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EXPLAINABLE MACHINE LEARNING FOR PREDICTING THE FIRE RESISTANCE OF PERFORMANCE-BASED COMPOSITE FLOOR SYSTEMS

Chenzhi Ma[1], Ali Namin[2], Thomas Gernay[3], Mohsen Zaker Esteghamati[4]

ABSTRACT

Composite steel–concrete floor systems are widely used in multi-story buildings but are vulnerable to fire because steel components degrade rapidly at elevated temperatures. Although prescriptive fire design remains the default approach, performance-based fire design can deliver higher performance and/or more efficient designs. However, broader adoption is limited by the cost and expertise required for nonlinear thermo-mechanical simulations. This study develops a fast, interpretable machine-learning surrogate to predict the fire response of composite floor systems and identify key design drivers. The surrogate is trained on experimentally validated thermo-mechanical simulations spanning a range of floor designs. A suite of regression models were evaluated to map geometric and design parameters to system response, and Shapley Additive Explanations (SHAP) analysis was performed to quantify feature importance and reveal governing trends. The best model accurately predicts both peak and residual displacements at the slab centre. Results indicate that fire load is the dominant driver of maximum and residual displacements, while slab geometry and ventilation primarily influence peak response.

Keywords: Performance-based fire design; composite floor systems; explainable machine learning; surrogate models

1 INTRODUCTION

Composite steel–concrete structures, particularly composite floor systems, are widely used in the U.S. due to their high strength-to-weight ratio and construction efficiency [1]. However, steel components heat rapidly under fire exposure and experience marked reductions in strength and stiffness at elevated temperatures [2]. Fire safety for these systems in the United States has traditionally been ensured through prescriptive building-code provisions [3]. This approach is clear and easy to implement, but it can be restrictive for complex or irregular buildings. These issues have increased interest in performance-based design (PBD) [4]. In PBD, structural response is evaluated directly against explicit performance objectives under credible hazard scenarios [5]. For composite floor systems, performance in fire is strongly influenced by system-level load redistribution [6]. When designed appropriately, composite slabs can develop substantial membrane forces through tensile

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membrane action (TMA) at large deflections, sustaining gravity loads even after significant flexural capacity has been lost [7].

Evidence for this behaviour has been reported in several major test programs. Full-scale eight-story steel-framed fire tests conducted at Cardington in 1995 and 1996 [8] found that, even when steel beam temperatures exceeded 1150 °C, composite floors developed large deflections (approximately span/20) without collapse. Following Cardington, the FRACOF [9], COSSFIRE [10], and FICEB [11] programs also showed that composite floors with unprotected central beams can survive selected ISO or natural fire exposures through TMA. More recently, the National Institute of Standards and Technology (NIST) conducted three full-scale fire tests on composite floor systems [12–14]. The first specimen, designed for a 2-hour prescriptive rating, did not survive the 2-hour ASTM E119 exposure due to slab integrity failure. The second and third tests incorporated additional reinforcement, with the third adopting a PBD-oriented strategy that omitted fire protection on the central steel beams; neither showed signs of failure within two hours. Though experimental tests provided valuable data on the performance of composite floor systems, developing numerical models to deepen understanding and expand on the experimental findings is still necessary. For example, advanced simulations can be used to identify the critical design parameters and the probability of failure [15,16].

Despite these advances, PBD for composite floor systems has not yet been implemented in practice in several countries, such as the United States. A key barrier is the reliance on advanced nonlinear analysis to predict structural behaviour under fire. Accurate assessment typically requires advanced thermal–mechanical finite element simulations that incorporate temperature-dependent material degradation, geometric nonlinearity, and large-deflection response. When calibrated and validated against experiments, these models can provide a reliable system-level assessment. However, they are computationally expensive, especially for parametric studies, reliability analyses, design optimization, or early-stage design work. The need for specialized modelling expertise and the difficulty of interpreting high-dimensional results further limit routine application. In practice, given typical project constraints, undertaking a PBD for fire may be less attractive due to the reliance on complex, time-consuming models. The computational burden, therefore, remains a major obstacle to broader implementation.

