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Simple Visual Aids for Predicting Fire Response of RC Columns: Nomograms via Machine Learning

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Abstract:
Assessing the ability of reinforced concrete (RC) columns to withstand the effects of fire is a multifaceted and intricate problem due to the various factors that influence their fire response. As such, engineers may find it challenging to precisely predict such fire resistance. While some codal provisions exist and fire testing/advanced modeling can be adopted, the same methods may suffer from poor predictivity and can be costly and/or complex. In this paper, we shift focus toward machine learning techniques (by means of Nomograms) that can produce simple visual aids to assess the fire resistance of RC columns. Our analysis shows that Nomograms can be accurate, account for a series of factors currently absent from our domain knowledge and provisions, and outperform existing methods adopted in building codes. Our analysis also infers that such Nomograms could be possible candidates for adoption in standardized settings, given their simplicity, ease of use, and lack of multi-stepped procedures.

Keywords:
Nomograms, Fire resistance, Fire rating, Concrete columns, Machine learni

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Pages (45 –69)

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1.0 Introduction

Due to its superior properties, concrete (and hence reinforced concrete) has become one of the most widely used construction materials, especially in environments where fire or extreme temperatures are expected [1]. However, despite its resilience, elevated temperatures cause concrete to undergo a series of chemical and physical changes that result in damage. This damage can include loss of mechanical and bond strength and may trigger the structure to collapse [2]. The study of reinforced concrete (RC) under elevated temperatures has thus become significant in understanding the type and magnitude of damage fire can cause and predicting thermal and structural response [3]. However, an examination of existing literature reveals a continued challenge in predicting the wide variety of fire effects on RC members at elevated temperatures [4], such as fire resistance and fire rating.

One of the key factors that can influence the fire resistance of RC columns is the compressive strength of concrete. Several studies have concluded that columns made from higher strength (i.e., high strength and ultra-high-performance concrete) tend to have a lower fire resistance than normal strength concrete [5, 6]. For example, Dwaikat and Kodur [7] attributed the loss in fire resistance to the occurrence of spalling. Bolina et al. [8] fabricated 16 concrete columns of equal dimensions with four different mix designs for strength. In each group of four, the concrete cover was varied. Each element was then tested in a standard furnace using the ISO 834 standard fire for 240 minutes. Results showed a correlation between the propensity of spalling and fire resistance and noted that the concrete cover thickness and diameter of reinforcement had a greater influence on fire resistance than mix design.

Other key factors, i.e., the geometry, loading, and restraint conditions, can affect the fire response of RC columns. Such properties include the cross-sectional dimensions, section shape and length (square, circular, etc.), loading amount and eccentricity, and axial or bending restraint. Kodur and Phan [9] noted an increase in cross-sectional dimensions decreases heat flux (and therefore increases fire resistance); such an increase results in a more significant thermal gradient [10]. This effect can lead to a loss in confinement and fire resistance. Martins and Rodrigues [11] studied the effect of column length on fire performance. They found that an increase in column length tends to increase the member's slenderness ratio, leading to P-δ effects that decrease the fire resistance.

Studies [12–14] each concluded that increasing load level decreases the fire performance of concrete columns. Similarly, increasing eccentricity also results in a decrease in fire resistance [15, 16]. Finally, the type and location of restraints also play a crucial role in the fire resistance of RC members. Recently, Yang et al. [17] found that increasing the restraint ratio for axially restrained square tube RC columns resulted in increased fire resistance. The previous studies have demonstrated the complexity of studying RC members in fire scenarios and the difficulty in predicting their behavior [18].

At a different front, O'Meagher and Bennetts [19] developed a mathematical model to analyze RC walls under fire exposure, and this method can be extended to other building elements such as walls, floors, beams, and columns. Further, Harmathy [20] created another method to tie real fires to standard fires and proposed its use for structural design. More recently, researchers have attempted to tackle the lack of available fire tests in the literature by using machine learning (ML) to predict fire resistance. Studies [21, 22] used various algorithms and model approaches to accurately predict the fire resistance of RC members with a variety of geometric and practical scenarios. For example, Naser and Kodur [23, 24] used the random forest, extreme gradient boosted tree, and deep learning algorithms trained with a database of 494 RC columns to predict fire resistance. When deployed, such a model can accurately predict the fire resistance of over 5,000 RC columns in under 60 seconds.

In addition to its use for predicting RC behavior in fire, ML has also been shown to benefit the field of structural fire engineering greatly. For example, much work has been done to model fire dynamics in an effort to reduce the current limitations of equations and methods. Similar studies, including [25–27], show the need for more realistic fire modeling capabilities. Other ML studies have explored a variety of structural materials and member types, each showing that ML can provide improved accuracy and understanding of such complicated phenomena. For example, Khan et al. [33] used a hybrid simulation approach to analyze restrained composite beams exposed to fire. Such a method makes studying realistic boundary conditions and the behavior of an entire structural system exposed to fire possible, and their study demonstrated good agreement with the test results of actual composite beams. Research on concrete slabs and floor systems [28–30], timber structures [31], and steel structures [32] using ML further demonstrates the versatility of the approach for evaluating structural performance in fire scenarios.

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In this paper, we continue the notion of adopting ML, but rather than creating blackbox models, we utilize ML to generate simple and visual aids to assess the fire resistance of RC columns. Such methods fall under Nomograms. We create a series of Nomograms to cover regression (i.e., fire resistance prediction) and classification (fire rating) problems. These Nomograms can have similar accuracy to traditional ML models while accounting for a series of factors currently absent from our domain knowledge and provisions [33]. Our analysis also shows that the proposed Nomograms can also outperform currently adopted prediction methods in building codes.

2.0 Statistical description of the dataset

We gathered 248 full scale fire tests of RC columns for our investigation from diverse literature sources [34, 35]. This dataset consists of ten independent variables that describe the geometry, loading, and mechanical properties of reinforced concrete columns, namely, column width (*b*), steel reinforcement ratio (*r*), column effective length (*L*), effective length factor (*k*), concrete compressive strength (f'_c), steel yield strength (f_y), concrete cover (*C*), eccentricity in the x-direction (e_x) and y-direction (e_y), and applied load (*P*), and one dependent variable, the column fire resistance (*R*). Table 1 lists key statistical insights about these collected factors. Overall, this dataset satisfies the recommendations of data useability and health as noted by:

- Van Smeden et al. [36] – having a minimum set of 10 observations per feature.
- Riley et al. [37] – having a minimum of 23 observations per feature.
- Frank and Todeschini [38] – maintaining a ratio of 3 and 5 between the number of observations to the number of features.

Table 1 Statistical insights of the dataset

Factors	Mean	Standard Deviation	Kurtosis	Skewness	Minimum	Maximum
b (mm)	306.90	56.27	0.40	-0.06	200.00	406.00
r (%)	2.12	0.64	2.39	0.53	0.89	4.39
L_e (m)	3.99	0.73	1.45	0.25	2.10	5.70
f'_c (MPa)	45.94	25.94	2.84	1.90	24.00	138.00
f_y (MPa)	461.55	60.70	-0.44	0.38	354.00	591.00
k	0.83	0.22	-1.47	-0.64	0.50	1.00
C (mm)	38.67	8.24	-0.86	-0.24	25.00	64.00
e_x (mm)	18.78	31.73	7.83	2.70	0.00	150.00
e_y (mm)	2.10	10.42	28.21	5.28	0.00	75.00
P (kN)	1103.75	991.22	5.26	2.16	0.00	5373.00
R (min)	150.48	101.05	2.00	1.16	22.00	636.00

2.1 Data distribution

The histograms in Fig. 1 show the distribution of each variable in the dataset graphically. These graphic depictions of the data are a helpful tool for comprehending the underlying patterns and trends, which can guide additional analysis and result interpretation.

