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MACHINE LEARNING-DRIVEN ASSESSMENT OF FIRE-INDUCED CONCRETE SPALLING OF COLUMNS.

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Biography:

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ABSTRACT

The past few years have witnessed the rise of serious research efforts directed towards understanding fire-induced spalling in concrete. Despite these efforts, one continues to fall short of arriving at a thorough examination of this phenomenon and of developing a modern assessment tool capable of predicting the occurrence and intensity of spalling. Unlike other works, this papers presents an approach that leverages a combination of machine learning (ML) techniques; namely *k*-nearest neighbor (*k*-NN) and genetic programming (GP), to examine spalling in fire-tested reinforced concrete (RC) columns. In this analysis, due diligence was taken to examine 11 factors known to influence spalling and to identify those of highest impact to be then used to develop a predictive tool. The outcome of this analysis shows that it is possible to predict the occurrence of spalling (with a successful rate ranging 77%- 90%.) through a simple, robust, and easy to use ML-driven tool.

Keywords: fire-induced spalling; pattern recognition; machine learning; artificial intelligence; *k*-nearest neighbor; principal component analysis.

INTRODUCTION

The inert thermal diffusivity of concrete facilitates slow rise in cross-sectional temperature and moderate loss in strength and stiffness of concrete structural members, thus permitting the use of concrete materials without special treatment/handling in severe working conditions i.e. power/chemical/nuclear plants.[1] As such, it is a common practice not to externally fire-proof concrete structures given that a sufficient cover to embedded reinforcement is provided.[2] This practice continues till this present day despite observations from recent fire tests as well as post-fire on-scene investigations reporting the tendency of concrete to spall.[3,4]

Fire-induced spalling is generally defined as the breakage of concrete chunks or cover due to thermally-induced effects.[5] In the case that spalling occurs, the integrity of a concrete member is adversely threatened on two fronts. The first is related to the fact that breakage of concrete cover exposes steel (or in some cases fiber reinforced polymer (FRP)) reinforcement to direct flames and heat – causing severe degradation in mechanical properties and development of higher core (internal) temperatures in RC members. The second being; any loss in cross

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sectional size would also lead to a reduction in load bearing capacity (i.e. moment capacity in beams etc.). Unfortunately, the above two fronts are seldomly accounted for during the design stage of a concrete structure and this negligence has been shown to trigger unexpected failure/collapse mechanisms due to spalling in the event of a fire breakout.[6,7]

As such, a number of studies have alluded to the notion that without properly addressing the phenomenon of fire-induced spalling, then an accurate evaluation of fire performance of concrete structures may not be fully realized.[8,9] The same studies also pointed out that the complexity and randomness of spalling may limit the ability of practicing engineers to arrive at optimal designs for RC structures. This is especially true for those of unique/complex functionality such as mega buildings, bridges and tunnels where fire is considered a major threat.[10]

On a parallel note, this incompetence in properly evaluating fire-induced spalling also hinders ongoing standardization efforts aimed at promoting performance-based fire design solutions and in a way handicaps future developments in this niche research area. It is unfortunate to note that currently adopted (prescriptive) codal provisions falls short of providing an adequate guidance to mitigate or to account for spalling.[2,11] While such provisions do provide tabulated listings that can be used to estimate the required concrete cover thickness to satisfy a given fire rating, the same listings were not derived to account for the adverse effects of spalling. As such, the application of these listings is limited in practical applications, as well as in scenarios utilizing modern types of concretes i.e. high strength concrete (HSC) and ultra-high performance concrete (UHPC).

Fire-induced spalling can potentially be classified under explosive (violent) spalling and surficial spalling.[12,13] Spalling is often explained through either: 1) development of pore

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pressure build up facilitated by moisture migration in temperature range of 250-420°C; which once exceeds the tensile strength of concrete leads to spalling, or 2) thermomechanical processes (i.e. thermal dilation/shrinkage gradients) that occur within heated RC members.[14–16]

However, it is interesting to note that there is enough experimental evidence to verify the validity, as well as to contradict the principles of the aforementioned theories.[17,18] For example, Harmathy[16] noted that spalling of concrete occurs early into fire exposure (within the first 25 minutes), yet tests carried out by Han et al.[19] reported occurrence of spalling during later stages (60-90 minutes) of fire exposure and in few incidents during the cooling phase as well.[20] While the development of high thermal gradients (due to rapid heating) has been shown to yield high risk of spalling, Noumowe et al.[21] reported severe spalling in uniformly heated concrete at a low rate equivalent to 0.5°C/min. On a separate front, Kalifa et al.[22] noted the positive effect of incorporating polypropylene fibres in minimizing spalling, however Klingsch[18] reported that incorporating such fibers did not positively reduce spalling in concrete. The effect of non-uniform heating was reported to cause spalling in RC columns tested by Raut and Kodur[23], while the same effect was shown not to cause any spalling in tests carried out by Xu and Wu[24]. Another aspect that needs to be remembered is that the majority of the above works investigated fire-induced spalling either through experimentation, or theoretical derivation/numerical simulation.[17,25–27] As such, these are confined to specific concrete mixtures and testing set-ups and hence are hard to replicate and lack thorough verification due to the lack of sample duplication.