Recent studies in structural engineering have shown that design-oriented and explainable machine learning models can provide efficient prediction while preserving physical interpretability, including applications to fire resistance of timber columns and seismic response, fragility, and loss assessment of steel building inventories [17,18]. This study develops a surrogate-based framework for predicting the fire response of composite floor systems designed using performance-based principles. The surrogate model is trained on an extensive database of nonlinear thermo-mechanical simulations previously validated against full-scale composite floor system tests conducted at NIST. A large suite of ML models is compared to identifying the best model for predicting the response (maximum and residual vertical deflection at the slab center), using regression-based techniques. Shapley Additive Explanations (SHAP) quantify the effects of structural, thermal, boundary, and fire parameters on predicted performance. The proposed framework enables efficient evaluation of PBD composite floor configurations and provides parameter-level insight into membrane-action-dominated fire behaviour. This approach links validated simulations with design-oriented decision support, facilitating a more practical implementation of PBD for composite floors under fire.

2 METHODOLOGY

The training data inventory is adopted from numerical models developed by Ma et al. [16], based on the NIST two-story, two-by-three-bay steel gravity frame with composite floor systems subjected to compartment fires. Thermal and structural analyses are performed in SAFIR using a validated single-slab model that preserves global behaviour while reducing computational cost. Natural fires are represented using the Eurocode

parametric fire model to capture heating and cooling phases, with fire load varied from 100 to 2100 MJ/m² and ventilation captured through the opening factor.

The selected model inputs included:

(1) Fire load which is the total combustible energy per unit floor area measured in units of MJ/m²(ranging from 100 to 2100 MJ/m²).

(2) Aspect ratio (AP) of the slab panel (1:1, 1:1.5, and 1:3).

(3) Opening factor (O) that controls ventilation condition and oxygen supply (ranging from 0.02 to 0.0535 $m^{1/2}$).

(4) BC_x and BC_y that represent boundary conditions in x and y directions. Three boundary conditions are considered in the dataset, including simply supported slab, restrained thermal expansion in the x-direction, and restrained thermal expansion in both x and y directions.

(5) Slab reinforcement area per unit width (As) that represents total steel area available to carry tensile member forces. Three values are considered in this study: 142, 230, and 345 mm²/m.

(6) Yield strength of reinforcement steel (f_y), and lastly three parameters related to spray fire-resistive material (SFRM) which were (7) thermal conductivity (K_i), (8) specific heat capacity (C_i), and (9) density (ρ_i)). In this study, at ambient temperature (20 °C), the reinforcement yield strength f_y ranges from 392 to 526 MPa, K_i ranges from 0.039 to 0.10 W/(m°C), C_i from 172 to 1098 J/(kg·K), and ρ_i from 232 to 383 kg/m³.

Ten regression models (as listed in Table 1), spanning linear, kernel-based, tree-based, and neural network models, were selected in this study. The model performance was quantified using several metrics, including (1) coefficient of determination (R^2), (2) root mean squared error (RMSE), (3) mean absolute error (MAE), (4) mean squared relative error (MSRE), (5) Root Mean Squared Relative Error (RMSRE), and (6) standard deviation of error (SD). Table 2 provides the notation, formulation, and explanation of the accuracy metrics selected in this study. To interpret the best-performing models, we use SHAP value to quantify both global feature importance and feature–response trends.