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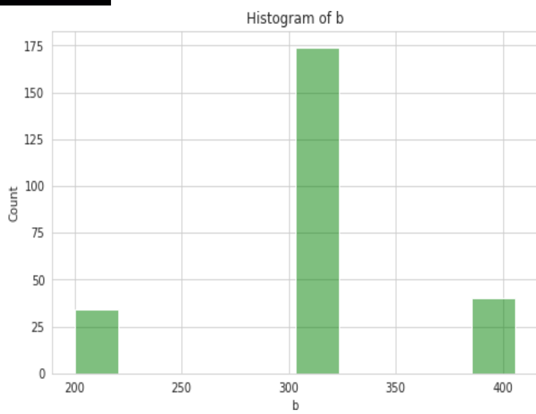

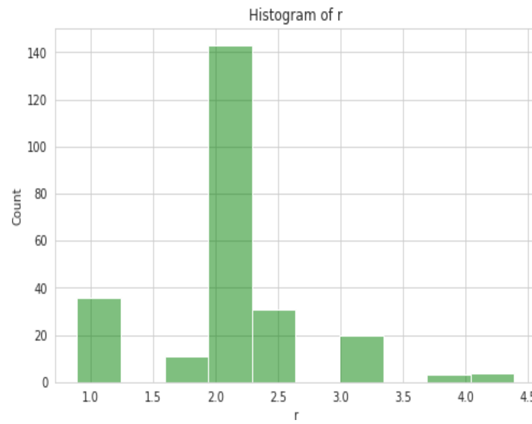

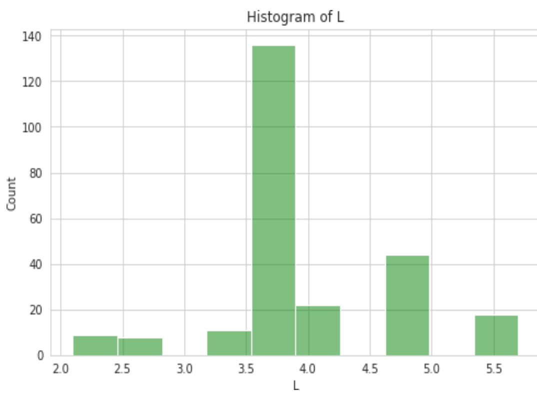

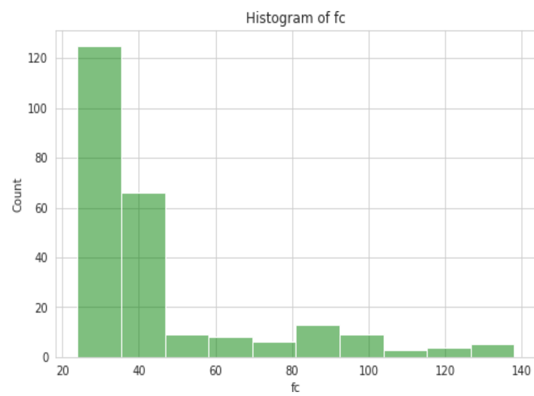

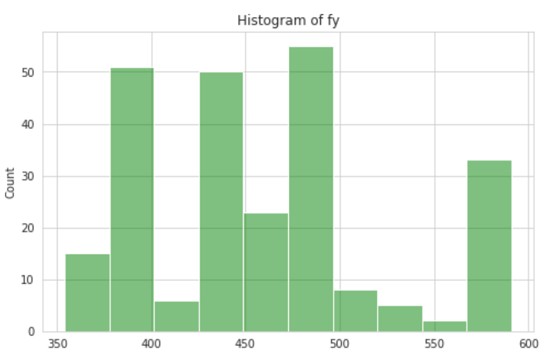

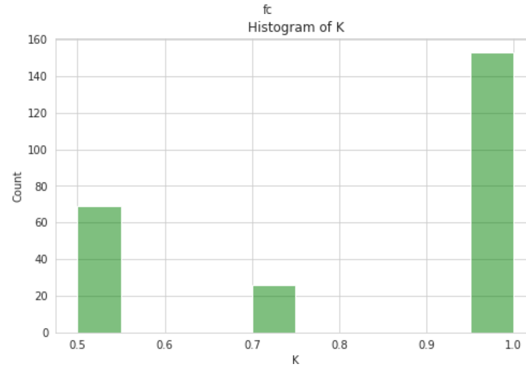

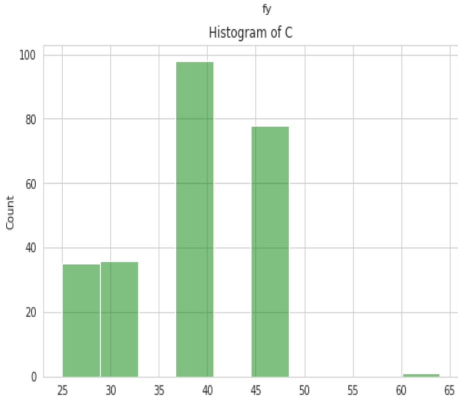

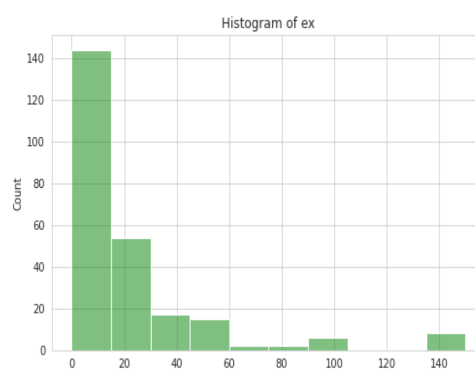

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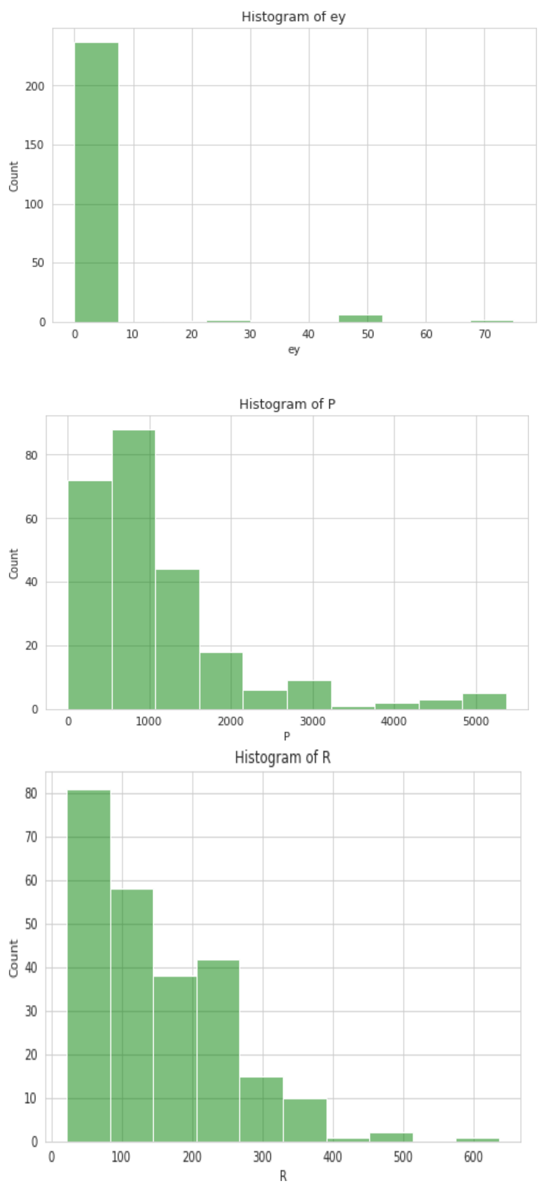
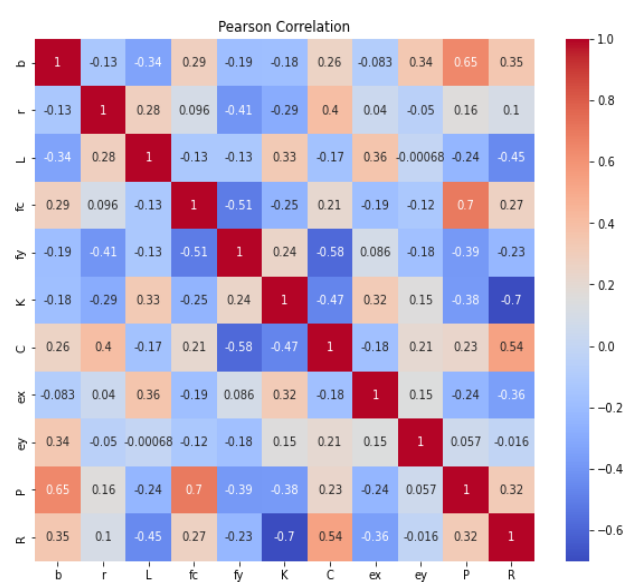


Fig. 1 Histograms for all variables in the dataset

2.2 Correlation investigation

Correlation is frequently used to uncover general patterns between distinct variables to help engineers visualize how changes to one variable may affect the other. Simply, correlation is a statistical method for describing the direction and intensity of the link between the listed variables herein. The most common correlation methods, *Pearson* and *Spearman*, gauge the *linear* and *monotonic* relationships between two dataset variables. Other correlation techniques, like *Chatterjee* and *Mutual Information*, can also be used to detect *dependence* and *nonlinear* correlations, respectively. Figure 2 presents a heatmap matrix that visually represents the results of the four correlation methods listed above. The results from the various correlation methods reveal several key findings. For example, concrete cover (*C*) exhibits the strongest positive correlation with fire resistance (*R*). Additionally, these methods reveal a strong negative correlation between effective column length (*K*) and the fire resistance of reinforced concrete columns, with negative values of -0.71 for Spearman, -0.70 for Pearson, and -0.57 for Chatterjee. In contrast, the mutual information model predicts a strong correlation between applied load (*P*) and fire resistance (*R*), with a coefficient of 4. At the same time, eccentricity in the y-direction (e_y) and steel ratio (*r*) exhibit the weakest correlations in most methods.

One can think of these four heatmaps as guiding tools to visualize the type and strength of relationships between the factors from the different lenses of each method. In other words, the intention of showing these maps is to educate the readers on the existence of possible relations between the factors and not to identify the best relation type – as, in reality, all of these relations are calculated through the principles of each method.