Building upon the collective findings of past and recent works, combined with the fact that fire-induced spalling is believed to be triggered by a complex chain of reactions involving multi-dimensional parameters, this study aims at leveraging modern techniques in order to examine the influence of geometric, material and loading features on the susceptibility of RC columns to spall under fire conditions. Due to the randomness of spalling, understanding this phenomenon can better be attained via an ML-driven perception. Unlike other works in which AI-derivatives were primarily used to optimize concrete mix proportions[28–30] or predict properties of concrete[31–34], this study applies contemporary approaches that falls under artificial intelligence (AI) and machine learning (ML) i.e. pattern recognition (PR) and genetic programing (GP) to identify the hidden relations that govern both the occurrence as well as magnitude of fire-induced spalling. The identified critical parameters are then used to develop a simple and easy-to-apply GP-powered assessment tool that can accurately predict propensity and magnitude of spalling in fire-exposed RC columns. This tool indirectly takes into account how material properties of concrete and reinforcement vary with temperatures, is freely available, can be continuously upgraded and hence is attractive for both researchers and practitioners.

RESEARCH SIGNIFICANCE

The use of ML has been steadily rising over the past few decades; thanks in part to the rapid advancements in computing and data analytics. Due to the complex nature of fire-induced spalling, this paper explores the potential of ML in examining the susceptibility of reinforced concrete columns to spalling. This work leverages two distinct ML algorithms, i.e. PR and GP, to showcase the merit in adopting ML as a modern technique, in parallel to traditional methods e.g. testing and simulation. Adopting ML is expected to open the door towards research opportunities encompassing performance-based fire design of concrete structures.

AN OVERVIEW TO FIRE-INDUCED SPALLING PHENOMENON

This study recognizes the multidimensionality of spalling as highlighted by past and recent studies[14–18,25,26,35–40] and in order to accommodate a collective view into this phenomenon, spalling is said to be governed by factors that can be grouped under three categories: 1) material characteristics, 2) geometric configurations, and 3) loading conditions. These factors are further examined in the following subsections and are also summarized in **Table 1**. It should be stressed that a more inclusive review on other key factors, including; cement type, degree of pore saturation, fire cooling phase, with regard to spalling is spared for brevity and can be found elsewhere.[41–45]

Material characteristics

The material characteristics that primarily govern spalling behavior comprises of concrete mix components such as aggregate and cement type, additives (fibers, superplasticizers etc.), and water/binder ratio. In the case of aggregates, carbonate aggregate often delivers a comparatively better resistance to heat effects than other types of aggregates (e.g. silicate). This can be attributed to the capability of carbonate aggregates to develop an endothermic reaction at temperatures close to 700°C which reduces temperature rise and slows down strength degradation.[1] In the case of additives, incorporating steel fibers (~1.75% by weight) or polypropylene fibers (~0.15% of volume) seems to minimize the extent of fire-induced spalling.[36,46] Using silica fume or limestone fillers is expected to increase spalling occurrence as these lower permeability and limit vapor release. On a similar line, concretes with high moisture content or water/cement ratio or those of low permeability also tend to spall due to

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developing high pore pressure. Thermal incompatibility between mix components may also promote spalling.[5,38]

Geometric size and reinforcement configuration

The geometric configuration of concrete components can also affect its susceptibility to fire-induced spalling. For instance, edged, as opposed to round, components attract higher magnitudes of heat via bi-lateral heat transmission which may facilitate spalling.[5] Hertz[38] and Kanéma et al.[47] reported that members of bigger sizes have increased tendency to spall as they: 1) hold larger amounts of moisture, and 2) can develop sharp thermal and pressure gradients across their cross sections. The configuration of embedded steel reinforcement is another governing factor to the phenomenon of spalling. In general, columns incorporating closely space hooked ties (bent at 135°) do not seem to spall as much as columns with traditional or spaced-out ties.[44]

Loading conditions

The arrangement and magnitude of loading and heating regimes also affect spalling behavior of RC members. While the existence of axial or eccentric forces put a loaded member under a constant state of compression; which in a way limits cracking development, stressed members may also become susceptible to spalling due to the amplifying effects of pore pressure.[5] From a thermal point of view, a fire with a rapid and intense heating rate has the potential to thermally shock concrete material and to develop large thermal gradients, causing high thermal stresses and non-uniform expansion within exterior and interior layers of concrete thus promoting spalling.