Table 1. Selected regression models

	Model	Model family
MLR	Multiple Linear Regression	Linear
Lasso Reg	Lasso Regression	Linear
XGB	Extreme Gradient Boosting Regressor	Boosting
LGBM	Light Gradient Boosting Machine Regressor	Boosting
AdaBoost	AdaBoost Regressor	Boosting
DT	Decision Tree Regressor	Tree-based
RF	Random Forest Regressor	Tree-based
ERT	Extra Trees Regressor	Tree-based
SVM	Support Vector Machines	Kernel method
MLP	Multi-Layer Perceptron Regressor	Neural network

Table 2. Selected accuracy metrics to evaluate ML models

Category	Notation	Metric Name	Formulation	Explanation
Regression	R^2	Coefficient of Determination	$1 - \frac{\Sigma(y_i - \hat{y}_i)^2}{\Sigma(y_i - \bar{y})^2}$	Variance explained relative to mean predictor

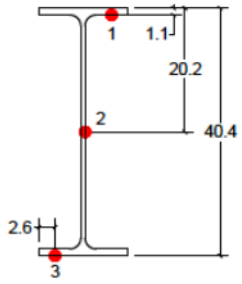
	RMSE	Root Mean Squared Error	$\sqrt{\frac{1}{n}\Sigma(y_i - \hat{y}_i)^2}$	Penalizes large errors
	MAE	Mean Absolute Error	$\frac{1}{n}\sum\lvert y_i - \hat{y}_i\rvert$	Average absolute error
	MSRE	Mean Squared Relative Error	$\frac{1}{n}\sum\left(\frac{y_i - \hat{y}_i}{y_i}\right)^2$	Scale-normalized squared error
	RMSRE	Root Mean Squared Relative Error	$\sqrt{\text{MSRE}}$	Relative error on normalized scale
	SD	Standard Deviation of Error	$\sqrt{\frac{1}{n-1}\Sigma(e_i - \bar{e})^2}$	Error variability

3 RESULTS

3.1 Structural fire response of the composite flooring system

The numerical modelling strategies are validated against experimental results for both thermal and structural responses. Figure 1 compares the temperature distribution in the steel beam predicted by SAFIR (bold lines) with measurements from NIST Test #1. Overall, the numerical model reproduces the measured temperature profiles well, supporting the reliability of the thermal modelling approach. A more detailed validation for the concrete slab, steel reinforcement, and other components is provided in Ref. [15].

Structural validation is presented in terms of both global behaviour (vertical displacement) and local behaviour (damage patterns) in the concrete slab. Figure 1(c) compares the slab-centre vertical deflections from the tests (solid lines) and simulations. The simulations show good agreement with the experimental response, reasonably capturing the partial displacement recovery during cooling. In particular, the close match in residual displacement for Test #2 (where the applied load was maintained throughout the cooling phase, whereas it was removed during cooling in Tests #1 and #3) supports the model's ability to reproduce the cooling-stage response. The model does not capture abrupt changes in displacement rate associated with the formation of large, discrete cracks (e.g., the shift at 69 min in Test #1). However, it successfully predicts the change in displacement rate observed during the transition to tensile membrane action (at 13 min) in Test #3.



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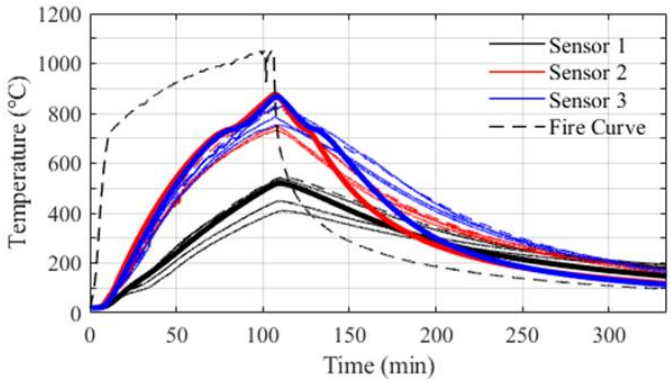

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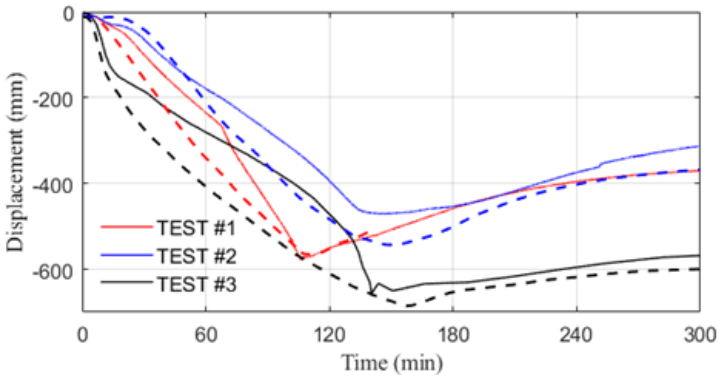