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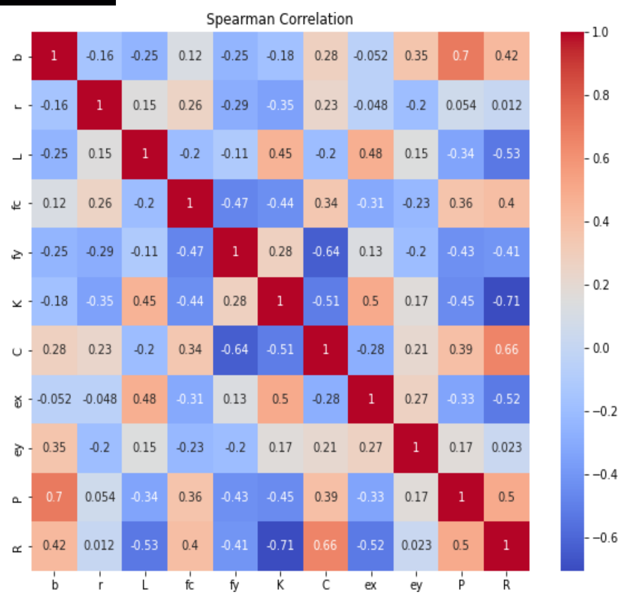

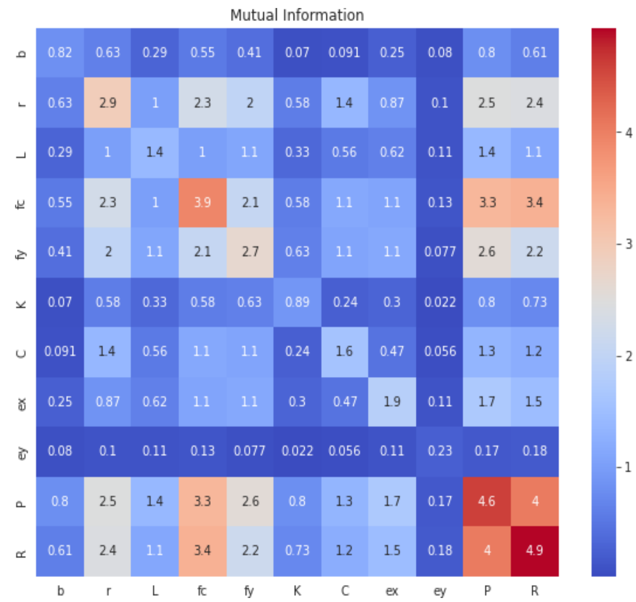

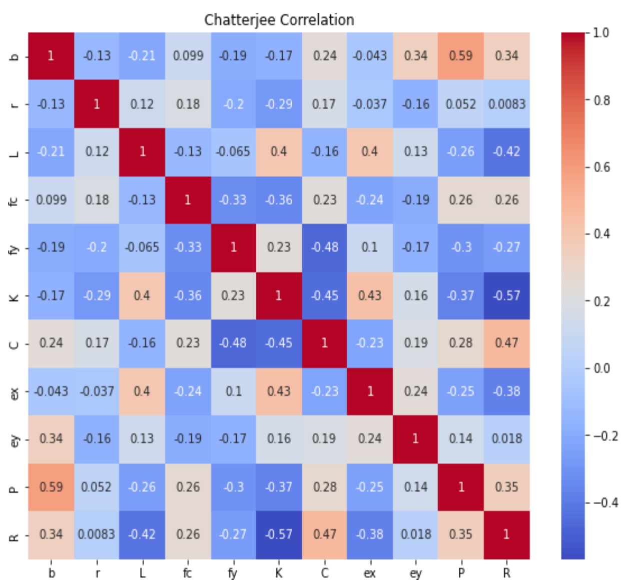

Fig. 2 Correlation matrices for Pearson, Spearman, Chatterjee, and Mutual Information

3.0 Detail of machine learning algorithms

The detailed procedures and techniques used in this study are described in this section for the reader's convenience. All models, with their full settings, can be found in their cited works. The analysis of the model was carried out using RapidMiner's [39] automated platform. We opted to use this automated platform to examine a different approach to that practiced in an earlier study by our group wherein traditional (i.e., coding-based) ML was used, as cited in the introduction section [23, 24].

3.1 Linear regression

The goal of linear regression is to find a linear relationship between a set of parameters. This relationship is fitted via coefficients and mapped using a linear equation that connects the dependent and independent variables. Setting the intercept to zero in linear regression models is a common practice to ensure that the model does not predict any response when all input variables have values of zero – which is valuable for our analysis of fire resistance prediction. This is because the model would not be physically realistic to forecast fire resistance when all the parameters are set to zero. In addition, the *Lrm* (Logistic regression modeling) is an extension of the linear model and aims to reduce the squared sum of differences between the predicted and actual values. The *Lrm* can be adopted to transform a linear relation between a dataset into a

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classification problem (such as fire rating, as will be shown in a later section) [40], [41].

3.2 Deep learning

A deep learning model is a subclass of ML that uses 2+ hidden layers [42]. This model seeks to replicate human cognition and uses a comparable methodology to comprehend the underlying pattern in various fields of study. We opted for a model with Multi-Layer Perceptron (MLP) with Rectified Linear Unit (ReLU) activation function and Adam optimizer. The minimum batch size was 1, the learning rate was set at 0.001, and the number of layers and neurons was set to 3 and 113, respectively.

3.3 Decision tree

The decision tree is a simple ML algorithm [35]. Recursively partitioning the data allows the model to run until the conditions are met and terminated. The simplicity of presentation and interpretation is this model's key benefit. However, decision trees have a high risk of overfitting – especially when working with noisy data. Based on the optimal parameter analysis, the decision tree model had a depth equal to seven.

3.4 Random forest

Like a decision tree, a random forest is a tree-based method in which several trees are simultaneously formed [43]. The results from all the trees are combined to make the final forecast. This model performs well regarding overfitting and their ability to handle high-dimensional data. The analysis's best parameters, which comprised 20 trees, a maximum depth of 7, and an error rate of 22.4%, were applied to the random forest model.

3.5 Gradient boosting trees

Another tree-based model attempts to improve model performance by reducing the impact of the erroneous feature in each modeling iteration [43]. This model finds the error in the first tree and builds a new tree model with the error as a new feature. Although the model performs well in classification and regression, it may be less appealing to use with big data because of the high volume of computations. The gradient boosting approach performs best with the number of trees set to 30, the maximum depth they can grow, and the learning rate of 0.1.

3.6 Support vector machine

While the support vector machine is frequently used for classification problems, it may also be utilized for regression [44]. The model operates by fitting a hyperplane that best distinguishes between a dataset's various clusters or classes. As already said, the technique can handle high-dimensional datasets, but it can be challenging to work with because the ideal tuning parameters require careful research. To minimize overfitting, the kernel gamma and complexity constant for the gradient-boosting tree model were found to be 0.05 and 1000, respectively.

3.7 Model performance evaluation

Finding the appropriate metrics' evaluation process for the research datasets is a crucial step that must be completed to ensure the quality of analysis in a machine learning analysis. In this study, we employed two sets of metrics that belong to regression and classification. All these metrics are commonly used in ML studies [45].

On the regression front, we used the *squared error (SE)*, which measures the discrepancy between projected values and their corresponding actual values, is used. In addition, the *relative error (RE)* is used. This metric evaluates the accuracy of a prediction by the ratio of the absolute error to the ground truth. A relative error has the benefit of being a dimensionless quantity, allowing comparison of prediction accuracy across many scales and units of measurement. The *mean absolute error (MAE)*, which measures the average size of the errors between the anticipated and actual values, is also used. One benefit of using MAE is that it offers a more perceptible measure of prediction error than other metrics like mean squared error. Also, we used the *R-squared (R^2)*, which shows how much of the variance in the dependent variable can be predicted based on the independent variable (s). Higher R^2 values indicate a better fit between the expected and actual values. Then, The last regression metric used is the *Root Mean Squared Error (RMSE)*, which calculates the average of the squared differences between predicted and actual values. As predicted and actual values are squared before being averaged, employing RMSE has the advantage of penalizing large errors more severely than small errors. Table 2 lists the above metrics.

