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A machine learning-based approach to evaluate the fire resistance of timber columns

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ABSTRACT: Timber construction offers substantial advantages in terms of sustainability, ease of modular construction, and aesthetics. In recent years, structural members made from timber have been increasingly used in residential and commercial buildings. When used in building applications, structural timber members must meet required fire resistance ratings. Fire resistance of timber members can be evaluated by standard fire testing, which requires sophisticated and expensive testing facilities, and is labor-intensive and time-consuming. An alternative to fire testing is using advanced numerical models, which is computationally intensive. This study leverages machine learning (ML) methods to overcome the complications of fire testing and complex numerical modeling. Therefore, an ML workflow is developed and applied to a database of 70 fire tests reported in the literature to accurately evaluate the fire resistance of timber columns. The input parameters considered for training the models comprise geometric and material properties and loading conditions during the fire tests. Four different ML algorithms were implemented, namely, multiple linear regression, support vector machines, light gradient boosting, and random forest. The ML models benefited from an automated training procedure comprising hyperparameter tuning and cross-validation. Furthermore, Shapley additive explanations were used to interpret the relationship between timber column geometry, material properties, and fire resistance. The results show that random forest provides a higher accuracy with an R-squared of 0.84 on the test set, where column capacity, width, depth, and load level are the most critical parameters.

In recent years, there has been a consistent increase in the application of timber for load-bearing members in residential and commercial construction (Braun et al. 2022; Gasparri and Aitchison 2019). The growing use of timber as a primary building material is mainly driven by sustainability considerations. For example, using wood with lower embodied carbon in place of steel or concrete for construction can lower greenhouse gas emissions by 2 metric tons per cubic meter of installed timber products (Sathre and O'Connor 2010). Timber construction permits offsite modular prefabrication, reducing construction time and labor costs. Moreover, timber components are relatively light due to the high strength-to-weight ratio of timber, which results in savings in foundation materials (Zaker Esteghamati et al. 2022).

Different jurisdictions are now permitting the use of timber for framing in mid-rise and high-rise buildings. However, the fire safety of timber construction is still an area of concern. This concern stems from the unique fire behavior of timber. Timber is combustible under fire exposure, which complicates the structure's overall fire dynamics and associated fire performance (Gorska et al. 2021). Under fire scenarios, burning timber can contribute to additional fuel load, increasing the fire growth rate, extending the period of fire exposure, and negatively impacting structural performance. Furthermore, the combustion of timber produces smoke and harmful incomplete combustion gases, which can be detrimental to evacuating occupants and firefighters (Cheng et al. 2022). Lastly, timber members are susceptible to failure even after the end of the heating phase due to smoldering combustion after flame extinction and significant loss in the mechanical properties of timber at low temperatures of 100°C. At this temperature, timber loses up to 65% and 75% of its modulus and compressive strength, respectively (Gernay et al. 2022; Wiesner et al. 2019).

The fire performance of a structural member is captured in terms of fire resistance, which is the duration of time for which a member sustains the applied loading and limits deformations to a specified limit. The fire resistance of timber structures can be evaluated through standard fire testing. However, fire tests are expensive, time-consuming, and require specialized testing equipment and skilled personnel. More recently, advanced analysis procedures have been incorporated using nonlinear finite element methods (Banerji and Kodur 2022). Despite the relatively good agreement between finite element models and fire tests, advanced numerical simulations require significant computational efforts and prior training or experience. In addition, the accuracy of advanced finite element analyses is essentially dependent on reliable input data on high-temperature anisotropic material properties of wood, which has a significant variation in the current literature.

For the past two decades, machine learning (ML)-based approaches to address traditional structural engineering problems have been gaining momentum (Zaker Esteghamati and Flint 2021). Compared to experiments and advanced numerical modeling, ML-based models can address the complexities associated with nonlinear interdependencies among influencing parameters and high levels of data variability, thus saving considerable time and resources. However, the incorporation of ML in structural fire engineering is infrequent. This gap is partly caused by the limited availability of data from intricate fire tests for validating and testing ML models. The majority of the research in structural fire engineering has been conducted on predicting the fire resistance of reinforced concrete, steel, and composite members (Li et al. 2021; Naser 2021; Zhao 2006). Some studies have focused on estimating the high-temperature material properties of concrete and steel (Banerji 2022; Naser 2018). Unlike other construction materials, there have hardly been any ML-based studies on the fire behavior of timber. Among the few ML-based studies are the works by Naser (Naser 2019), wherein Artificial Neural Networks (ANN) and genetic algorithms were utilized to develop high-temperature response relations for timber at material and member levels.To address the current gaps in literature, this study implements ML approaches to understand the fire resistance of timber columns based on a carefully compiled database of experimental tests. The results of this study aim to answer two key research questions: (1) How well can ML models predict the fire resistance of timber columns? (2) What geometric and material parameters are more critical for the fire resistance of timber columns? To this end, an ML workflow is developed, and the predictive capabilities of four ML algorithms are assessed. Model-agnostic interpretation methods are then implemented to interpret the underlying relationship between fire resistance and columns' geometric and mechanical properties.

