsewhere [9,15].

In lieu of above discussed factors, spalling phenomenon seems to be also governed by a number of factors that are predominantly associated with concrete material and mix proportions, geometric and configuration/size features, and those relating to applied loading, intensity, heating rate, and exposure duration (i.e. loading and fire conditions)[28]. This section sheds lights on some of these critical factors:

2.1 Material and mix proportions

The factors that govern fire behavior of concrete structures at the material level comprises of mix proportion/components (i.e. aggregate type, water/cement ratio etc.) along with any supplementary additives (e.g. superplasticizers, fibers, silica fume etc.). There are two main types of aggregates that are commonly used in concrete mix; carbonate (limestone) and silicate (containing quartz). When compared, carbonate aggregate provides a relatively higher fire resistance than that of silicate aggregate concrete (by up to 10%). This is due to the development of an endothermic reaction occurring around 700°C in carbonate aggregates which: 1) lowers the rate of temperature rise, and 2) slows down strength deterioration [28].

Incorporating fiber additives often positively improves key characteristics of concrete such as strength and durability. Two types of fibers; steel and polypropylene, are of interest to fire researchers as these fibers have been linked to control/minimize the extent of fire-induced spalling. In general, Kodur [14] suggests that adding steel fibers (of about 1.75% by weight) can mitigate fire-induced spalling through improving tensile strength property of concrete, as well as slowing down rate of degradation in tensile strength at elevated temperatures. In case polypropylene fibers are added (at about ~0.15% of mix volume), these fibers can also minimize fire-induced spalling. The mechanism at which polypropylene fibers enhance fire behavior of concrete can be summed by the fact that these fibers melt at 160–170°C and thus create additional pores to facilitate releasing and/or reducing concentration of pore pressure in concrete [3]. In other words, the melting of polypropylene fibers increases the permeability of dense concretes.

On a similar note, the type/proportion of materials used in concrete mix highly influence the compressive strength of hardened concrete; which is another factor that seems to govern breakout and intensity of fire-induced spalling. In general, concretes of relatively higher compressive strength (e.g. exceeding 70 MPa) are normally achieved through addition of auxiliary fillers i.e. silica fume, fly ash etc. Incorporating such products increases density, lowers permeability of concrete, and limits the creation of interstitial voids and hence indirectly promotes spalling [29]. Since the naturally low permeability of dense microstructures can entrap moisture for prolong periods, high moisture content (or relative humidity exceeding 80%) has also been linked to increasing concrete's vulnerability to spalling. Other factors that may also influence occurrence of spalling may arise from physio-chemical transformations occurring in cement paste, as well as thermal incompatibility between different materials used in concrete mix etc. [28].

2.2 Member configuration

While increasing the cross sectional size of a concrete member positively improves its fire resistance, this also comes with an increased risk of spalling; simply due to the fact that enlarging the volume of a concrete member also increases the amount of moisture it can hold. In two separate studies, both Hertz [21] and Kanéma et al. [30] reported that fire-induced spalling occurs more often in large concrete specimens as oppose to specimens made of the same concrete mix but of smaller size. In fact, Kanéma et al. [30] noted that smaller specimens did not spall despite undergoing similar levels of thermal gradient to that in larger specimens. Liu et al. [9] explained

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this phenomenon by rationalizing how small-sized specimens can better facilitate escape of vapor; consequently, resulting in a lower pore pressure than that in large specimens.

The shape of a concrete member can also influence its performance under fire conditions together with its susceptibility to spalling. For example, an edged specimen often has a poorer fire resistance as that of a round (circular) specimen of equivalent area/volume [14]. This is credited to the observation that sharp edges easily attract heat through bi-directional transmission of temperature i.e. from adjacent surfaces [5]. This effect promotes quicker evaporation of trapped moisture as well as faster degradation in mechanical properties. This has been noted by a number of researchers and been well-documented in a number of fire codes and standards [5,12].

The type and configuration of embedded steel reinforcement are other factors that can be grouped under member/specimen this category. For example, RC members reinforced with traditional (non-prestressed) reinforcement often achieve higher fire resistance and experience less susceptibility to spalling. This is unlike that of members incorporating prestressed reinforcement as these members: 1) are of slimmer cross section (lower thermal mass), 2) are of denser nature due to inclusion of fillers (inclination to entrap moisture), and 3) undergo faster degradation of properties and higher tendency to creep in prestressing steel. On a similar note, the size and configuration of transverse reinforcements (i.e. ties, spirals) has also been shown to affect fire-induced spalling of RC columns. Kodur [14] noted how columns with improved tie configuration (i.e. bent ties at 135°, and with closer tie spacing) can achieve better fire performance than that in columns with regularly bent ties at 90° or of ties spaced at larger spacing.

2.3 Loading and fire conditions

The magnitude and arrangement of structural (gravity) loading can equally be of a positive or negative impact upon heated concrete. From one end, presence of loading places the material under a continuous compression state and this inhibits the development of cracks. Khoury [5] has noted how such effect can lead to a lower degradation in compressive strength and modulus properties in loaded and heated concrete cylinders as oppose to heated and unloaded specimens. On the other end, a stressed specimen may become susceptible to spalling as the applied loading generates an additional component of stress that could add (amplify) the effect of steam-based pore pressure. This can further worsen in the case where a member is loaded with eccentric loading. Such a loading configuration develops tensile stresses/cracking on the side experiencing tensile forces.

As thermal energy resulting from fire is the main cause behind evaporating of moisture as well as generating temperature-induced transformations, the intensity (i.e. maximum temperature reached and heating rate) and duration of heating also influence behavior of concrete under elevated temperatures. A number of researchers have identified critical temperatures that mark transition points in the behavior of concrete material [5,9]. These temperatures can be roughly summed into three ranges, namely; 250-420°C which is associated with fire-induced spalling[‡], 300°C indicating initiation of strength loss in concrete, and 550-600°C marking the dominance of severe mechanical degradation and creep effects in concrete.