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Vol 1 Issue 1 (2023)
Pages (45 –63)
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Table 2 List of used regression and classification metrics

Metric	Formula
E (Error)*	$E = A - P$
SE (Squared Error)	$SE = \sum_{i=1}^{n} E^2$
RE (Relative Error)	$\mathrm{RE} = \frac{\lvert y_i - \bar{y} \rvert}{y}$
MAE (Mean Absolute Error)	$\mathrm{MAE} = \frac{\sum_{i=1}^{n} \lvert E_i \rvert}{n}$
R^2 (Coefficient of Determination)	$R^2 = 1 - \sum_{i=1}^{n} (P_i - A_i)^2 \,/\, \sum_{i=1}^{n} (A_i - A_{mean})^2$
RMSE (Root Mean Absolute Error)	$RMSE = \sqrt{\frac{\sum_{i=1}^{n} E_i^2}{n}}$
TPR (True Positive Rate) or Sensitivity	$TPR = \frac{TP}{TP + FN}$
TNR (True Negative Rate) or Specificity	$TNR = \frac{TN}{TN + FP}$
ACC (Accuracy)	$ACC = \frac{TP + TN}{TP + TN + FP\_FN}$

The *A* and *P* letters stand for Actual and Predicted values, and *n* is for the number of points. On the classification front, we used the confusion matrix to visualize the performance of the classification quantity models. This matrix presents the accuracy of classifiers by providing statistics on actual and predicted classifications. This matrix's rows indicate real cases, whereas its columns reflect predicted events. A given set of predictions corresponding to true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN) numbers are shown in the matrix. Calculations based on the values in the confusion matrix can be made for three standard performance metrics: *sensitivity*, *specificity*, and *accuracy*. The percentage of real positives the model correctly classifies is measured by sensitivity. While accuracy gauges the general accuracy of the model's predictions, specificity quantifies the percentage of actual negatives that the algorithm accurately detects (see Table 2).

4.0 Results and discussion

4.1 Predicting the fire resistance time of RC columns

We start our discussion by presenting a comparison among the various ML models examined, including linear regression, gradient boosted trees, decision trees, support vector machines, random forests, and deep learning. In this analysis, our goal is to predict the fire resistance (time to failure) of the collected RC columns in this study.

We note that the gradient boosted trees and linear regression model yielded the first and second best performance – as can be seen in Table 3. However, the gradient boosted trees, as well as the other used ML models, are considered blackboxes and cannot be used in an intuitive manner or without the use of coding. Unlike the gradient boosted trees, linear regression can be used to create Nomograms; hence, this model is used, as will be discussed in a later section.

While we acknowledge the modest performance of the linear regression model (e.g., $R^2 = 0.64$), we will show that this model

still outperforms existing codal provisions in predicting the fire resistance of RC columns. First, we compared predictions from the linear model to predictions

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obtained from Eurocode 2 (Eq. 1) and AS3600 (Eq. 2) – see Table 3 and Fig. 3. As one can see, the accuracy of the latter two models fall short than that of the linear model.
However, the same two models are not applicable to eccentrically loaded RC columns. Thus, our analysis listed in Table 3 and Fig. 3 also shows the predictivity of these two codal provisions when only applied to concentrically loaded columns, and to columns primarily made from normal strength concrete. Here, we also show that the predictivity of these provisions is lesser than that of the linear model.

Table 3 Evaluation of different models performance in terms of fire resistance time

Model	R^2	SE	MAE	RMSE	RE
Linear regression	0.64	148507	37.34	54.49	0.39
Gradient boosting	0.77	102257.04	31.07	45.22	0.32
Decision tree	0.51	215923.84	43.74	65.71	0.47
Support vector	0.47	232278.89	52.93	68.15	0.49
Random forest	0.63	160781.63	34.25	56.70	0.41
Deep learning	0.23	342179.31	66.60	82.72	0.59
Codal provisions					
AS3600	-9.70	108859.28	209.83	329.93	2.38
AS3600 (without eccentricity)	-7.36	77262.85	172.83	277.96	0.99
Eurocode 2	0.42	5803.80	55.96	76.18	0.57
Eurocode 2 (without eccentricity)	0.23	7048.67	63.05	83.95	0.37

$$R = 120\left(\frac{R_{fi}+R_a+R_l+R_b+R_n}{120}\right)^{1.8}, \text{ and } R_{fi} = 83\left(1-\mu_{fi}\frac{1+\omega}{\alpha_{cc}+\omega}\right), \omega = \frac{A_s f_{yd}}{A_c f_{cd}} \quad (1)$$

where,
R = fire resistance of column (min),
α_{cc} = coefficient for compressive strength,
$R_a = 1.6(a-30)$; a is the axis distance to the longitudinal steel bars (mm); 25 mm $\leq a \leq$ 80 mm,
$R_l = 9.6(5-l_{o,fi})$; $l_{o,fi}$ is the effective length of the column under fire conditions; 2 m $\leq l_{o,fi} \leq$ 6 m; values corresponding to $l_{o,fi}$ = 2 m give safe results for columns with $l_{o,fi}$ < 2 m,
$R_b = 0.09b'$; $b' = A_c/(b+h)$ for rectangular cross-sections or the diameter of circular cross sections,
$R_n = 0$, if 4 rebars are used, and 12 for more than 4 rebars.

$$R = \frac{k \times f_c^{1.3} \times B^{3.3} \times D^{1.8}}{10^5 \times N^{1.5} \times L_e^{0.9}} \quad (2)$$

where,
R = fire resistance of column (min),
k = a constant dependent on cover and steel reinforcement ratio (equals to 1.47 and 1.48 for a cover less than 35 mm and greater than or equal to 35 mm, respectively),
f_c = 28-day compressive strength of concrete (MPa),
B = least dimension of column (mm),
D = greatest dimension of column (mm),
N = axial load during fire (kN),
L_e = effective length (mm).

Emirati Journal of Civil Engineering and Applications
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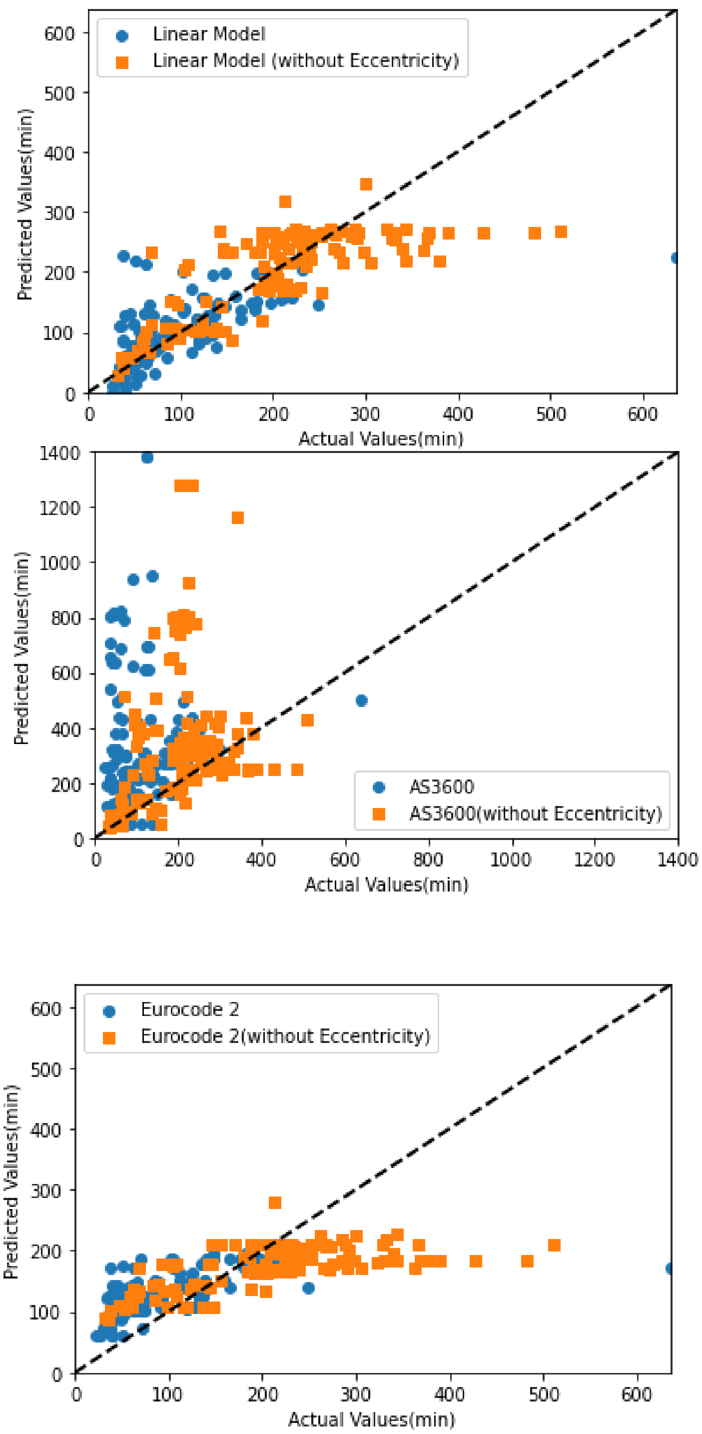

Fig. 3 Actual versus predicted fire resistance regarding three models (Linear model, Eurocode 2, and AS3600 from top to bottom) [Note that the axes of the AS3600 model had to be extended beyond 600 min as this equation yields relatively larger fire resistance times]

4.2 Predicting the fire resistance rating of RC columns

In this stage of analysis, our goal is to predict the fire resistance rating of RC columns. Our goal is to create visual aids that continue to account for a wide range of features that are absent from codal existing provisions. Such ratings can become handy for quick evaluation of RC columns in design and analysis scenarios. Since these ratings are primarily given in 60 min, this analysis turns into a classification problem. As such, all fire resistance times in the collected dataset were converted into classes, namely, 0-60 min [Class 1], 60-120 min [Class 2], 120-180 min [Class 3], and 180-240 min [Class 4]. It should be noted that some columns were reported to fail beyond 240 min, and hence these were labeled as 240 min.