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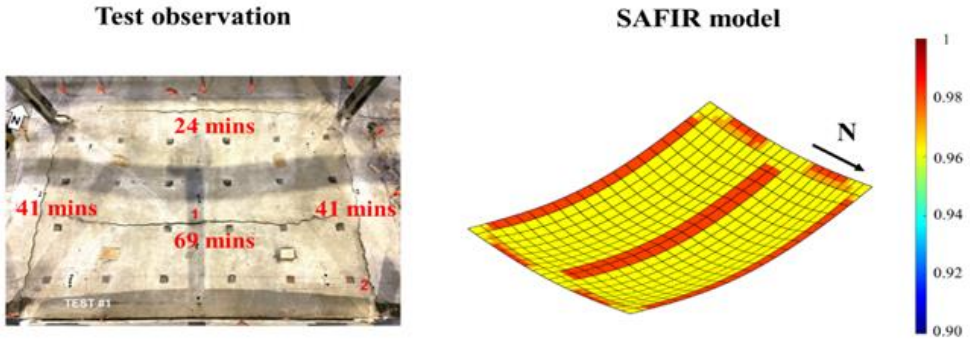

(d)

Figure 1. (a) Temperature sensor location in experiment; (b) comparison on the steel beam temperature between the test and simulation; (c) comparison on the vertical deflection at slab centre between tests (solid lines) and simulation (dashed lines); (d) computed tensile damage in the concrete slab and comparison with observations for Test #1.

The simulations also agree with the experiments in terms of local behaviour and limit states. Figure 1 (d) compares the simulated tensile damage distribution in the slab for Test #1 with the post-fire crack pattern. Good agreement is observed in the slab centre and along the north and south edges. The asymmetric response and damage along the west and east edges are not reproduced, primarily because the unexposed slab region is not included in the model. Similar agreement in tensile damage distribution is obtained for the other two tests. Additional details on the numerical model validation are provided in Ref. [15].

3.2 Accuracy of regression-based models for response estimation

Figure 2 and Table 3 present the scatterplots of the performance of different ML algorithms for predicting slab maximum responses and the corresponding accuracy metrics, respectively. Overall, ensemble tree-based methods outperform other methods in predicting the maximum displacement at the centre of the flooring slab. RF, ERT, and LGBM achieved the highest accuracy on the test set, with test R^2 values of 98%, the lowest RMSE among the considered models (i.e., 2.7-3 cm), and MAEs (1.3-1.5 cm). These models show significantly higher performance than the linear models, where the model RMSE is approximately 65% lower than the test RMSEs of the linear models. The normalized accuracy metrics show that the error level remains small across the response range, with MARE < 3% and RMSRE and RRMSE ranging from 4.8% to 6%. This is a notable deviation from linear models, which often show higher normalized error, such as an RMSR of 41%. Notably, SVM shows an MARE and RMSREs that are 7% and 16% larger than those of RF/LGBM models. AdaBoost, DT, and MLP constitute the lower performance tier of the study's models. While they achieved a reasonable test R^2 (i.e., 86%-96%), they show higher RMSE (more than 3.5 cm), where MLP and Adaboost reach the

same level of RMSE as the linear models. Particularly, these models show lower normalized accuracy metrics. For example, RMSRE exceeds 26% for MLP, and RRMSE attains its highest value among all the studied models.