[‡] Spalling may also occur at relatively higher temperatures in the range of 700-1200°C due to decarbonation of calcium carbonate and complete dehydration of concrete [9]. This spalling is referred to as thermo-chemical spalling and often occurs in later stages of fire.

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While this section delivered a broad picture of influencing factors that govern occurrence of fire-induced spalling in concrete structures, it is worth noting that a more comprehensive review on other parameters such as those grouped under material and mix proportion (e.g. cement type, degree of pore saturation, strain rate, air-entraining agents etc.), member configuration (grade and size of reinforcement, supplementary mesh reinforcement, installation of thermal barriers etc.), and loading and fire conditions (viz. restraint conditions, gas temperature, cooling phase etc.) which may also influence fire behavior of concrete structures is spared herein for brevity but can be found in the following works [31–33].

3.0 INSIGHTS INTO IPR MODEL DEVELOPMENT

Artificial intelligence (AI) encompasses a realm of modern and especially designed computational techniques that attempts to mimic human-like reasoning process to solve complex phenomena [34,35]. Such phenomena may not be truly understood (nor analyzed) through traditional methods (i.e. statistical analysis, analytical derivation etc.) or may require advanced computing environments (software/workstations) to be realized. Intelligent pattern recognition (IPR), a sub-field of AI, thrives on developing evolutionary algorithms that are able to analyze large observations with a multitude of dimensions (i.e. inputs) hoping to establish a relation between such variables (inputs) and expected output(s) of a given phenomenon. These algorithms learn patterns hidden in data points through systematic analysis and once an initial pattern is identified, this pattern becomes the first step into solving the complex phenomenon through training and adaptive learning [36].

In this study, traditional multi-linear regression (MLR) is applied together with a hybrid combination of contemporary IPR techniques i.e. deep learning (DL) and genetic programing

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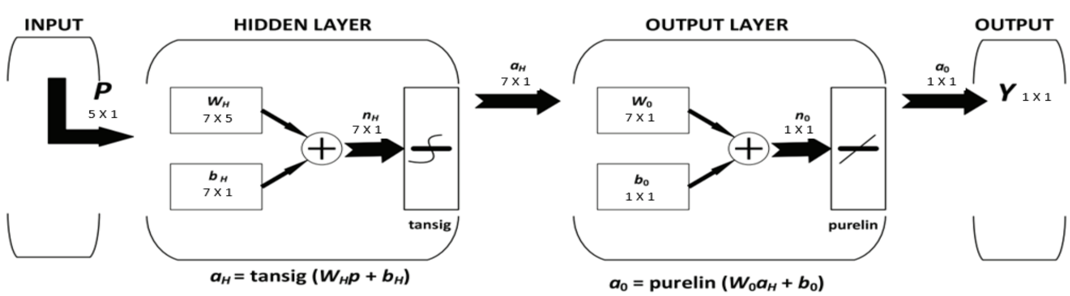
(GP), to understand fire-induced spalling as well as fire resistance of axially loaded RC members. First, MLR is a technique often used to model the linear relationship between a number of independent variables and one dependent variable. In this technique, a phenomenon is realized through minimizing the sum of squares of differences between the predicted and observed values. In order to optimize the number of input parameters and increase the prediction accuracy of the MLR model, the selection of input dataset combinations was performed in accordance with principal component analysis (PCA) [37]. In PCA, the influence of individual parameters on fire-induced spalling as well as fire resistance of axially loaded RC members was evaluated. Then, based on this sensitivity analysis, the combination of inputs showing highest correlation was employed in this research and was also selected for further usage in the development of MLR and IPR models, respectively.

DL, on the other hand, is an advanced computational tool developed in analogy with biological neural networks. DL comprises of multiple layers, each containing a number of neurons (i.e. processing units). These layers and neurons are arranged into a network as can be seen in Fig. 1a. In this network, the first layer contains the input parameters and is connected to a number of hidden layers with the ability to establish linear and/or non-linear relations. The hidden layers are also connected to the output layer comprising of predictions to a given phenomenon. Finding a proper model topology to accurately predict a phenomenon is by itself is a critical process; as there is not an explicit method to predetermine the number of layers or neurons before the start of the training process. For this reason, in this study, a trial-and-error approach was followed to determine the network's topology (see Fig. 1a). To determine the best network topology, logistic and linear transfer functions are employed for hidden and output layers, respectively, and the best fitting model is then statistically evaluated as discussed herein. Once a DL model is developed, training begins to solve the phenomenon on hand and the analysis terminates once predictions from DL falls within a tolerable range to that of actual observations [38]. Usually, the development of a DL model and its implementation are perceived to be perilous and tedious. This due to the fact that DL technique, unlike other approaches, provides the users with a functioning matrix instead of mathematical expression to represent the outcome of analysis (i.e. relation between inputs and output(s)). This matrix comprises of weights (W_H and W_O) and biases (b_H and b_O), where H and o are subscripts to represent these factors for hidden and output layers, respectively. Once such matrix is arrived at, this matrix can then be used to examine new input parameters and run the developed DL network. This analysis can conveniently be carried out using dedicated software such as Matlab DL toolbox [39]. For further information regarding generation and implementation of DL the readers are referred to [40,41].