We used the same approach followed in the previous section and applied the same ML models to predict all four classes at once. In this process, we noticed difficulty in training the machine learning models on all classes (see Table 4). After several attempts, it became clear that this approach does not yield acceptable results. Yet, we note that the logistic model (with a sigmoid function) ranked within 1.3% of the highest two models.

Table 4 Evaluation of models' performance on all classes in terms of fire resistance rating

Model	Accuracy
Logistic regression	63.4%
Gradient boosting trees	49.3%
Decision tree	46.6%
Support vector	40.0%
Random forest	64.3%
Deep learning	65.7%

To further improve the accuracy of the models, a sensitivity analysis was conducted to realize that combining the database into two alternate classes (Class 1 and Class 3) and (Class 2 and Class 4) would lead to arriving at the best classification metrics. Thus, we repeated the and also noted that the logistic model continued to rank top three[1] (in terms of Class 1 or 3) and as the leading model (for Class 2 or 4).

[1] While some ML models outperform the logistic model, such models can not be easily converted into a simple visual

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According to our analysis, the logistic regression model performs on par with sophisticated ML models. The logistic regression model demonstrated strong performance in predicting the dataset's two classes (Classes 1 and 3) with an overall accuracy of 0.88, sensitivity of 0.93, and specificity of 0.80. Furthermore, the logistic model achieved an accuracy of 0.95 on the other two classes. This model showed a high sensitivity of 0.91 and a specificity of 0.97 (see Table 5).

Table 5 Evaluation of different models' performance on two alternate classes in terms of fire resistance rating

Model for fire Classes 1 and 3	Accuracy	Sensitivity	Specificity
Logistic regression	88.7%	93.3%	80.0%
Gradient boosting trees	93.3%	93.3%	93.3%
Decision tree	93.3%	86.7%	100.0%
Support vector	48.0%	0.0%	100.0%
Random forest	93.3%	93.3%	93.3%
Deep learning model	85.3%	93.3%	73.3%
Model for fire Classes 2 and 4	**Accuracy**	**Sensitivity**	**Specificity**
Logistic regression	95.8%	91.7%	97.7%
Gradient boosting trees	91.1%	89.3%	95.0%
Decision tree	86.7%	100.0%	63.3%
Support vector	68.1%	53.3%	88.3%
Random forest	93.3%	96.7%	88.3%
Deep learning	86.4%	96.7%	70.0%

5.0 Nomograms

Engineers, practitioners, and medical professionals historically used Nomograms, also known as alignment charts, to solve mathematical equations or to depict complex interactions within phenomena [46, 47]. Typically, a Nomogram has one output variable and several input variables and can vary between simple parallel line scales or more intricate parabolic shapes. In comparison to other informational aids like equations or tables, Nomograms can be more user-friendly and do not require calculations beyond simple addition.
Nomograms are flexible tools that may be constructed using various techniques, including software packages like *Pynomo* in Python and *Lrm* in R. The standard process for creating a Nomogram entails analyzing the relations between independent and dependent variables, choosing a layout, deciding on the right scales for the variables, and drawing the Nomogram. From the perspective of this work, this process is tied to the use of linear regression and logistic regression[2].

5.1 Nomogram development

In this paper, we utilized Nomograms to predict the fire response of RC columns to fire via regression and classification. In the first case, a regression-based Nomogram utilizing linear regression was developed, and in the second case, logistic regression-based Nomograms utilizing the total point approach to determine the probability of different classes for RC columns were created.
To create the first Nomogram, the linear regression model was selected. The coefficients corresponding to each variable in this model work as a function to scale the axis associated with each parameter. The Nomogram was produced by plotting the resulting alignment chart with ratios and dimensions according to the functions and coefficients. The *isopleth ()* function, also known as a contour map, was used to predict a fire test from the dataset in the Nomogram. Our codes for creating the Nomograms are provided in the Appendix.
In order to create a target variable for the second Nomogram type, we divided it into four classes: the first class represents columns with fire resistance of lesser than 60 minutes, the second class represents columns with fire resistance of between 60 and 120 minutes, the third class represents columns with fire resistance of between 120 and 180 minutes, and the fourth class represents columns with fire

[2] The use of other forms of regression (i.e., nonlinear regression) is possible but is likely to require a more complex approach to that presented in this work.

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Emirati Journal of Civil Engineering and Applications
Vol 1 Issue 1 (2023)
Pages (45 –63)
DOI: 10.54878//EJCEA.109

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resistance of between 180 minutes and 240 minutes. As

mentioned above, we opted to filter Classes 1 and 3 together, followed by Classes 2 and 4. After training and testing the dataset, we fitted a linear regression that adheres to the Eq. 3 to determine the relationship between parameters. Then, using a logistic regression prime, we convert the values into binary classes Eq. 4.

$$R \sim b + r + L + f_c' + f_y + K + C + e_x + e_y + P \quad (3a)$$

$$R = (0.53 \times b) + (0.15 \times r) + (-14.6 \times L) + (0.92 \times f_c') + (0.21 \times f_y) + (-231.9 \times K) + (3.47 \times C) + (-0.37 \times e_x) + (-0.10 \times e_y) + (-0.03 \times P) \quad (3b)$$

$$\text{Propensity of a given class} = \frac{1}{(1 + e^{-(\beta_0 + \beta_1 x1 + \beta_2 x2 + \beta_3 x3 + \cdots)})} \quad (4)$$

Where, $\beta 0$, $\beta 1$are coefficients derived during the training process, and $x1$, $x2$, $x3$, etc., are the features identified in the study (those are listed in Table 1). Now, the model can predict the expected classes using the above equations. We again used the Lrm packages to make the model explainable for the engineer and practitioner by creating a Nomogram model via the Nomogram () function and plotting the derived result.

5.2 The Nomograms in use: step-by-step examples

In this section, we illustrate the practical applicability of the derived Nomograms by applying them to a specific RC column. Through this demonstration, we provide step-by-step instructions for effectively using the Nomograms to predict reinforced concrete columns' fire resistance. Utilizing a fire test with the following features:

- b (column width) = 406 mm,
- r (reinforcement ratio) = 2%,
- L (effective length) = 4 m,
- f′c (compressive strength of concrete) = 100 MPa,
- fy (steel yield strength) = 400 MPa,
- K (effective length factor) = 1,
- C (column concrete cover) = 48 mm,
- ex (eccentricity in the x direction) = 0 mm,
- ey (eccentricity in the y direction) = 0 mm,
- P (applied load) = 1410 kN

Using the Nomogram shown in Fig. 4, a user can:

1. Locate the two first parameters (b and r) on their respective axes, then draw a straight line to intersect with the R1 line. In this example, we find the values 406 and 2 and connect them to their corresponding R1 line.
2. Locate the third value, L (find the value four on the L axis), then draw a straight line from the previous point found in step 1, intersecting with the R2 line.
3. Locate the fourth value f′c (find the value 100 on the f'c axis), then match the last line to intersect with the R3 line.
4. In the fourth step, search for fy values (find the value 400 on the fy axis) and match this quantity with the value of line 3 to intersect with the corresponding value on line R4.
5. In the fifth step, search for the effective column length K (in this case, K=1) and follow the same process as step 4 to locate the value on the R5 line.
6. In this step, find the concrete cover C on the C axis (search for the value 48), then draw a straight line that passes the C axis and intersects with the R6 line.
7. Locate the eccentricity in the x direction ex (search for the value 0) and match R6 with R7.
8. Find the eccentricity in the y direction ey (search for the value 0) and match R7 with R8.
9. The final step involves finding the R value (fire resistance). In this step, locate the applied load on the P axis, draw a straight line to intersect with R8, then follow the line to intersect with the R axis, which gives the predicted (R) value.

As a result, as it can be read from Fig. 4, the value for the fire resistance of the column is 231 minutes, which is equal to what we have from the test experiments.