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PATTERN RECOGNITION AND GENETIC PROGRAMMING MODEL RATIONAL AND DATABASE DEVELOPMENT

This work formulates the following hypothesis, "*if observations on fire-induced spalling are collected from independent fire tests, then it is possible to intelligently tie such observations to factors governing the phenomenon of spalling through a systematic analysis*". Given the complexity and high dimensionality of successfully completing such analysis, a decision can be justifiably taken to utilize ML as an exploratory engine. ML-based techniques mimic human-like reasoning process in order to resolve phenomena that may not be truly understood by means of conventional methods or may necessitate resource-intensive experimentations or specialized computing software/workstations. Of these techniques, pattern recognition (PR) and genetic programing (GP) are of interest to this work and hence are applied herein. These techniques have been widely used during the last decade in various structural and fire engineering applications.[35,48]

The followed investigation philosophy starts by collecting information on spalling observations from standard fire tests. Thus, a thorough analysis of published fire tests[49–55], together with recommendations of notable works[5,38,44,56], was carried out to pinpoint the critical parameters that influence spalling as outlined earlier. These parameters include: 1) concrete type, f_c, 2) cross sectional size, W, 3) boundary conditions, BC, 4) tie spacing, S, 5) stirrup configuration, SC, 6) steel reinforcement ratio, r, 7) aggregate type, A, 8) fiber type, f, 9) humidity, H, 10) magnitude, P, and 11) eccentricity of applied loading, e.

This compiled observations are then put into a database. This database is examined using PR to identify most critical parameters (out of all 11 collected parameters) that govern spalling phenomenon. Once identified, then GP is applied to generate simple expressions that can be

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used to predict the occurrence, as well as expected magnitude of spalling (see Fig. 1). These expressions are finally encoded into a simple assessment tool. One can see that carrying out the proposed ML analysis is quite dissimilar to traditional analytical/simulation methods as these require inputting appropriate temperature-dependent constitutive models and development of thermal and structural models.

It should be noted that it is due to the complex nature of fire testing, and lack of instruments capable of surviving harsh temperatures or measure the magnitude of fire-induced spalling, this phenomenon continues to be reported qualitatively (i.e. binary notation – spalling/no spalling or descriptive notation – no, minor, major spalling) without being actually measured. This work maintains the same notation in order to show the validity of the proposed framework. In more details, if a fire test reported that a particular column underwent "minor spalling", then this column is also labeled to undergo "minor spalling". This approach was followed since the majority of selected fire tests did not report specific information pertaining to spalling magnitude (i.e. average spalling depths or max spalling depths). A future work is currently in its early stages to develop quantitative measurements of spalling through ML.

Pattern recognition (PR)

PR thrives to learns patterns hidden in varying dimensions of observations as to establish a relation between input parameters and expected output(s).[57,58] Among the different PR techniques, *k*-nearest neighbors (*k*-NN) has been widely used in the field of damage detection and condition assessment, and hence is applied herein.[59] In general, *k*-NN is a non-parametric classification algorithm belonging to the instance-based learning methods. Further, the *k*-NN algorithm: 1) makes no assumption about the data distribution, thus yielding a flexible decision boundary with minimum learning process and higher accuracy, 2) tends to be robust even with noisy training data, 3) has the ability to learn complex concepts by local approximations, and 4) is easily implemented and fully tractable. As such, *k*-NN is used to analyze spalling-related data collected from 87 fire tests (as 18 columns from the originally compiled database lacked essential details on some input parameters and hence were deemed unsuitable for analysis).

The *k*-NN classification algorithm is formulated by assuming the pair (x_i, $\varphi(x_i)$) which denotes the feature vector x_i and its corresponding label $\varphi(x_i)$; where i=1, 2,…, n and $\varphi\{1, 2, …, m\}$ where n and m are the number of training feature vectors and the number of classes, respectively. Considering x_i as an arbitrary feature vector, the distance between this feature and feature vector x_j is calculated by:

$$d(i,j) = f(x_i, x_j) \tag{1}$$

where $f(x_i, x_j)$ is a distance function that can be defined as:

$$f(x_i, x_j) = (x_i - x_j)^T \sum (x_i - x_j) \tag{2}$$

Equation (2) is the generalized distance, and for the case of $\Sigma = I$ it denotes the Euclidean distance (T herein denotes the transpose function). The distance vector $D(i)$ is defined by Equation (3):

$$D(i) = \{d(i,j) \mid i = 1,2,\ldots,n_{test}, j = 1,2,\ldots,n_{train}\} \tag{3}$$

The $D(i)$ vector is arranged in an increasing order ($D_n(i)$,) and the *k*-nearest vote vector is defined by using the first K elements as follows

$$V = \{\varphi(D_n(i)(1),\ldots,\varphi(D_n(i)(K))\} \tag{4}$$

The classification is then performed by determining the *k*-nearest vote vector V. In this regard, the test feature x_i is classified to the class that has the most votes in V. In this procedure, the 11 parameters identified above e.g., compressive strength, width, steel ratio, etc., were considered as pattern features. Thus, each pattern was represented with 11 features ($z_1, z_2, z_3, \ldots, z_{11}$) i.e., the dimension of the PR problem herein is 11. To implement the *k*-NN algorithm, data set was classified to two and three classes for binary and multiple spalling classification, respectively. For the case of binary spalling classification, the dataset was split to '*class N'* denoting patterns with no spalling and '*class S'* representing patterns of spalling. For the case of multiple spalling classification, the dataset was classified to three classes, where '*class N'* presents no spalling, '*class MN'* represent patterns due to minor spalling, and *class 'MJ'* denotes patterns as a result of major spalling. The dataset for the *k*-NN analysis was randomly classified into three subsets; namely, training, validation, and testing. The training set was used to train the classifier, while the validation set was used to compute the optimal *k* for the *k*-NN classifier. The best models were selected based on their performance on the validation data. Performance of the classifier with optimal *k* was then investigated on the test set.