(a) DL model architecture

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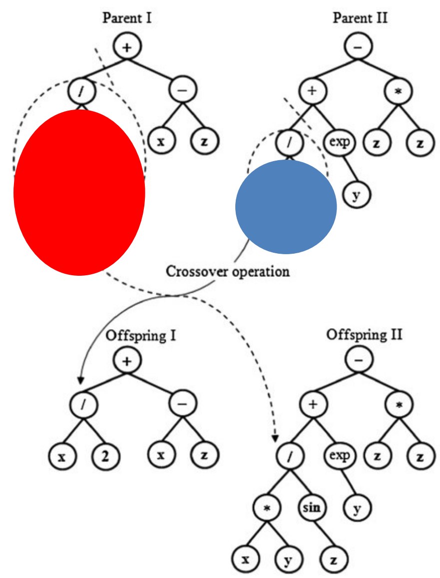

(b) GP

Fig. 1 Typical architecture of an IPR-based model

In the case of genetic programing, this computing technique strives on the Darwinian concept of survival and reproduction to arrive at predictive expressions. This technique was introduced by Holland [42] and Koza [43] and utilizes supervised learning processes to attempt to express relations hidden between a number of factors through mimicking the natural selection process. In such technique, predefined strings of expressions strive to arrive at mathematical representations to express a certain phenomenon. The GP analysis starts by randomly populating a set of individuals often referred to as "trees" (consisting of functions and terminals). For instance, a function (F) may contains basic mathematical operations (+, × etc.), power functions (^, log, exp), among others, while a terminal (T) comprises of arguments or numerical constants/variables. These functions and terminals (i.e. form expressions) are then processed via few operation that may include mutation (randomly changing a fit candidate) and/or crossover (combining two, or more, candidate solutions to get an improved solution) – see Fig. 1b; to arrive at a suitable solution.

As discussed earlier, this study investigates two phenomena associated with concrete subject to elevated temperatures. The first phenomenon being fire-induced spalling, and the second phenomenon is fire resistance of RC columns. In order to evaluate these two phenomena, a thorough analysis of published fire tests [9,26,29,44–48], together with recommendations of notable works [5,6,14,21], was conducted to identify the critical parameters that governs these phenomena. The identified critical parameters in this study include: 1) compressive strength/concrete type, f_c, (normal strength, high strength and high performance), 2) cross sectional dimensions of a concrete member, width b and height h, (203-400 mm^2), 3) concrete cover, c, (24-48 mm), as well as 4) load magnitude, P, (0-5373 kN), and 5) arrangement of applied loading, e_c, (concentric or eccentric with varying eccentricities from 0-150 mm). These input parameters where then collected for various RC columns from published fire tests [9,26,29,44–48]. In addition, the outcome of above fire tests in terms of 1) occurrence of spalling (if a column spalls), and 2) fire resistance of column (i.e. the point in time when a column fails under fire conditions) are also collected and arranged into a database comprising of 102 fire tests.

During this collection process, a few issues arise primarily due to complexities associated with fire testing, and availability of instrumentation that can survive or reliably operate under such severe condition. For a start, actual measurements and/or tools to measure fire-induced spalling rarely exist, if at all, and hence spalling continues to be reported qualitatively (i.e. binary notion – spalling/no spalling) without being actually measured. Thus, the true magnitude/level of spalling may not be evaluated nor reported. Another complexity is the fact that there are different styles in documenting fire tests. For example, a number of studies only report the addition of superplasticizers or fibers to concrete mix without specific details on the type and composition of such additives. Thus, details on such additives as well as their influence on fire-induced spalling/fire resistance are seldom realized. Further, only a few studies out of all reviewed studies reported certain parameters such as: humidity level, or level of moisture content in concrete before testing. It should still be noted that the developed IPR-based framework can account for a multitude of input parameters far exceeding those listed above. All that is needed is to collect information on a new variable (i.e. moisture content of concrete) and add this factor as a new input parameter.

The thought process behind this work stems from the following hypothesis, "*if observations (i.e. spalling or fire resistance time) is collected form a large number of independent fire testing programs, then it is possible to link such observations with the above identified critical parameters through a relationship or set of relations*". Since there are a number of critical parameters that influence the examined phenomena, then an accurate relationship that connects such inputs to the final output(s) (being; spalling or fire resistance) is complex and would require tedious analysis/simulation to realize. As a result, a decision is made to explore the feasibility of solving such highly nonlinear relationships through integrating IPR as this technology aims at deriving mathematical functions through logical understanding of a phenomenon.

It can be seen that performing an analysis through the proposed IPR framework is fundamentally different than that through simple or advanced calculation methods such as finite element analysis. Traditional fire resistance analysis requires collecting appropriate temperature-dependent material properties/constitutive models as well as the development of two models; a thermal and structural. Material properties/constitutive models are often obtained from tedious materials tests or in some cases can be taken from fire design codes. However, codal provisions may still not accurately capture the behavior of certain concretes (i.e. concretes incorporating fibers or high performance concretes) as codal models are primarily adopted for normal strength concrete. On the other hand, in IPR, a fire related phenomenon can be evaluated through applying a simple expression without the need to compile temperature-dependent property, or carrying out complex/lengthy analysis procedure, or requiring special computing workstation. This can be achieved knowing that the outcome of a fire test is a function of applied loading (i.e. fire scenario, magnitude of applied loading), as well as behavior of the tested concrete specimen. For the sake of this study, all selected columns were tested under standard fire conditions and hence they were exposed to similar temperature-time scenarios and heating rates, thus neutralizing the effect of varying thermal loading/heating rate; at least for this study.

In contrast, the behavior of a typical concrete column is mainly governed by 1) column's initial geometric configuration, e.g. cross section, and 2) how concrete and reinforcing steel degrade under elevated temperatures. In this first case, the cross section of the column can be assumed to be constant throughout fire exposure, unless spalling occurs. Once spalling breaks out, the cross section of the column reduces, and this adversely affects the behavior of column (i.e. decreases axial capacity). In the second case, the magnitude and rate of temperature-induced degradation in strength properties can be assumed to be consistent for a given concrete mix and steel grade i.e. two identical RC columns made of same concrete mix as well as steel grade/configuration and subjected to similar fire and gravity loading are likely to fail at the same point in time solely due to the fact that degradation in strength properties in both of these column is same. In this scenario, the observed outcome of a fire test (i.e. susceptibility to spalling/fire resistance) is a result of how selected input parameters react under fire. In other words, the outcome of a fire test implicitly accounts for temperature-dependent properties of concrete and steel.