Emirati Journal of Civil Engineering and Applications
Vol 1 Issue 1 (2023)
Pages (45 –63)
DOI: 10.54878//EJCEA.109

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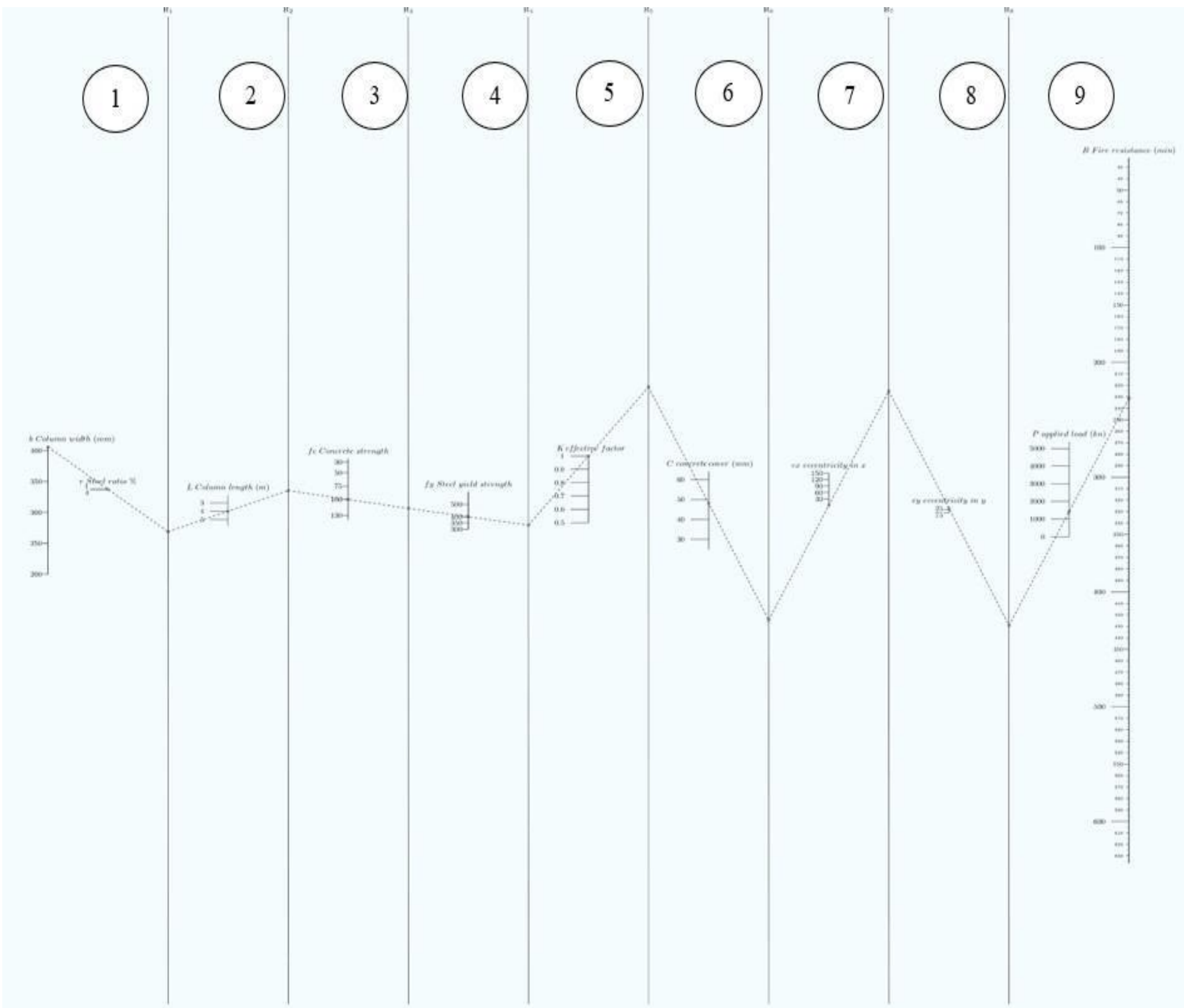

Fig. 4 Nomogram for predicting fire resistance of concrete columns in minutes. [Note: Numbers in circles refer to steps].

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Emirati Journal of Civil Engineering and Applications
Vol 1 Issue 1 (2023)
Pages (45 –63)
DOI: 10.54878//EJCEA.109

Available at www.emiratesscholar.com

We followed a similar procedure for the same RC column to demonstrate the practical application of the classification Nomograms. First, we locate the appropriate axes related to the parameters we were looking for and draw a perpendicular line from each axis to the point axis to determine the value of each parameter using the Nomogram. Next, we sum all the values we found and use the total point line to determine the probability of fire resistance classes.

Here, one must consider the two generated classification-based Nomograms simultaneously. In this example, the RC column will be classified through Nomogram A and Nomogram B. If the column falls under the 50% probability line in Nomogram A, then this column is unlikely to fall under Class 3 (effectively implying that the column is likely to be labeled as Class 1 and vice versa if the column falls above the 50% probability line to be labeled as Class 3). The same column is also examined in Nomogram B to evaluate its probability of falling under Class 2 or Class 4. Then, the arrived at probabilities from the two Nomograms are compared, and the larger probability is used to identify the fire rating class for the column at hand3.

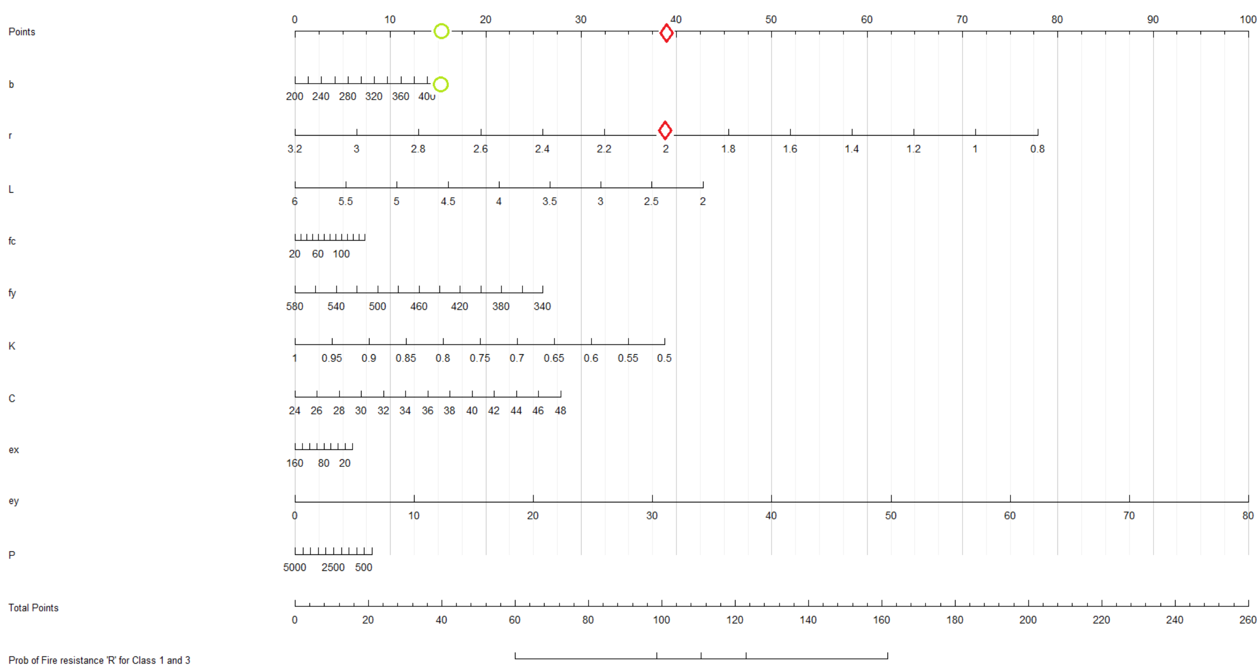
For example, applying the above procedure and utilizing the Nomograms in Fig. 5 for the same RC column used in the regression example, we obtain the following scaled values (which can be obtained visually from the Nomograms or via the complimentary Table 6):

· Nomogram A: b = 14.1, r = 39, L = 21, f′c = 5, fy = 19, K = 0, C = 28, ex = 0, ey = 0. The sum of these values equals 138.1 with a probability of 0.84 (interpolated linearly).

· Nomogram B: b = 74, r = 8, L = 17, f′c = 43, fy = 6, K = 0, C = 33, ex = 54, ey = 17.5. The sum of these values equals 327. 5 with a probability larger than 0.99.

Since the probability of this column falling under Class 4 is larger than the other classes (i.e., 0.99 > 0.84.3 [for Class 3]), then we can conclude that this column could be considered under Class 4 (indicating a fire resistance rating between 180-240 min). Considering the actual observed fire resistance is 231 min, then our analysis is valid.

[3] In the rare event that the two Nomograms return identical probabilities, then we advise selecting the more conservative class.