Genetic programming (GP)

Fundamentally, GP follows the Darwinian philosophy of "survival of the fittest" to develop solution candidates with high arrive at predictive capabilities. In this method, a population comprising of candidate solutions is first randomly generated through arithmetic operators and mathematical functions i.e. addition (+), trigonometric functions (i.e. tangent) etc.[60] Suitable solutions are then manipulated via operations such as mutation (randomly changing a the layout of candidate) and/or crossover (combining two, or more, candidate solutions to get an improved solution) – see **Fig. 2**. The theory and application of GP into fire-based problems have been thoroughly documented in companion works and hence is avoided herein for brevity.[35,61,62]

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Development of database

As discussed in a previous section, the proposed methodology requires compiling data on spalling from fire tests. This section provides a brief description to such selected tests wherein full details can be found at their respective references.[14–18,25,26,35–40] For a start, the National Research Council of Canada (NRCC) carried out numerous tests on columns made of different concretes (normal, high, fiber-reinforced concrete) and various features (*shape:* square, rectangular, and circular; *cross-sectional size*: 203 mm – 406 mm; *ratio of longitudinal steel rebars:* 2-4%; *aggregates:* carbonate, siliceous and lightweight etc.).[26,40,50] These tests proved to be very valuable from the point of this work.

Another testing program was carried out by Hass.[55] In their tests, RC columns of two sizes: 200×200 mm^2 and 300×300 mm^2 that were reinforced with two sizes of reinforcement (diameter of 14 and 20 mm) were tested. Buch and Sharma[63] tested 11 RC columns (six of which were normal strength concrete columns (NSC) and five were made of HSC). All columns were 3.15 m in height, had a square cross-section of 300×300 mm^2, and were reinforced with longitudinal and transverse reinforcements with an average yield tensile strength of 491.5-499.5 MPa. These columns were tested to explore the effect of loading arrangement (i.e. eccentricity) on spalling. Shah and Sharma[17], Myllymaki and Lie[52], Rodrigues et al.[54] also conducted fire resistance experiments on RC columns and varied restraint conditions, concrete type, loading magnitude etc. Observations from all of the above tests were organized into a database which can be accessed online.[64]

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VALIDATION OF METHODOLOGY AND DEVELOPMENT OF SPALLING ASSESSMENT TOOL

The developed database was then input into Matlab simulation environment for analysis. The compiled tests were randomly shuffled in order to maintain an unbiased ML analysis. At the beginning of the analysis, the initial classification accuracy of the PR analysis was low (i.e., around 60%) primarily due to the higher dimensionality of spalling phenomenon (i.e. 11 features/dimensions). Thus, incorporating ML optimization techniques was deemed necessary. A data compressing technique is used to reduce the dimensions of feature space through finding principal components (i.e. those of maximum variance for the dataset). This technique is referred to as principal component analysis (PCA).[65] Using this technique, the original input feature vector (z) is projected on the first two principal components for single and multiple spalling classification (see **Fig. 3**). As can be seen from this figure, the defined classes for all cases (e.g., binary spalling and multiple spalling) overlap even using first two principal components $z=[z_1,z_2]^t$, thus resulting in a low classification accuracy.

Since these preliminary results indicate the necessity of using feature selection techniques to enhance classification accuracy, sequential forward selection (SFS) and sequential backward selection (SBS) were applied. The SFS feature selection method starts with an empty set of features and adds the best feature z^+ sequentially (from the set of full features) which gives the highest value for the objective function $J(X_k + z^+)$. On the other hand, SBS feature selection method starts with the full set of features and removes the worst feature z^- sequentially that gives the lowest value for the objective function $J(X_k + z^-)$ – see **Fig. 4 and Fig. 5**. It is worth noting that *k*-fold cross validation technique was also used to prevent overfitting of the *k*-NN algorithm. In this study, 10-fold cross validation (i.e. assuming *k*=10) was considered.