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4.0 DATABASE DEVELPOMENT AND VALIDATION OF IPR-BASED APPROCH

As discussed above, the development of IPR-based expressions requires collecting data points obtained from actual fire tests. A brief description of selected fire tests and related studies is provided herein as full details on collected tests, together with material properties and loading conditions etc., can be found elsewhere. For a start, the National Research Council of Canada (NRCC) carried out extensive research programs to examine fire behavior of columns made of various types of concretes. The first experimental program was carried out by Lie and Woollerton [44] who tested forty-one 3.8 m long RC columns under standard fire conditions. These researchers varied a number of parameters such as shape (square, rectangular, and circular) and cross-sectional size (203×203 mm^2 – 406×406 mm^2, percentage of longitudinal steel rebars (2.19 – 3.97%), type of aggregate (carbonate, siliceous and lightweight) and compressive strength of concrete, load magnitude (0 – 90%) etc. All columns were cast of normal strength concrete and had a concrete cover thickness of 38 mm; except one which had a cover of 64 mm. Also at NRCC, Kodur et al. [26,29,49] carried out fire tests on RC columns with similar dimensions to that tested by Lie and Woollerton [44] but made of high strength and high performance concrete with compressive strength reaching 138 MPa. Kodur et al. [36-38] reported the high vulnerability of tested columns to fire-induced spalling. Unlike previous tests carried out at NRCC, Kodur et al. [26,29,49] varied other features such as spacing of ties, and heavily investigated the effect of eccentric loading on columns made of high strength and high performance concrete.

Hass [48] also performed fire tests on RC columns in Germany. In these tests, 39 square and rectangular RC columns were subjected to standard fire conditions. Two geometrical sections were studied: 200 × 200 mm^2 and 300 × 300 mm^2 as well as two sizes of reinforcement bar (diameter of 14 and 20 mm). The major factors investigated in this program included concrete strength, ratio of steel reinforcement, load level, and magnitude of eccentricity of loading. Shah and Sharma [25] conducted fire resistance experiments on eight RC columns, six of which were made of normal strength concrete and two of high strength concrete. These columns were longitudinally reinforced with eight steel rebars each of 16 mm diameter and were embedded behind 40 mm concrete cover. Other fire tests were also carried out by Myllymi and Lie [45], Rodrigues et al. [47] etc.

Data points collected from above tests, were input into the IPR-based database to be used in a developed program code in Matlab simulation environment [39]. The compiled input parameters were randomly arranged such that no specific test/study was used as a benchmark in order not to influence the IPR analysis. The developed software accommodates traditional and IPR analysis through MLR, DL and GP and derives mathematical relations in each scenario. In each case, the analysis completes once a derived expression satisfies fitness conditions governed by error metrics i.e. difference (mean squared error).

Out of all complied datasets, 70% is used to train the IPR-based model and the remaining 30% were evenly split to validate and then test the performance of the developed IPR-derived expressions [34,41]. Each approach was engaged to predict occurrence of spalling as well as fire resistance of RC columns. In the first phenomenon, expression(s) from each method is derived using a binary output (i.e. “no spalling” or “spalling”). In the second phenomenon, one expression is derived to predict fire resistance of RC columns. These expressions, together with their coefficient of determination (R^2), and mean squared error (MSE) are listed in Table 1. Further, Fig. 2 illustrates the plots for each phenomenon.

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Table 1 IPR-derived expressions to be used to evaluate fire response of RC columns and statistics.