1. TIMBER COLUMN DATABASE

1.1. Data sources

A detailed literature review was conducted to compile data from experiments on timber columns. A database was collected from about 70 tests reported in the works of Fackler (Fackler 1961), Stanke et al. (Stanke et al. 1973), Malhotra and Rogowski (Malhotra and Rogowski 1967), and Ali and Kavanagh (Ali and Kavanagh 2005). The dataset did not include numerical modeling results since the selected material models, solver techniques, mesh sizes, and other assumptions considerably impact the numerical predictions.

The selected studies carried out fire tests on timber columns uniformly exposed (i.e., all four sides) to fire curves equivalent to standard fire ISO 834 (ISO 834-1 1999). These tests capture the

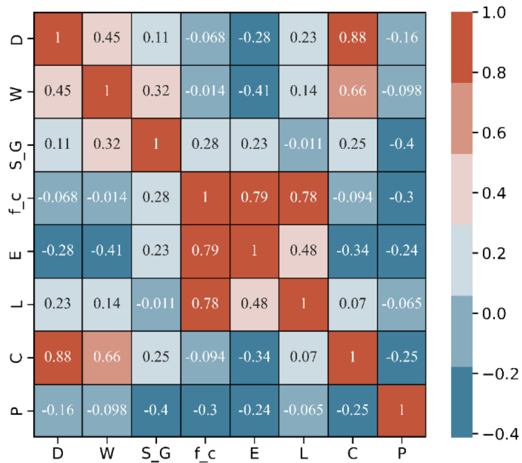

Figure 1: Correlation structure of the compiled database

effect of varying parameters on the fire resistance of timber columns, including temperature-dependent material properties, cross-sectional dimensions, and loading level. The tests carried out by Fackler (Fackler 1961), Stanke et al. (Stanke et al. 1973), and Malhotra and Rogowski (Malhotra and Rogowski 1967) are also summarized in the Technical Report (TR) no. 10 prepared by the American Wood Council (AWC) (American Wood Council (AWC) 2018).. The AWC report utilizes 2012 National Design Specification (NDS) behavioral equations for calculating the effective length and resisting capacity of these tested columns, and these calculated values have been utilized for the database used in this study. The compiled database provides information on experiment time (t), smaller dimension of column (D), larger dimension of column (W), specific gravity (S_G), compressive strength (f_c), modulus of elasticity (E), length (L), capacity (C) and load level (P), and column fire resistance (R).

1.2. Statistical properties of the database

Spearman correlation was used to measure the relationship between different features. Unlike Pearson correlation, which can only capture linear data association, Spearman correlation measure can account for both linear and nonlinear data association. Figure 1 shows the Spearman

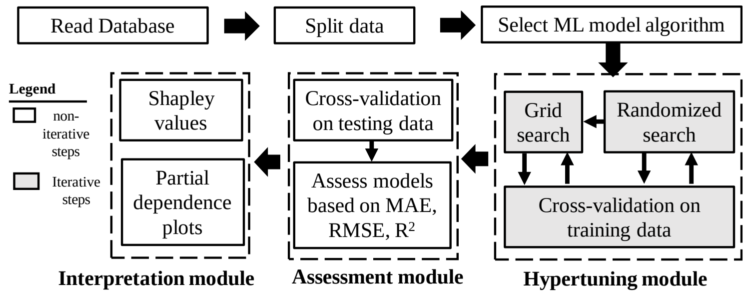

Figure 2: ML development framework

correlation values (ρ_s) between different input features. Capacity has a strong positive correlation to shorter dimension of column, D (ρ_s = 0.88) and longer dimension of column, W (ρ_s =0.66), which is intuitive as column capacity is related to its geometric configuration. In addition, the columns' compressive strength is strongly related to the modulus of elasticity (ρ_s =0.79) and column length (ρ_s =0.78). In addition, there is a moderate correlation between depth and width, and between the modulus of elasticity and column length.