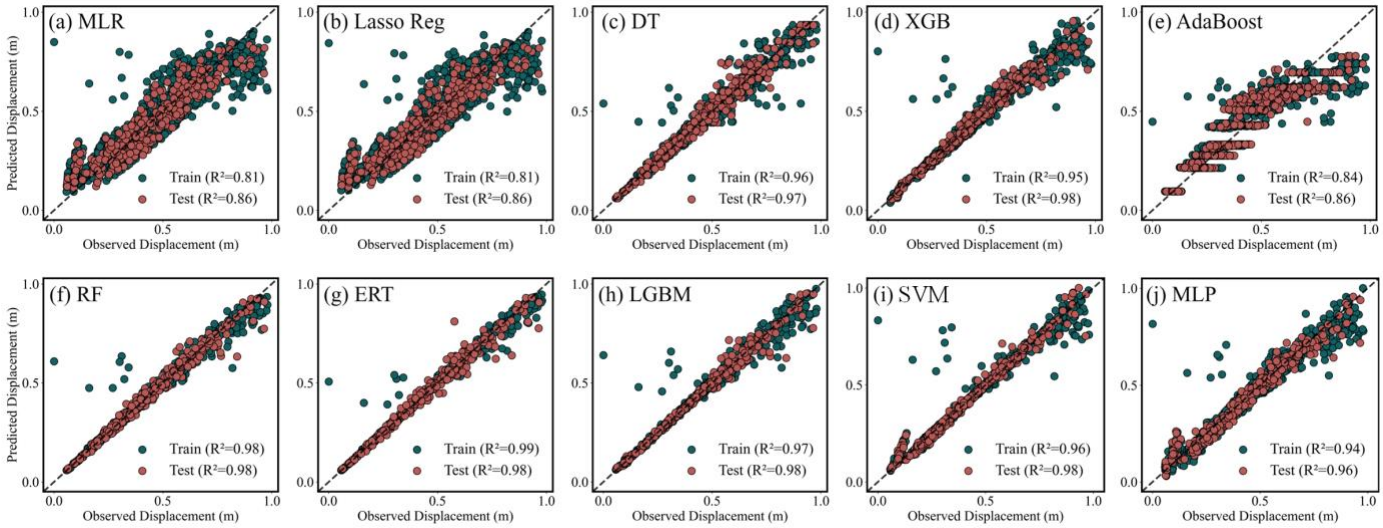

Figure 2. Regression-based ML models performance to predict the maximum displacement responses of the slab

Table 3. Summary of ML Accuracy metrics for maximum and residual displacement of slab for testing set

Algorithm	Maximum displacement					Residual displacement				
	R^2	RMSE	MAE	MSRE	RMSRE	R^2	RMSE	MAE	MSRE	RMSRE
MLR	0.86	0.076	0.062	0.232	0.419	0.87	0.089	0.070	1.605	7.190
Lasso	0.86	0.076	0.062	0.233	0.423	0.87	0.089	0.069	1.521	6.385
DT	0.97	0.037	0.025	0.056	0.075	0.93	0.066	0.037	0.454	4.742
XGB	0.98	0.032	0.020	0.047	0.066	0.96	0.048	0.027	0.285	1.397
AdaBoost	0.86	0.076	0.057	0.139	0.185	0.81	0.106	0.084	2.561	14.857
RF	0.98	0.028	0.016	0.035	0.050	0.96	0.047	0.029	0.325	2.286
ERT	0.98	0.030	0.016	0.034	0.052	0.95	0.052	0.030	0.284	1.739
LGBM	0.98	0.027	0.014	0.029	0.048	0.96	0.046	0.028	0.471	3.047
SVM	0.98	0.028	0.017	0.070	0.156	0.96	0.051	0.035	2.269	16.223
MLP	0.96	0.039	0.027	0.101	0.204	0.95	0.057	0.041	1.692	10.404

3.3 Feature importance analysis and contribution on the prediction

Figure 3 presents SHAP plots for one of the best-performing models across both tasks, i.e., LGBM, illustrating the contribution of model inputs to the predicted maximum and residual displacement of flooring systems. For maximum displacement, the impact of the fire scenario is more pronounced than that of material and structural parameters. Specifically, fire load is the most influential parameter. This aligns with previous studies which identified fire load as a key parameter to characterize fire fragilities [19–21]. The opening factor has a more modest influence within the studied range. AP and BC_x are secondary influential features where lower