<table>
<tr><th>Case</th><th>Remarks</th><th>Derived expressions</th><th>Coefficient of determination (R^2)</th><th>Mean squared error (MSE)</th></tr>
<tr><td rowspan="4">Fire-induced spalling</td><td>MLR</td><td>$FIS = 2.213 - 0.01139f_c - 0.00071b - 0.0e_c - 0.000099P$</td><td>0.49</td><td>0.13</td></tr>
<tr><td>DL</td><td>
<table>
<tr><th rowspan="2">Element no.</th><th colspan="4">Weight matrix for the hidden layer (W_H)</th><th rowspan="2">Bias vector for the hidden layer (b_j)</th><th rowspan="2">Weight vector of the output layer (W_0)</th><th rowspan="2">Bias for the output layer (b_0)</th></tr>
<tr><th>1</th><th>2</th><th>3</th><th>4</th></tr>
<tr><td>1</td><td>-2.8322</td><td>4.8977</td><td>-5.7333</td><td>-1.037</td><td>-0.97</td><td>-1.5433</td><td>-0.5932</td></tr>
<tr><td>2</td><td>-1.5049</td><td>-11.0959</td><td>1.0315</td><td>0.2203</td><td>5.6455</td><td>-2.644</td><td></td></tr>
<tr><td>3</td><td>-0.2746</td><td>-5.5977</td><td>-4.1132</td><td>-0.9614</td><td>6.0515</td><td>0.636</td><td></td></tr>
<tr><td>4</td><td>-5.2241</td><td>1.1965</td><td>3.751</td><td>-0.4177</td><td>0.9059</td><td>1.3939</td><td></td></tr>
<tr><td>5</td><td>-1.5216</td><td>-8.8275</td><td>1.1507</td><td>0.9632</td><td>3.329</td><td>1.7091</td><td></td></tr>
</table>
</td><td>0.78</td><td>0.06</td></tr>
<tr><td rowspan="2">GP</td><td>$No\ spalling = Logistic(63 + 4.64\tan(14.8 + 14.9f_c) + 5.52\tan(5.52 + P + \tan(14.8 + 14.9f_c)) + \tan(69.3 + P) - f_c - \tan(b))$</td><td>0.95</td><td>0.01</td></tr>
<tr><td>$Spalling = Logistic(37.9f_c + 46.7\tan(b) + 37.9\tan(0.9707P) + 66.06\tan(f_c + 0.9669P) + 97.02\tan(37.9f_c + 46.74\tan(b) + 37.9\tan(0.9707P) + 61.04\tan(f_c + 0.9669P)) - 2.57 \times 10^3)$</td><td>0.94</td><td>0.01</td></tr>
<tr><td rowspan="3">Fire resistance (FR)*</td><td>MLR</td><td>$FR = -1.491 + 11.61bh + 0.01733f_c + 0.078C - 0.01745e_c - 0.000537P$</td><td>0.59</td><td>0.60</td></tr>
<tr><td>DL</td><td>
<table>
<tr><th rowspan="2">Element no.</th><th colspan="5">Weight matrix for the hidden layer (W_H)</th><th rowspan="2">Bias vector for the hidden layer (b_j)</th><th rowspan="2">Weight vector of the output layer (W_0)</th><th rowspan="2">Bias for the output layer (b_0)</th></tr>
<tr><th>1</th><th>2</th><th>3</th><th>4</th><th>5</th></tr>
<tr><td>1</td><td>-0.1815</td><td>-11.4838</td><td>2.3818</td><td>1.7032</td><td>6.1226</td><td>-2.3796</td><td>-2.2623</td><td>0.1159</td></tr>
<tr><td>2</td><td>-3.4937</td><td>2.8374</td><td>0.7356</td><td>-3.7874</td><td>-10.1781</td><td>8.2018</td><td>-3.2178</td><td></td></tr>
<tr><td>3</td><td>2.038</td><td>-5.5698</td><td>1.5277</td><td>-3.9621</td><td>1.1971</td><td>7.62</td><td>-2.4806</td><td></td></tr>
<tr><td>4</td><td>-0.3493</td><td>1.3327</td><td>2.0654</td><td>0.0299</td><td>-8.2731</td><td>4.0583</td><td>4.1113</td><td></td></tr>
<tr><td>5</td><td>-0.4778</td><td>4.1981</td><td>-28.7632</td><td>0.1072</td><td>-12.9604</td><td>14.6524</td><td>-0.2616</td><td></td></tr>
<tr><td>6</td><td>1.0301</td><td>-1.9836</td><td>-2.0465</td><td>0.3786</td><td>-0.1405</td><td>1.7374</td><td>0.9085</td><td></td></tr>
<tr><td>7</td><td>-1.4904</td><td>2.2639</td><td>1.5687</td><td>-6.5502</td><td>2.837</td><td>-1.5974</td><td>0.9669</td><td></td></tr>
</table>
</td><td>0.86</td><td>0.25</td></tr>
<tr><td>GP**</td><td>$FR = e_c + 912\ln(f_c) + 0.0984f_c^2 + 31.9\cos\left(\frac{22.6P}{b}\right) - \frac{2.49P\cos\left(\frac{22.6P}{b}\right)}{b} - 2.18 \times 10^3 - 28.1f_c - 90.4\tanh(e_c) - 21.3\cos(-336f_c^2) - 50.3\cos\left(-1.57e^{\frac{P}{b}}\right) - 54.7\cos\left(\frac{P\operatorname{asinh}\left(\frac{P}{b}\right)}{b}\right) - 32.8\cos\left(3.91 + 31.9\cos\left(\frac{22.6P}{b}\right)\right)$</td><td>0.62</td><td>0.45</td></tr>
</table>

*Valid for 5 hours of exposure to standard fire

This is a preprint draft. The published article can be found at: https://doi.org/10.1007/s00366-019-00805-1