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To visualize the outcome of PCA-based PR analysis, a confusion matrix that contains information on actual and predicted classes is employed as the main metric to assess performance of the carried out methodology. The performance of the damage detection model with *k*-NN method was thus measured using the detection performance rate defined in Equation (5). MATLAB was utilized for implementing *k*-NN algorithm and to compute confusion matrices.

$$\textit{Damage Detection Accuracy} = \textit{Number of patterns correctly classified} / \textit{Total number of patterns} \quad (5)$$

Accordingly, the best feature vectors were selected by the SFS and SBS algorithms for binary and multiple spalling classifications. To obtain the best classification performance, the optimum value of *k*, i.e., number of neighbors for the *k*-NN algorithm, was determined through computing the classification accuracy on training, validation and test data. It should be noted that different combinations in terms of size of data subsets used for training, validation, and testing were considered in this study for binary and multiple classification, and the performance of the *k*-NN method was evaluated based on each combination. Yet, the presented results are based on the combinations for which the accuracy of the *k*-NN was highest. On this basis, for the scenario of binary spalling, 50% of data was used for classification and 10-fold cross validation and 50% of data was used for testing. On the other hand, for the case of multiple spalling classification, 60% of data was used for training and 10-fold cross validation and the remaining 40% of dataset was used for testing the *k*-NN classifier.

The *k*-NN algorithm, without feature selection techniques, was initially used to determine the classification accuracy on test data for both binary and multiple spalling classification (see **Table 2** and **Table 3**, respectively). These tables show that the optimal number of *k* for the case of binary and multiple spalling classification was found as 5 and 12, respectively. Still,

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results of k-NN classification with different number of neighbors using original set of features and SFS and SBS feature selection methods are also plotted and presented in **Fig. 6**, where classification results confirm the optimal number of k noted above.

In the next phase of analysis, the best features for the case of binary spalling were selected as compressive strength, eccentricity, and humidity, as well as width, stirrup spacing, eccentricity, humidity, and load level using SFS and SBS methods, respectively. For the multiple spalling scenario, best features using SFS algorithm were chosen as compressive strength and additive fibers type, whereas SBS algorithm resulted in similar features as for the case of binary spalling.

As noted above, a confusion matrix containing information regarding actual and predicted classes/patterns was used to explore the performance of the k-NN algorithm. The diagonal entries of the confusion matrix denote the spalling cases that are correctly classified. Also, entries in the off-diagonal cells represent the spalling cases that are misclassified. Confusion matrices on test data based on optimal k for both binary and multiple spalling with original feature sets and SFS and SBS feature selection algorithms are presented in **Table 4** to **Table 6**, from which it can clearly be seen that using feature selection methods reduced classification accuracy error from 29% to 25%. This is while, classification error for *class S* (denoting spalling occurs) decreased from 32% to 23% using selected features, confirming the importance of feature selection techniques in this study.

Similarly, confusion matrices on test data for multiple spalling classification demonstrate that classification accuracy is also increased using SFS and SBS methods. As can be seen from **Table 7** to **Table 9**, the total k-NN classification error decreased from 47% (in the case of original features) to 39% (with SBS algorithm), i.e., classification accuracy increased from 53% to 61%. It is noted that although the maximum accuracy achieved using SBS algorithm is

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not particularly high, such accuracy is still acceptable given the size of dataset and complexity of the spalling phenomenon. The outcome of this analysis is also in agreement with experimental studies indicating that factors such as compressive strength, width, stirrup spacing, eccentricity, humidity, and load level have significant effect on the extent of spalling. In fact, the above SBS-arrived feature selections led to highest classification accuracy in term of prediction of spalling. While these features are known to govern spalling, however the relation/magnitude of their governance was not quantified till now.

Then, these six features are input into the developed GP model to arrive at simple expressions that can be used to predict the occurrence as well as intensity of spalling (SP) by substituting the values of the governing parameters. Similar to PR analysis, two sets of expressions are developed; the first for No spalling/Spalling and the second for No spalling/Minor spalling/Major spalling classification. These expressions are listed in Table 10 which also shows their coefficient of determination (R^2) metric. The same table also lists the range of limitations and applicability of these expressions.

It can be seen from above table that there is a strong correlation between predicted and measured data points and that the GP-derived expressions succeeded in capturing spalling occurrence. For simplicity, these derived expressions are used to develop a dedicated spalling assessment tool (see **Fig. 7**) to enable fellow researchers/engineers from examining and using such tool in a plug-and-play mode without needing to re-conduct the ML analysis shown herein. This tool will be made available at the authors' website.

As noted earlier, fire tests on RC columns are very scare and limited. While the compiled database presented herein is the most comprehensive database developed up to date, we cannot but acknowledge that having additional data points could potentially lead to better training of

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the developed ML model and, thus improving its prediction capability. One of the contributions of this paper is to show that even using a limited data set, the proposed AI-based model is capable to predict the spalling for reinforced concrete columns.

While the developed database herein accounts for various independent parameters, this database can be further improved by adding outcome of other studies as well as future fire tests (of standard fire or design fire nature). It is expected from future tests to give due consideration to AI-based modeling, training, and validation – this accommodation can be through testing replicates specimens and specimens of varying sizes and configurations; a feature that lacks in those testing programs discussed earlier. As such, the developed fire assessment tool is anticipated to undergo a series of improvements and calibrations in the near future. For example, efforts at the moment are being taken to enable manual and automatic updating of the developed tool via a procedure that allows a centralized repository to harvest data from users to evolve the developed tool such that all users will have the ability to use the most up-to-date tool at all times. Future editions of this tool are expected to be able to propose solutions and spalling mitigation strategies as to aid designers into arriving at safe and optimal designs of RC structures for standard and design fire conditions.