AP ratios and restraints in the X direction reduce displacement. While increasing the amount of axial restraint at the boundary has been shown to reduce the probability of failure [22], it increases the maximum deflections because the floor is prevented from thermally expanding laterally. Lastly, the thermal properties of SFRM show a minor impact. This is because the deflections are influenced by the heating of the unprotected steel beam and the development of membrane action in the composite slab, whereas the protected steel beams on the perimeter maintain their integrity even with the most detrimental values for the thermal properties of the SFRM. In other words, in composite flooring systems in which the behaviour is governed by large deformations of the unprotected beams and membrane action of the floor, variability in SFRM properties has negligible effect on the response as long as the protection is sufficient to avoid a failure of the protected members. For residual displacement, while the fire load remains the most influential parameter, the importance of material and boundary conditions parameters increases compared to maximum displacement. In particular, F_y and A_s play a more notable role, where their higher values reduce residual displacement.

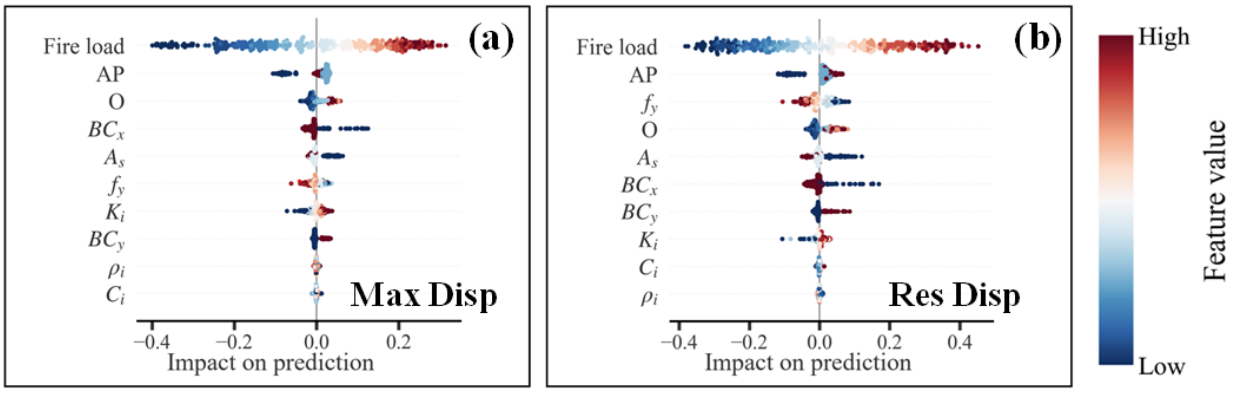

Figure 3. SHAP plots of LGBM for all model outputs

4 CONCLUSIONS

This study developed explainable ML-based surrogate models to predict the fire response of composite flooring systems using a large database of experimentally validated thermo-mechanical FE simulations. The models link key hazard parameters (e.g., fire load and opening), slab design variables (e.g., reinforcement capacity, aspect ratio, and boundary conditions), and material thermal properties to maximum/residual displacement. Among the regression approaches, ensemble tree-based models performed best: LGBM, ERT, and RF achieved consistently high accuracy on the test set ($R^2 > 0.95$) with RMSE on the order of ~3 cm, whereas DT, AdaBoost, and MLP showed noticeably lower predictive performance. Explainability analyses indicates that fire severity (as measured by fire load) is the most influential predictor of both maximum and residual displacement. Structural design parameters, including the aspect ratio and tensile reinforcement capacity, have a secondary influence.

The results of this study are limited to the ranges of parameters used to generate the underlying training data. As this study serves as a preliminary effort in this domain, future research is needed to understand the sensitivity of these models to small variations in the parameter ranges used, and to evaluate the suitability of the models for a broader range of composite flooring systems.

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