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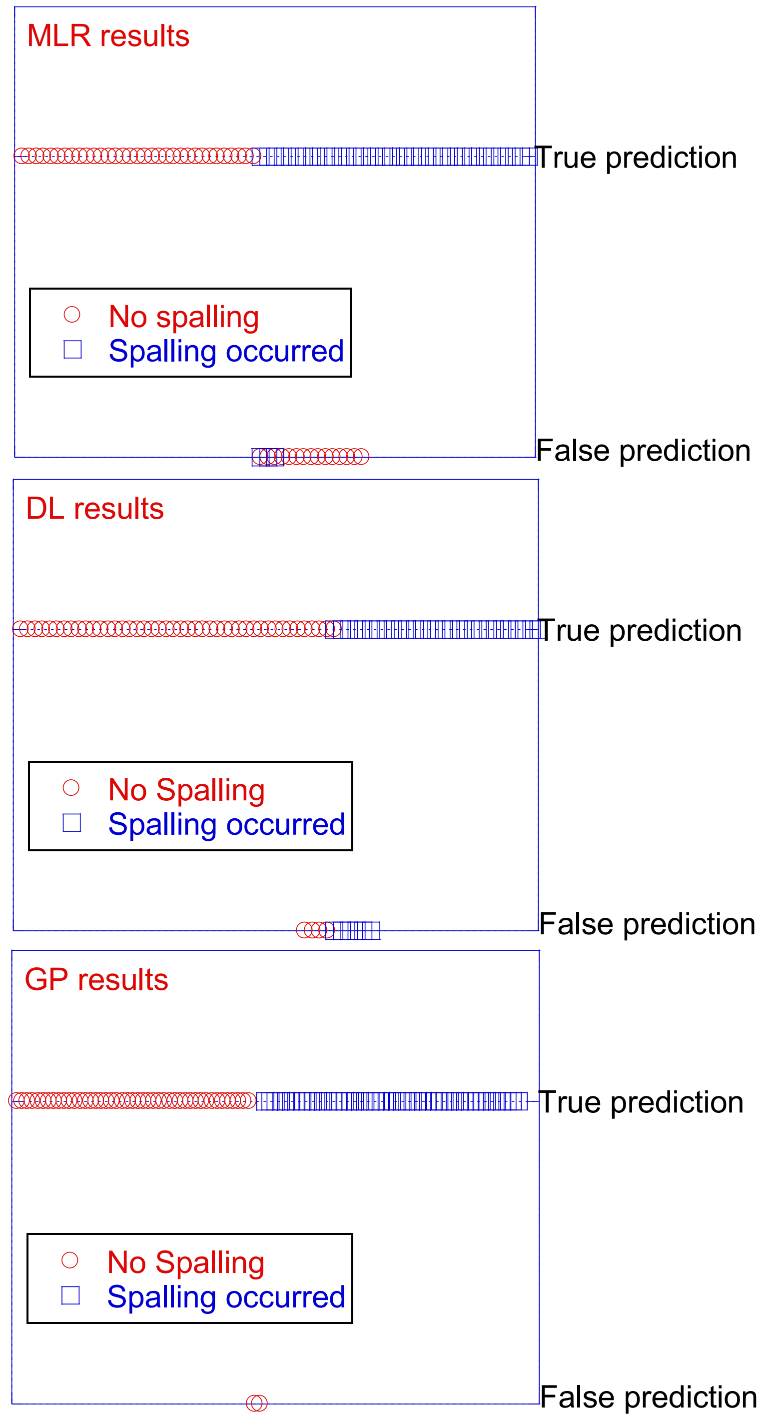
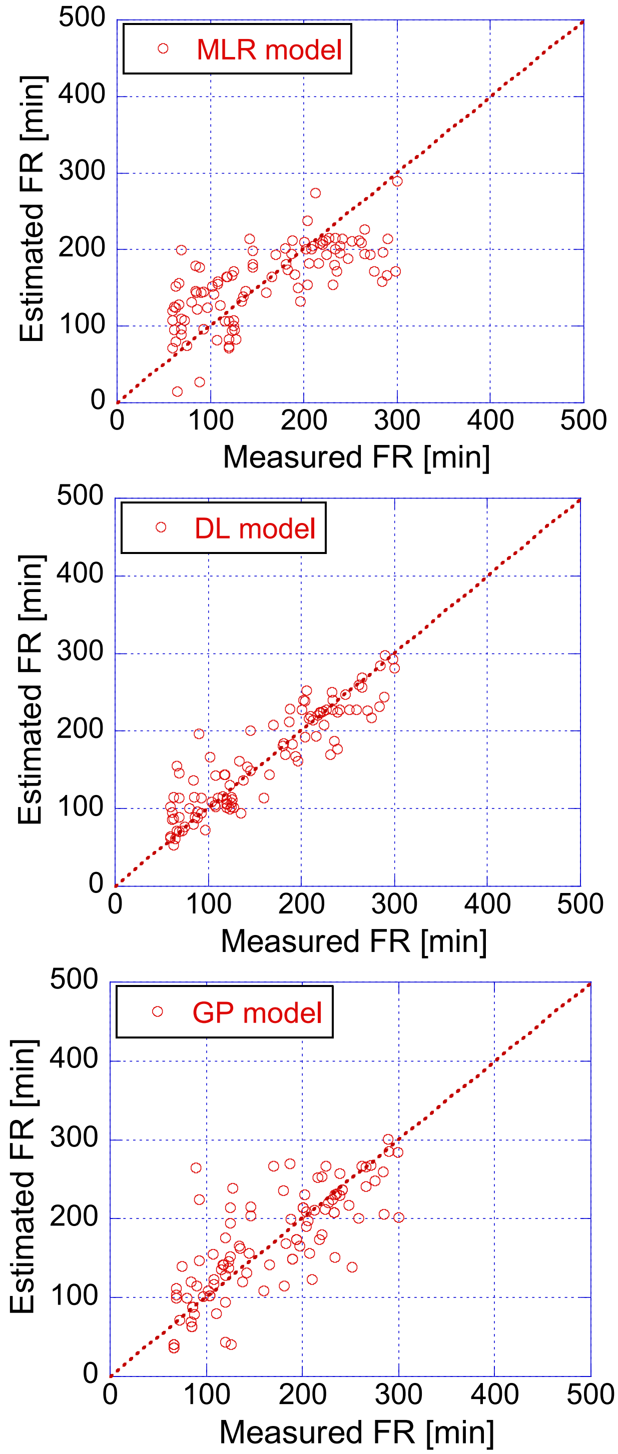
**Gives fire resistance in minutes



(a) Fire-induced spalling



(b) Fire resistance

Fig. 2 Validation of the IPR-derived expressions

It can be seen from above table as well as Fig. 1 that there is a good correlation between predicted and measured data points. Overall, predictions obtained from MLR are the poorest in terms of accuracy; for both phenomena. In the case of predicting fire-induced spalling, the simple expressions provided by GP provide high accuracy followed by that obtained through DL. As can be seen in Fig. 2a, these two techniques managed to capture spalling occurrences in most tested columns and only failed in two and six incidents for GP and DL, respectively. These two techniques comprehend the vulnerability of RC columns to fire-induced spalling and may provide an easy tool to researchers and engineers given that there is a serious lack of methods/approaches that can be used to predict occurrence of fire-induced spalling. In fact, current fire codes and standards still do not provide any assessment methods/approaches to evaluate fire-induced spalling in concrete. The developed expressions can serve as a benchmark (i.e. first generation) to realize such methods/approaches.