CONCLUSIONS

This paper integrates PR and GP techniques to examine the phenomenon of fire-induced spalling in RC columns. Based on the analysis carried out in this study, the main factors that affect this phenomenon were shown to be compressive strength, width, stirrup spacing, eccentricity, humidity, and load level. As such, these factors were used to develop a userfriendly fire assessment tool capable of predicting the occupancy of spalling in RC columns. The following conclusions could also be drawn from the results of this study:

- There is a need to incorporate ML techniques to develop modern computational methods that can comprehend fire behavior of concrete structures. These approaches can conveniently be developed through PR and GP.
- Results confirm that PR using SBS feature selection technique can be effectively used to predict spalling with an accuracy reaching 77%, even with limited dataset. Further, GP-based analysis is also capable of successfully identifying fire-induced spalling with >90% accuracy.
- Fire-induced spalling is a complex phenomenon that is not fully understood yet. Future works are expected to deepen the knowledge and understanding on tendency of concrete to spall.
- It is noted that the performance of the proposed AI-based model can be notably improved by increasing the number of data set (number of fire tests) used in training and testing the developed model. In fact, results obtained based on the limited number of dataset used in this study further showcase the acceptable performance of the developed AI-based model.

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TABLES AND FIGURES

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Table 1– Factors affecting occurrence and magnitude of fire-induced phenomenon

	May lead to spalling	May minimize spalling	Mechanisms/Remarks
Material characteristics	Silicate/quartzite aggregate	-	• Due to a change in the quartzite phase at 573°C.
	-	Carbonate aggregates	• Lowers temperature rise • Slows down strength degradation
	-	Polypropylene fibers	• Melts at 160–170°C and thus create additional pores
	-	Steel fibers	• Improves tensile strength of concrete
	Silica fume, high content of cement and limestone fillers	-	• Dense microstructure • Low permeability
	High moisture content	-	• Facilitates development of increased pore pressure
Geometric configurations	Sharp edges	-	• Attracts heat through bi-directional transmission
	Larger size	-	• Holds higher amounts of moisture • Facilitates large thermal and pore pressure gradient
	-	Bent ties/close tie spacing	• Improves resistance to pore pressure
Loading conditions	Axial loading/fixed restraint conditions	-	• Continuous compression state • Inhibits development of cracks
	Eccentric loading	-	• Develops two states of stress
	Rapid/intense heating	-	• Causes thermal shock (leading to high thermal stresses and non-uniform expansion)

Table 2 – *K*-NN classification accuracy (binary spalling)

Number of Neighbors (k)	Classification Accuracy (%)
2	64%
3	71%
4	69%
5	72%
6	65%
7	64%

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Table 3 – *K*-NN classification accuracy (multiple spalling)

Number of Neighbors (k)	Classification Accuracy (%)
5	45%
7	50%
10	53%
12	58%
15	52%
17	50%

Table 4 – Confusion matrix for binary spalling (without feature selection)

True Classes	Predicted Classes		True Sum
	Class N	*Class S*	
Class N	8	11	19
Class S	2	23	25
Sum	10	34	44
Error (%)	0.20	0.32	0.29

Table 5 – Confusion matrix for binary spalling (SFS feature selection)

True Classes	Predicted Classes		True Sum
	Class N	*Class S*	
Class N	13	6	19
Class S	5	20	25
Sum	18	26	44
Error (%)	0.28	0.23	0.25

Table 6 – Confusion matrix for binary spalling (SBS feature selection)

True Classes	Predicted Classes		True Sum
	Class N	*Class S*	
Class N	10	9	19
Class S	2	23	25
Sum	12	32	44
Error (%)	0.17	0.28	0.25

Table 7 – Confusion matrix for multiple spalling (without feature selection)

True Classes	Predicted Classes			True Sum
	N	*MN*	*MJ*	
N	6	4	7	17
MN	2	3	1	6
MJ	2	1	10	13
Sum	10	8	18	36
Error (%)	0.40	0.62	0.44	0.47

Table 8 – Confusion matrix for multiple spalling (SFS feature selection)

True Classes	Predicted Classes			True Sum
	N	*MN*	*MJ*	
N	14	0	3	17
MN	3	1	2	6
MJ	7	0	6	13
Sum	24	1	11	36
Error (%)	0.42	0.00	0.45	0.42

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Table 9 – Confusion matrix for multiple spalling (SBS feature selection)

True Classes	Predicted Classes			True Sum
	N	*MN*	*MJ*	
N	15	0	2	17
MN	4	1	1	6
MJ	5	2	6	13
Sum	24	3	9	36
Error (%)	0.37	0.67	0.33	0.39

Table 10 – GP-derived expressions to be used to evaluate fire response of RC columns and statistics