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Emirati Journal of Civil Engineering and Applications
Vol 1 Issue 1 (2023)
Pages (45 –63)
DOI: 10.54878//EJCEA.109

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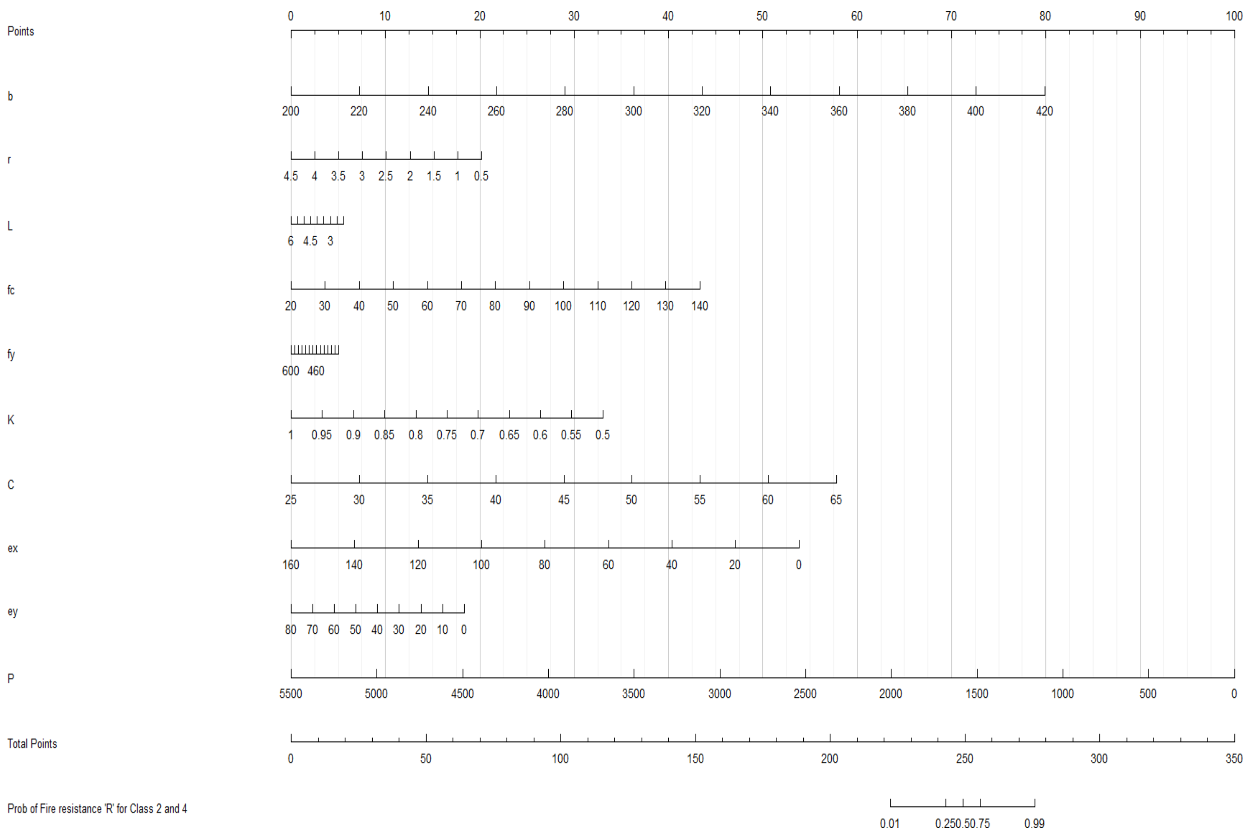
(a) Nomogram A for predicting Classes 1 and 3 [Note: only b and rare shown for eligibility]



(b) Nomogram B for predicting Classes 2 and 4 Fig. 5 Nomograms for fire rating

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Emirati Journal of Civil Engineering and Applications
Vol 1 Issue 1 (2023)
Pages (45 –63)
DOI: 10.54878//EJCEA.109

Available at www.emiratesscholar.com

Table 6 Companion tabulated values for Nomograms A and B

Companion for Nomogram A (for Classes 1 and 3)																			
b (mm)	Points	*r (%)*	Points	*L (m)*	Points	f'_c (MPa)	Points	f_y (MPa)	Points	*K*	Points	*C (mm)*	Points	e_x *(mm)*	Points	e_y *(mm)*	Points	*P (kN)*	Points
200	0	0.8	78	2	43	20	0	340	26	0.5	39	24	0	0	6	0	0	0	8
220	1	1	71	2.5	37	30	1	360	24	0.55	35	26	2	20	5	10	12	500	7
240	3	1.2	65	3	32	40	1	380	22	0.6	31	28	5	40	5	20	25	1000	6
260	4	1.4	58	3.5	27	50	2	400	19	0.65	27	30	7	60	4	30	38	1500	6
280	6	1.6	52	4	21	60	2	420	17	0.7	23	32	9	80	3	40	50	2000	5
300	7	1.8	45	4.5	16	70	3	440	15	0.75	19	34	12	100	2	50	62	2500	4
320	8	2	39	5	11	80	4	460	13	0.8	16	36	14	120	2	60	75	3000	3
340	10	2.2	32	5.5	5	90	4	480	11	0.85	12	38	16	140	1	70	88	3500	2
360	11	2.4	26	6	0	100	5	500	9	0.9	8	40	19	160	0	80	100	4000	2
380	12	2.6	19			110	5	520	6	0.95	4	42	21					4500	1
400	14	2.8	13			120	6	540	4	1	0	44	23					5000	0
420	15	3	6			130	7	560	2			46	26						
		3.2	0			140	7	580	0			48	28						

Total Points for Class 1 and 3	Probability
60	0.01
99	0.25
111	0.5
123	0.75
162	0.99

Companion for Nomogram A (for Classes 2 and 4)																			
b (mm)	Points	*r (%)*	Points	*L (m)*	Points	f'_c (MPa)	Points	f_y (MPa)	Points	*K*	Points	*C (mm)*	Points	e_x *(mm)*	Points	e_y *(mm)*	Points	*P (kN)*	Points
200	0	0.5	20	2	6	20	0	340	5	0.5	33	25	0	0	54	0	18	0	100
220	7	1	18	2.5	5	30	4	360	5	0.55	30	30	7	20	47	10	16	500	91
240	15	1.5	15	3	4	40	7	380	4	0.6	26	35	14	40	40	20	14	1000	82
260	22	2	13	3.5	3	50	11	400	4	0.65	23	40	22	60	34	30	11	1500	73
280	29	2.5	10	4	3	60	14	420	3	0.7	20	45	29	80	27	40	9	2000	64
300	36	3	8	4.5	2	70	18	440	3	0.75	17	50	36	100	20	50	7	2500	55
320	44	3.5	5	5	1	80	22	460	3	0.8	13	55	43	120	13	60	5	3000	45
340	51	4	3	5.5	1	90	25	480	2	0.85	10	60	51	140	7	70	2	3500	36
360	58	4.5	0	6	0	100	29	500	2	0.9	7	65	58	160	0	80	0	4000	27
380	65					110	32	520	2	0.95	3							4500	18
400	73					120	36	540	1	1	0							5000	9
420	80					130	40	560	1									5500	0
						140	43	580	0										

Total Points for Classes 2 and 4	Probability
222	0.01
243	0.25
249	0.5
256	0.75
276	0.99

5.3 Further remarks

As one can see, the created Nomograms are user-friendly and easy to use. These require basic information about RC columns, including the eccentricity of the applied load and boundary constraints, as well as account for some features absent from currently available codal provisions. Nomograms, like all other methods and procedures, can be utilized for various issues and fields of study, including the classification of fire severity, fire spread, and fire risk. Once fully validated, Nomograms have the potential to be incorporated into upcoming building regulations and standards, since they are visual tools engineers can efficiently utilize.

In addition, we would like to point out some limitations that need to be acknowledged. For example, additional diversified datasets, fire tests, and larger ranges of features can be better used to validate this approach further. It would also be advantageous to consider different Nomogram types that accommodate a broader range of model types. Further, while the generated linear regression model has a decent accuracy that exceeds those from Eurocode 2 and AS3600, we invite interested readers to further improve upon the developed model's accuracy and explore the use of other forms of regression, especially those for multi-classification analysis.

6.0 Conclusions

This study investigates the fire resistance of reinforced concrete (RC) columns using a dataset of 248 laboratory fire tests from various literature sources. The study's objectives were to create user-friendly aids to predict fire resistance and fire rating of RC columns and develop Nomograms capable of handling regression and classification problems. The following conclusions can also be drawn from the

Emirati Journal of Civil Engineering and Applications
Vol 1 Issue 1 (2023)
Pages (45 –63)
DOI: 10.54878//EJCEA.109

Available at www.emiratesscholar.com

findings of this study:

- The fire resistance of RC columns could be classified and predicted using the independent variables' geometry and mechanical characteristics. The correlation analysis showed that the boundary conditions and applied load significantly affected fire resistance, while the reinforcement ratio and yielding steel strength had less impact.
- This study shows that traditional linear regression can yield comparable accuracy to traditional ML and may outperform codal provisions.
- This analysis provides valuable insights into the fire resistance and fire rating of RC columns and lays the foundation for future research to improve the understanding and prediction of fire resistance in reinforced concrete structures.

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Conflict of interest statement

None.