On the other hand, predictions from DL seem to better capture the relation between input parameters and fire resistance of concrete columns. This can be attributed to the nature of DL in which it is a network of processing multiple layers and this can better comprehend complex phenomenon than that of MLR and GP. Predictions obtained from GP on the other hand, are surprisingly much lower than that from DL. This could be related to the different nature of this computing technique and limited number of input data points (102 fire tests) used to analyze this phenomenon.

While there exists few listings and calculation methods that can be used to evaluate fire resistance of concrete columns such as those adopted in fire codes: ACI 214.1 [50], Eurocode 2 [12] or Australian code AS 3600 [51], such methods may not appropriately account for fire-induced spalling, high strength/high performance concrete, nor eccentricity of applied loading, and are primary valid for 1-4 hours of exposure to standard fire. As a result, these methods may not be appropriately applied to examine fire resistance many of the selected columns in this study some of which were tested by Lie and Woollerton [44], Kodur et al. [26,29,49] or Hass [48] etc. However, fire resistance of columns of similar features to those examined herein can be obtained through DL or roughly estimated through MLR and GP and this presents the advantage of utilizing these methods. Even though the application of DL might seem cumbersome compared to the other two techniques, the presence of weights and biases provided in Table 1 can be directly used to apply this technique using Matlab DL toolbox. After feeding the required input data, say for a concrete column to be subjected to fire conditions, the developed functioning matrix applies weights and biases into the hidden layer which will then transfer the results to the output layer. The output layer will process the received data and allocate the final values of the network.

For simplicity, these derived expressions along with collected data points are used to develop a dedicated database and a fire assessment tool that is uploaded in a dedicated web page [52] such that fellow researchers/engineers can examine and further improve upon these tools. It is worth noting that a complete example is provided in the appendix to illustrate how to properly collect input parameters and to use derived expressions in predicting susceptibility of a RC column to spall under fire conditions as well as its fire resistance.

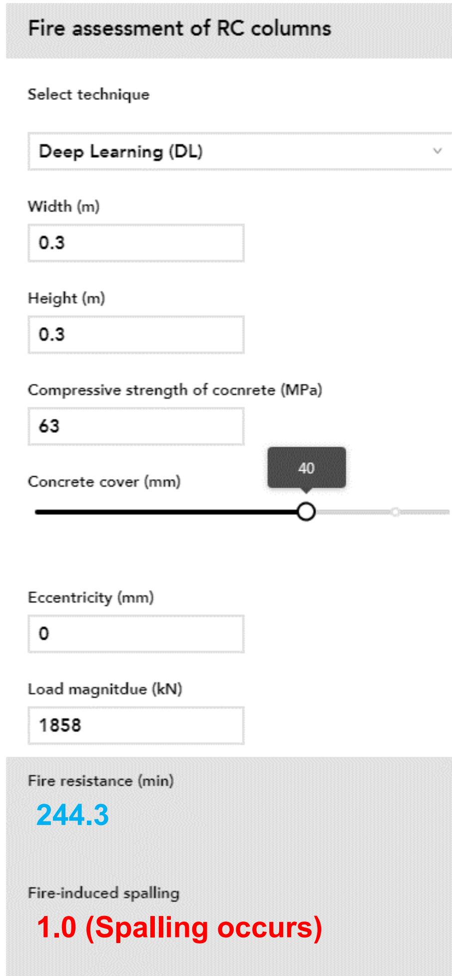


Fig. 3 Graphical interface of developed fire assessment tool

5.0 CURRENT CHALLENGES AND FUTURE RESEARCH NEEDS

Analysis through artificial intelligence (AI) heavily relies on the availability of data points (observations), which in this study are equivalent to those obtained from fire tests carried out on RC columns. A close examination of fire tests published over the past 30-40 years shows that there continues to be limited works in this research area. This is primarily due to the limited availability and accessibility of fire testing facilities as well as expertise in this field.

A proper AI analysis also requires the availability of analogous data points i.e. observations obtained from tests on duplicated specimens or on those with comparable features/properties but with varying end restraints, mix design, geometric configuration etc. Unfortunately, very few tests were ever undertaken on duplicated specimens and findings of these tests clearly show how the behavior of duplicated specimens can also vary even if made from same concrete mix and tested under similar fire conditions [53]. In addition to the limited number of fire tests, it is worth noting that the bulk of the fire-tested RC columns reported in notable studies [26,29,44,48,49] had: 1) similar configuration and size, 2) were reinforced with rebars/ties/spirals with one grade/size of steel, and 3) similar concrete cover thickness. In the case where columns were made of fiber-reinforced concrete, the amount/type/origin/composition of fibers was varied across a narrow range, if at all, presumably due to the limited number of specimens dedicated for fire testing.

The aforementioned challenges can be overcome through collaborative work and intelligent planning. While the database developed herein collected data points from 102 fire tests, this database can be further improved through compiling results of additional tests (whether past or planned). Future tests need be specifically designed to overcome limitations of traditional tests and give due consideration to prioritize AI-based modeling, training, and validation as the lack of adequate/quality data points can potentially lead to the rise of numerical complications i.e. overtraining etc. [54]. While this study primarily explored DL and GP-based algorithms, interested researchers are invited to explore the application of different AI techniques including fuzzy logic, decision tree learning, bee algorithm etc. [55–58] into solving phenomena investigated herein.