Remarks		Derived expressions	R^2
Binary classification	No spalling = 0 Spalling = 1	$SP = Step(f_c + e + 10.16\tan(S) + \tan(W) + \tan(2 + P) + \tan(H + 2.13S) + \tan(2.13 + 2f_c + 10.2\tan(S)) - 80.2)$	95.1
Multi-classification	No spalling = 1	$SP = Logistic(86\cos(e) + 0.0537{f_c}^2\sin(W) + 14.4\text{atan}\,(2.2 \times 10^{32}P - 3.813 \times 10^{35} - 55.35\sin(-4.64f_c) - 49\cos\,(S + H - 2.012W^2))$	96.7
	Minor spalling = 1	$SP = Logistic(e + f_c\sin(S) + \tan(321.7f_c) + \tan(2.047S) + \tan(0.5661f_c) + \tan(e - 5.45 - 0.000773P) - f_c - \tan(0.02782P - 48.27) - 13.67\cos(WH))$	97.2
	Major spalling = 1	$SP = Logistic(2769\log(f_c) + f_c\cos(P) + \frac{35H+48.09W cos(W)+449.8e cos(109.3P)}{\log(S)} - 1.016 \times 10^4)$	94.6
Range of applicability		*f_c= 23.8-138 MPa* *e= 0-40 mm* *S = 50-406 mm* *W = 203-406 mm* *P = 0-5373 kN* *H = 5-99%*	

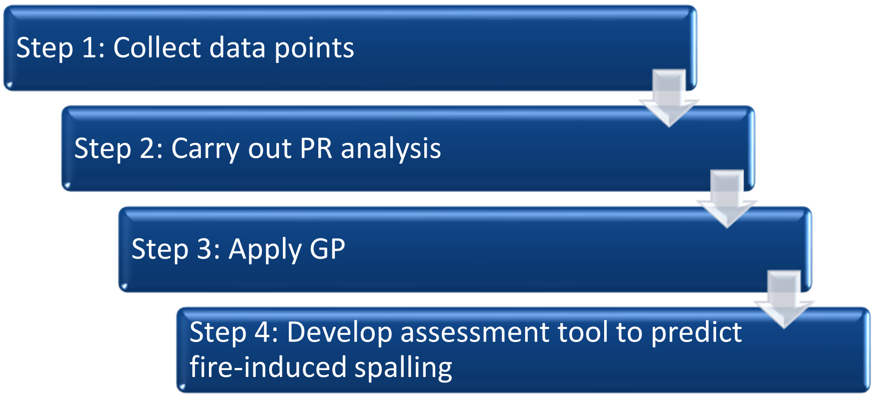

Fig. 1– Framework of proposed methodology.

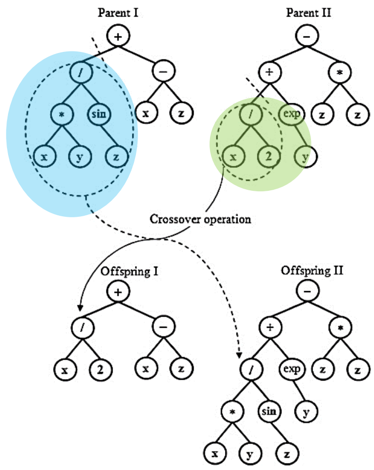

Fig. 2– Typical architecture of a GP model.

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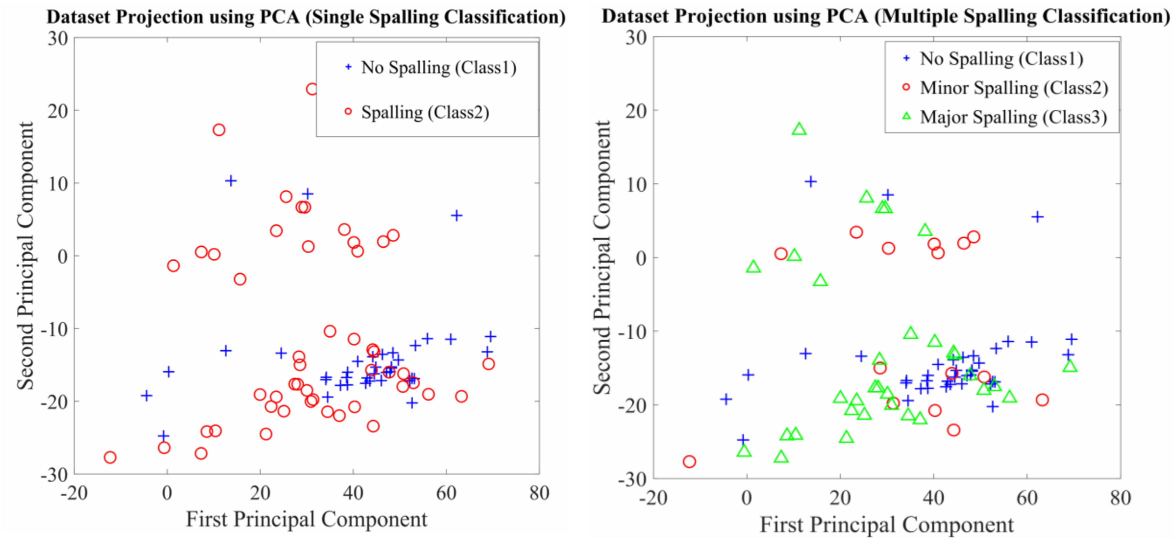

(a) (b)

Fig. 3– Data projection on to the first two principal components: (a) Single spalling classification, and (b) Multiple spalling classification.