2. ML MODEL DEVELOPMENT

ML models were developed to predict fire resistance using the discussed predictors in Section 1. As shown in Figure 2, the compiled database was split into 70% training and 30% testing data sets. Four algorithms of multiple linear regression (MLR), support vector machine (SVM), light gradient boosting (LGBM or LightGBM), and random forest (RF) were implemented to identify the best ML model. The selected algorithms cover a variety of alternatives in the flexibility-interpretability tradeoff. The hyperparameters of each ML algorithm were then tuned by performing a three-fold cross-validation on the training set through a hybrid randomized-grid search method. Lastly, the ML models' accuracy was measured using root mean squared error (RMSE) and coefficient of determination (R^2) performance criteria.

MLR algorithm extends a simple regression by assigning a separate slope (i.e., regression coefficient) to each predictor. Each model coefficient shows the average effect of a unit increase in the corresponding predictor on the response, if all other predictors are fixed. SVM was built as an extension of the maximal margin classifier algorithm and was later extended to regression problems. SVM aims to find a hyperplane that could separate training data based on their labels and deviate by a maximum of a given margin. LightGBM is a boosting algorithm with two key characteristics that accelerate training time. First, the conventional gradient boosting method is modified to focus on training samples with larger gradients (referred to as gradient-based one-side sampling). Second, an automatic feature selection method, exclusive feature bundling, is implemented to aggregate sparse mutually exclusive features (Ke et al. 2017). Lastly, RF (Breiman 2001) uses the bagging approach, and averages the prediction of an ensemble of RTs to achieve a low-variance and more accurate prediction. To this end, RF chooses repeated samples of training data (i.e., bootstrapping) and trains several regression trees on each training sample (Hastie et al. 2016).

3. ML MODELS ACCURACY

Figure 3 shows the ML model prediction for training and testing sets, and Table 1 shows the RMSE and R^2 values. Overall, the RF algorithm provides the best accuracy to predict fire resistance for test set data. The R-squared and RMSE of RF for testing sets are 84% and 5.55, respectively. In contrast, LGBM provides the lowest accuracy. For example, the R^2 of LGBM is 13% lower than the RF, whereas its RMSE is 61% higher than RF. The RMSE values of MLR and SVM are close, whereas MLR provides a higher R^2 value.

Figure 4 shows the relative importance of RF predictors. Overall, capacity has the highest importance. Column cross-sectional information

Table 1: Comparison of model accuracy

Algorithm	Training		Testing	
	RMSE	R^2	RMSE	R^2
MLR	6.06	0.88	6.10	0.81
SVM	6.74	0.85	6.70	0.77
LGBM	9.87	0.69	9.87	0.69
RF	4.87	0.92	5.55	0.84