6.0 CONCLUSIONS

This paper integrates intelligent pattern recognition techniques to derive expressions and fire assessment tools capable of predicting fire-induced spalling as well as fire resistance of RC columns. These expressions were derived to be easy-to-use, and to implicitly account for temperature-dependent material degradation. The following conclusions further highlight the main findings of this work:

- There is a need to develop a modern approach that can comprehend behavior of concrete, especially under extreme temperatures. Deep learning and genetic programing seem to be highest potential.
- The derived IPR-based expressions and fire assessment tool are able of predicting fire-induced spalling and fire resistance of RC columns for exposure durations of up to five hours under standard fire conditions. Both of these items are currently unaccounted for in current codal provisions or accepted methods for fire resistance assessment.
- According to the outcome of this work, predictions obtained from MLR are the poorest in terms of accuracy. In the case of predicting fire-induced spalling, GP provides the highest accuracy followed by that obtained through DL. These two techniques comprehend the vulnerability of RC columns to fire-induced spalling and may provide an easy tool to predict occurrence of fire-induced spalling. On the other hand, predictions using DL shows to better predict the relation between influencing factors and fire resistance of concrete columns.
- The developed assessment tools can be further improved by carrying out additional fire tests as well as collecting new data points. Other challenges that may limit the integration of IPR techniques, such as differences in reporting fire test observations etc., can be overcome through collaborative and interdisciplinary efforts.

7.0 DATA AVAILABILITY

The raw/processed data required to reproduce these findings cannot be shared at this time as the data also forms part of an ongoing study.

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9.0 APPENDIX

This section illustrates two examples with procedure into applying the IPR-derived expressions to evaluate susceptibility of a typical RC column to fire-induced spalling as well as fire resistance of the same column. This column, named M6S150, was tested by Shah and Sharma [25], and achieved a fire resistance of 289 min after undergoing spalling; and has the following features:

1) Concrete type, f_c = 63 MPa,
2) Cross sectional size, $b \times h$ = 300×300 mm^2,
3) Concrete cover, c, 40 mm,
4) Magnitude of applied loading, P = 1858 kN,
5) Concentric loading, e_c = 0 mm,

To check for fire-induced spalling in this column:

Using MLR:

$Spalling = 2.213 - 0.01139 f_c - 0.00071 b - 0.0 e_c - 0.000099 P$, where for MLR; 1- Spalling occurs, 2 - No spalling

$Spalling = 2.213 - 0.01139(63) - 0.00071(300) - 0.0(1) - 0.000099(1858) = 1$ (Spalling occurs)

Using DL:

Implementing the matrix provided in Table 1, DL reveals $Spalling = 1$(Spalling occurs)

Using GP:

$No\ spalling = Logistic(63 + 4.64 \tan(14.8 + 14.9 f_c) + 5.52 \tan(5.52 + P + \tan(14.8 + 14.9 f_c)) + \tan(69.3 + P) - f_c - \tan(b))$

$No\ spalling = Logistic(63 + 4.64 \tan(14.8 + 14.9 \times 63) + 5.52 \tan(5.52 + 1858 + \tan(14.8 + 14.9 \times 63)) + \tan(69.3 + 1858) - 63 - \tan(300)) = 0$ (Spalling occurs)

To verify this:

$Spalling = Logistic(37.9 f_c + 46.7 \tan(b) + 37.9 \tan(0.9707P) + 66.06 \tan(f_c + 0.9669P) + 97.02 \tan(37.9 f_c + 46.74 \tan(b) + 37.9 \tan(0.9707P) + 61.04 \tan(f_c + 0.9669P)) - 2.57 \times 10^3)$

$Spalling = Logistic(37.9 \times 63 + 46.7\tan(300) + 37.9\tan(0.9707 \times 1858) + 66.06\tan(63 + 0.9669 \times 1858) + 97.02\tan(37.9 \times 63 + 46.74\tan(300) + 37.9\tan(0.9707 \times 1858) + 61.04\tan(63 + 0.9669 \times 1858)) - 2.57 \times 10^3) = 1.0$ (Spalling occurs)

Fire resistance of this column can be evaluated using the following approaches:

Using MLR:

$FR = -1.491 + 11.61bh + 0.01733f_c + 0.078C - 0.01745e_c - 0.000537P$

$FR = -1.491 + 11.61(0.09) + 0.01733(63) + 0.078(40) - 0.01745(0) - 0.000537(1858) = 252.7\,min$ (within 13% of measured fire resistance)

Using DL:

Implementing the matrix provided in Table 1 and fire assessment tool shown in Fig. 3, the fire resistance of this columns comes to, *FR*= 244.3 min (within 18% of measured fire resistance)

Using GP:

$$FR = e_c + 912\ln(f_c) + 0.0984f_c^2 + 31.9\cos\left(\frac{22.6P}{b}\right) - \frac{2.49P cos\left(\frac{22.6P}{b}\right)}{b} - 2.18 \times 10^3 - 28.1f_c - 90.4\tanh(e_c) - 21.3\cos(-336f_c^2) - 50.3\cos\left(-1.57e^{\frac{P}{b}}\right) - 54.7\cos\left(\frac{P asinh\left(\frac{P}{b}\right)}{b}\right) - 32.8\cos\left(3.91 + 31.9\,cos\left(\frac{22.6P}{b}\right)\right)$$

$$FR = 0 + 912\ln(63) + 0.0984 \times 63^2 + 31.9\cos\left(\frac{22.6\times1858}{300}\right) - \frac{2.49\times1858\times cos\left(\frac{22.6\times1858}{300}\right)}{300} - 2.18 \times 10^3 - 28.1 \times 63 - 90.4\tanh(0) - 21.3\cos(-336 \times 63^2) - 50.3\cos\left(-1.57e^{\frac{1858}{300}}\right) - 54.7\cos\left(\frac{1858\times asinh\left(\frac{1858}{300}\right)}{300}\right) - 32.8\cos\left(3.91 + 31.9\,cos\left(\frac{22.6\times1858}{300}\right)\right) = 300\,min$$ (within 4% of measured fire resistance)