Algorithm 1 SFS Feature Selection

1. Start with empty feature set $X_0 = \{\emptyset\}$
2. Select the next best feature $z^+ = argmax_{z \notin X_k} J(X_k + z)$
3. Update $X_{k+1} = X_k + z^+; k = k + 1$
4. Return to step 2

Fig. 4–SFS feature selection algorithm

Algorithm 2 SBS Feature Selection

1. Start with empty feature set $X_0 = z$
2. Remove the worst feature $z^- = argmax_{z \in X_k} J(X_k - z)$
3. Update $X_{k+1} = X_k - z^-; k = k + 1$
4. Return to step 2

Fig. 5–SBS feature selection algorithm

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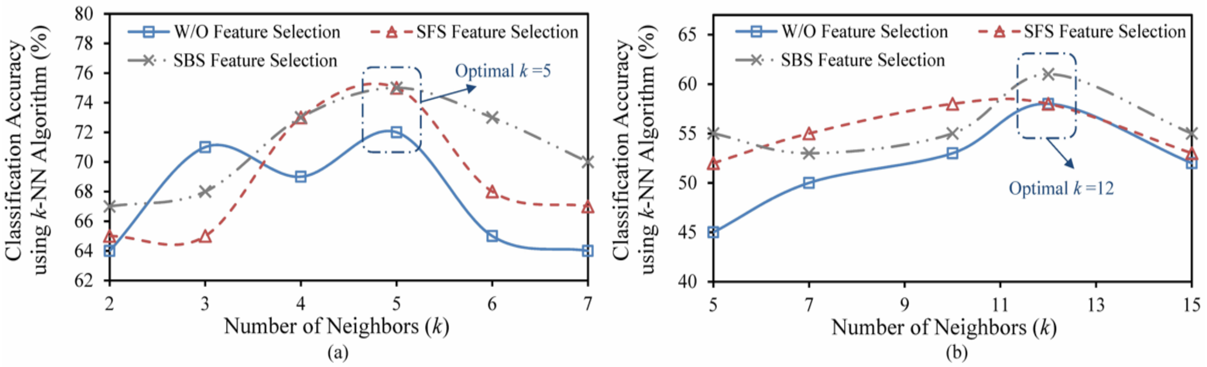

Fig. 6 – Classification accuracy with *k*-NN algorithm for different number of *k*: (a) Binary spalling classification, (b) Multiple spalling classification.

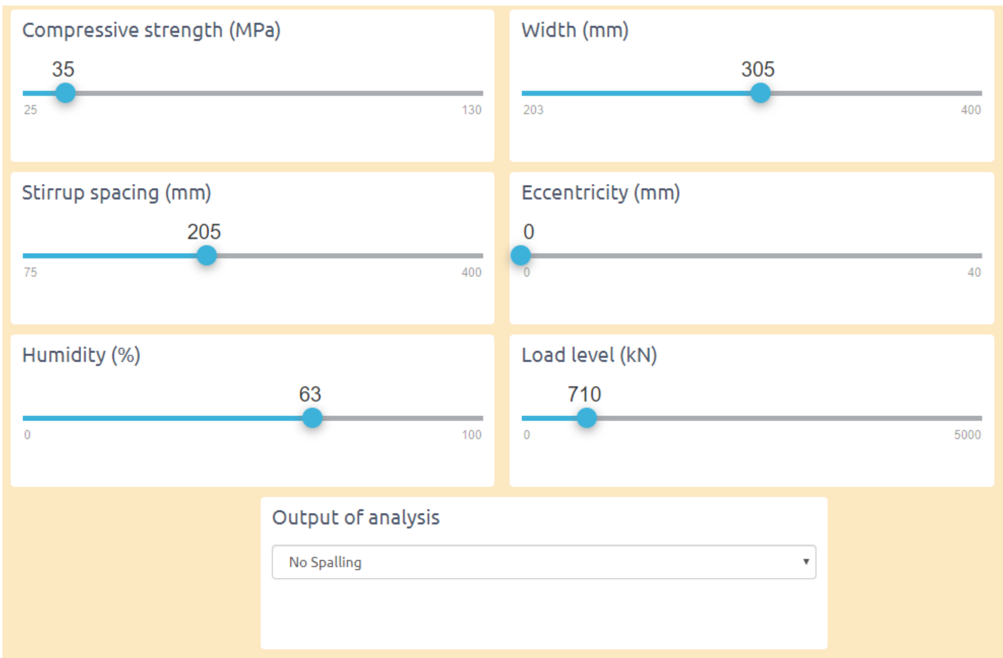

Fig. 7 – Graphical user interface of developed fire assessment tool.