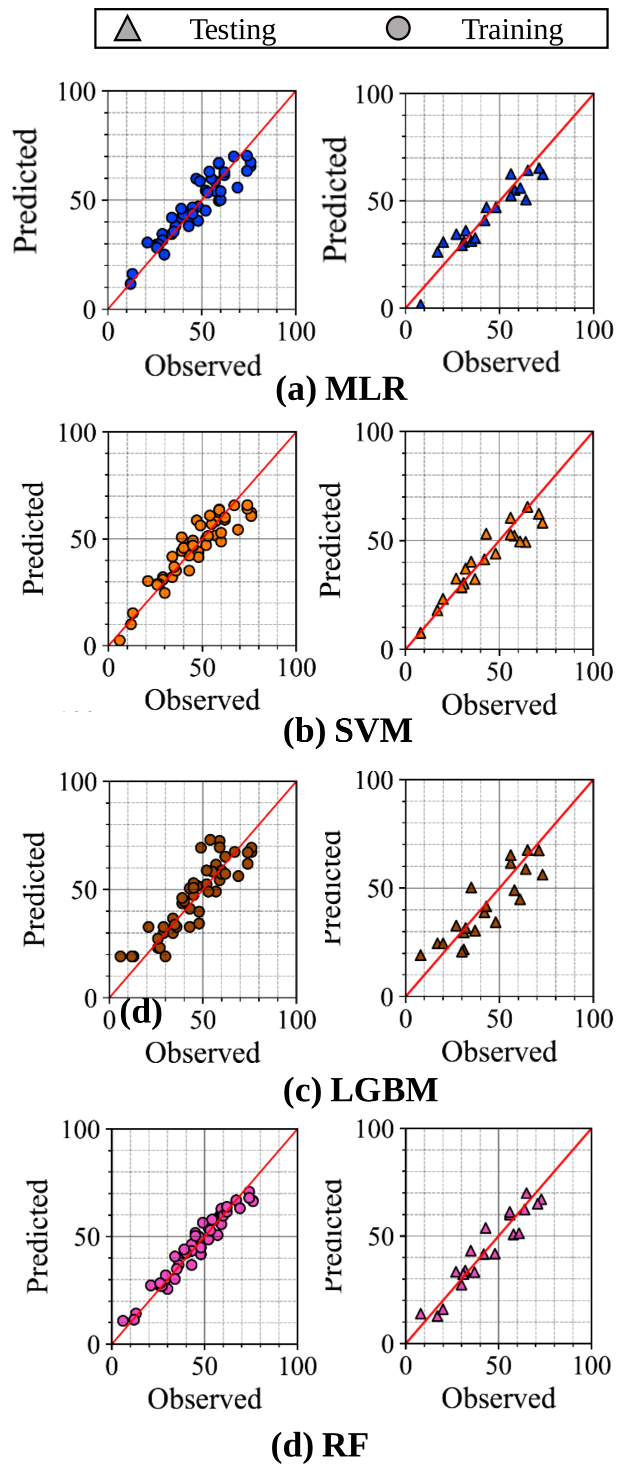

Figure 3: Comparison of different ML models accuracy

(i.e., width and depth) shows relatively higher significance than other parameters, whereas modulus of elasticity, specific weight, and column length are deemed unimportant for RF prediction.

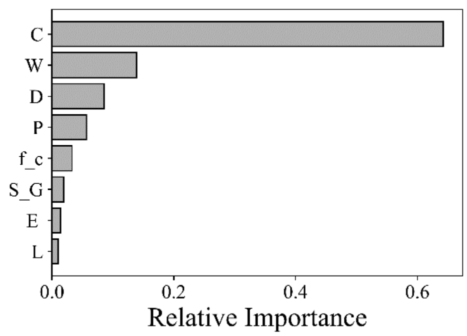

Figure 4: Importance of different predictors for RF model

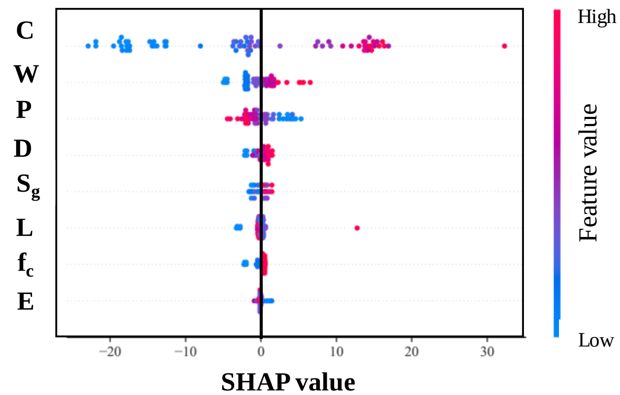

Figure 5: Shapley plots of RF model

4. ML MODELS INTERPRETATION

Shapley additive explanations (SHAP) (Lundberg and Lee 2017) explain the prediction of a given data instance by computing the contribution of each predictor to the prediction based on game theory. In this approach, the prediction (i.e., payout) is "fairly" distributed to the features (i.e., players) based on their coalition to receive profit. Each predictor's Shapley value is defined as the average marginal contribution of the predictor across all possible coalitions.

Figure 5 shows the SHAP summary plots for RF. In these plots, the impact of higher and lower values of features on the SHAP values are shown. In addition, the features are sorted based on their importance in descending order on Y axis. Figure 5 shows that for the RF model, timber columns with higher capacity and longer dimension (W) have higher fire resistance, whereas timber columns subjected to higher load levels show lower fire resistance. The contribution of other features is very small. However, it can be observed that columns with larger shorter dimension (D), specific weight and compressive strength show slightly higher fire resistance.

5. CONCLUSIONS

The study compiled a database of fire tests on timber column and compared the performance of different ML algorithms to develop predictive models. Furthermore, Shapley explanations were used to interpret the best trained model. The main findings from this study are as follows:

- Among the studied algorithms, the random forest model provided the highest accuracy with an R^2 of 84 on the test set.
- The performance of support vector machines and light gradient boosting algorithms was not better than a multiple linear regression model for the studied database.
- Among different predictors, column capacity was found to be the most influential feature in predicting the fire resistance of timber columns.
- Specific weight, modulus of elasticity, and column length had negligible impact on the fire resistance of timber columns.

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