References

1. Kodur V (2014) Properties of Concrete at Elevated Temperatures. ISRN Civil Engineering 2014:1–15. https://doi.org/10.1155/2014/468510
2. Khan MA, Khan AA, Usmani AS, Huang X (2022) Can fire cause the collapse of Plasco Building: A numerical investigation. Fire Mater 46:560–575. https://doi.org/10.1002/FAM.3003
3. Kodur V, Naser M (2020) Structural Fire Engineering, 1st ed. McGraw Hill Professional
4. (1988) Fire Resistance of Concrete Construction. Fire Technol 24:374–375. https://doi.org/10.1007/BF01040054/METRICS
5. Banerji S, Solhmirzaei R, Kodur VKR (2019) Fire Response of Ultra High Performance Concrete Beams. In: International Interactive Symposium on Ultra-High Performance Concrete
6. Dwaikat MB (2009) Flexural response of reinforced concrete beams exposed to fire. Michigan State University
7. Dwaikat MB, Kodur VKR (2010) Fire induced spalling in high strength concrete beams. Fire Technol 46:251–274
8. Bolina FL, Gil AM, Fernandes B, et al (2020) Influence of design durability on concrete columns fire performance. Journal of Materials Research and Technology 9:4968–4977
9. Kodur VKR, Phan L (2007) Critical factors governing the fire performance of high strength concrete systems. Fire Saf J 42:482–488
10. Wu B, Li YH, Chen SL (2010) Effect of heating and cooling on axially restrained rc columns with special-shaped cross section. Fire Technol 46:231–249. https://doi.org/10.1007/S10694-009-0091-Y/TABLES/3
11. Martins AMB, Rodrigues JPC (2010) Fire resistance of reinforced concrete columns with elastically restrained thermal elongation. Journal of Engineering Structures 32:3330–3337
12. Rodrigues JPC, Calmeiro dos Santos C, Pires TAC (2012) Fire resistance tests on concrete columns. In: 15th International Conference on Experimental Mechanics (ICEM15)
13. Bikhiet MM, El-Shafey NF, El-Hashimy HM (2014) Behavior of reinforced concrete short columns exposed to fire. Alexandria Engineering Journal 53:643–653
14. Ali F, Nadjai A, Choi S (2010) Numerical and experimental investigation of the behavior of high strength concrete columns in fire. Eng Struct 32:1236–1243
15. Yang D, Liu F, Huang S, Yang H (2021) Fire performance of eccentrically loaded square and rectangular tube-reinforced-concrete columns. Structures 33:1053–1076
16. Buch SH, Sharma UK (2019) Fire Resistance of Eccentrically Loaded Reinforced Concrete Columns. Fire Technol 55:1517–1552. https://doi.org/10.1007/S10694-019-00823-X/FIGURES/19
17. Yang D, Liu F, Huang S-S (2021) Structural behavior and design of end-restrained square tubed-reinforced concrete columns exposed to fire. Journal of Constructional Steel Research2
18. Huang X, Wu X, Usmani A, et al (2022) Perspectives of Using Artificial Intelligence in Building Fire Safety. Handbook of Cognitive and Autonomous Systems for Fire Resilient Infrastructures 139–159. https://doi.org/10.1007/978-3-030-98685-8_6
19. Behaviour of Concrete Walls in Fire | First National Structural Engineering Conference 1987: Preprints of Papers. Accessed 21 Mar 2023
20. How much fire resistance is really needed? - NRC Publications Archive - Canada.ca. https://nrc-publications.canada.ca/eng/view/object/?id=d5bfbc50-17ab-4691-9e96-358aed14f1f2. Accessed 21 Mar 2023
21. Naser MZ, Kodur VKR (2022) Explainable machine learning using real, synthetic and augmented fire tests to predict fire resistance and spalling of RC columns. Eng Struct 253:

*

Emirati Journal of Civil Engineering and Applications
Vol 1 Issue 1 (2023)
Pages (45 –63)
DOI: 10.54878//EJCEA.109

Available at www.emiratesscholar.com

22. Naser MZ, Ciftcioglu AO (2023) Causal discovery and inference for evaluating fire resistance of structural members through causal learning and domain knowledge. Structural Concrete

23. Ahmad A, Ostrowski KA, Maslak M, et al (2021) Comparative study of supervised machine learning algorithms for predicting the compressive strength of concrete at high temperature. Materials 14:

24. Tanyildizi H, Sengur A, Akbulut Y, Sahin M (2020) Deep learning model for estimating the mechanical properties of concrete containing silica fume exposed to high temperatures. Frontiers of Structural and Civil Engineering 14:1316–1330

25. He J, Huang X, Ning X, et al (2022) Modelling fire smoke dynamics in a stairwell of high-rise building: Effect of ambient pressure. Case Studies in Thermal Engineering 32:. https://doi.org/10.1016/J.CSITE.2022.101907

26. Zhang T, Wang Z, Huang X, Xiao F (2021) Real-time flashover prediction in compartment fire via computer vision and AI. In: 12th Asia-Oceania Symposium on Fire Science and Technology (AOSFST 2021). University of Queensland Library

27. Zeng Y, Zhang X, Su L, et al (2022) Artificial Intelligence tool for fire safety design (IFETool): Demonstration in large open spaces. Case Studies in Thermal Engineering 40:102483. https://doi.org/10.1016/j.csite.2022.102483

28. Jiang L, Orabi MA, Jiang J, Usmani A (2021) Modelling concrete slabs subjected to fires using nonlinear layered shell elements and concrete damage-plasticity material. Eng Struct 234:. https://doi.org/10.1016/J.ENGSTRUCT.2021.111977

29. Qiu J, Jiang L, Anwar Orabi M, et al (2022) A computational approach for modelling composite slabs in fire within OpenSees framework. Eng Struct 255:. https://doi.org/10.1016/J.ENGSTRUCT.2022.113909

30. Panev Y, Kotsovinos P, Deeny S, Flint G (2021) The Use of Machine Learning for the Prediction of fire Resistance of Composite Shallow Floor Systems. Fire Technol 57:3079–3100. https://doi.org/10.1007/S10694-021 01108-Y/FIGURES/19

31. Chen C, Jiang L, Qiu J, et al (2022) OpenSees development for modelling timber structural members subjected to realistic fire impact. Fire Mater. https://doi.org/10.1002/FAM.3115

32. Cai X, Jiang L, Qiu J, et al (2022) Dual-3D hybrid fire simulation for modelling steel structures in fire with column failure. J Constr Steel Res 197:. https://doi.org/10.1016/J.JCSR.2022.107511

33. Khan MA, Jiang L, Cashell KA, Usmani A (2018) Analysis of restrained composite beams exposed to fire using a hybrid simulation approach. Eng Struct 172:956–966. https://doi.org/10.1016/J.ENGSTRUCT.2018.06.048

34. Naser MZ, Kodur V, Thai H-T, et al (2021) StructuresNet and FireNet: Benchmarking databases and machine learning algorithms in structural and fire engineering domains. Journal of Building Engineering 44:102977. https://doi.org/10.1016/j.jobe.2021.102977

35. Naser MZ (2021) Observational Analysis of Fire-Induced Spalling of Concrete through Ensemble Machine Learning and Surrogate Modeling, J. Mater Civ Eng 33:. https://doi.org/10.1061/(ASCE)MT.1943-5533.0003525

36. Smeden M van, Moons KG, Groot JA de, et al (2018) Sample size for binary logistic prediction models: Beyond events per variable criteria: https://doi.org/101177/0962280218784726 28:2455–2474. https://doi.org/10.1177/0962280218784726

37. Riley RD, Snell KIE, Ensor J, et al (2019) Minimum sample size for developing a multivariable prediction model: PART II - binary and time-to-event outcomes. Stat Med. https://doi.org/10.1002/sim.7992

38. Frank I, Todeschini R (1994) The data analysis handbook

39. Altair Company (2023) RapidMiner Studio, Version 10.1 . https://academy.rapidminer.com/. Accessed 21 Mar 2023

40. Cox DR (1959) The Regression Analysis of Binary Sequences, J. R. Stat. Soc. Ser. B

41. Nelder JA, Wedderburn RWM (1972) Generalized Linear Models. J R Stat Soc Ser A 135:370. https://doi.org/10.2307/2344614

42. LeCun Y, Bengio Y, Hinton G (2015) Deep learning.Nature 521:436–444. https://doi.org/10.1038/nature14539

43. Freund Y, Schapire RE (1997) A Decision-Theoretic Generalization of On-Line Learning and an Application to Boosting. J Comput Syst Sci. https://doi.org/10.1006/jcss.1997.1504

44. Çevik A, KURTOĞLU AE, Bilgehan M, et al (2015) Support vector machines in structural engineering: A review. Journal of Civil Engineering and Management 21:261–281. https://doi.org/10.3846/13923730.2015.1005021

45. Naser MZ, Alavi AH (2021) Error Metrics and Performance Fitness Indicators for Artificial Intelligence and Machine Learning in Engineering and Sciences. Architecture, Structures and Construction 1:3. https://doi.org/10.1007/s44150-021-00015-8

46. Tapeh ATG, Naser MZ (2022) Discovering Graphical Heuristics on Fire-Induced Spalling of Concrete Through Explainable Artificial Intelligence. Fire Technol 58:2871–2898. https://doi.org/10.1007/s10694-022-01290-7

*

Emirati Journal of Civil Engineering and Applications
Vol 1 Issue 1 (2023)
Pages (45 –63)
DOI: 10.54878//EJCEA.109

Available at www.emiratesscholar.com

47. Arash Teymori Gharah Tapeh, Mohammad Khaled al-Bashiti, Alireza Ghasemi, et al (2022) A NOMOGRAM FOR PREDICTING FIRE-INDUCED SPALLING. SIF, Hong Kong

Appendix

Codes for running this analysis will be provided upon publication.

Nomograms (for blank nomograms) will be provided upon publication.