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ML prediction model for resisting capacity reduction of RC column exposed to fire

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ABSTRACT

Despite of the vulnerability of structure to fire damage, fire analysis on structure element has been often marginalized. One of the reasons to that is low accessibility to fire analysis, because the fire analysis on structural element has been done by finite element approach, which requires a lot of models and coefficient to be determined. This paper was devoted to model the residual strength of fire damaged RC column, with data generated under FEM approach which was verified to closely simulate the element level experiment.

To generate the FEM data, the RC column section set was determined with 4 sectional variables under the design practice. The residual strength of each RC section was expressed 4points reduced P-M interaction diagram form.

To model the FEM fire analysis data, 5 most representative ML regressor was chosen. That is first SVM, ANN, Random Forest (RF), XGB, and LGBM. However, direct application of regressor on the residual strength data revealed that overlapped prediction frequently occurred, violating the natural observation that the residual strength of RC column gets less with fire exposure time. To deal with this overlapped error, the partial monotonicity constraint was applied for XGB and LGBM. All the 5 chosen ML modelling achieved considerable accuracy with MAPE under 5%. It was concluded that LGBM with partial monotone constraint performed the best, and XGB followed.

1. INTRODUCTION

According to National Fire Agency of Korea, more than thirty thousand of fire cases occur only in Korea every year, which means there is no small risk of fire. Despite of the fact that large scale of fire severely damages the structural performance of structural member, the evaluation of structure performance under fire tends to be marginalized. One of the reasons for this is the low accessibility of fire analysis, since

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it is needed to determine numerous models or temperature depending coefficients of each materials under fire. This paper is devoted to enhance the accessibility to fire analysis, by machine learning modelling the fire behavior of RC column, which is the most widely used and adopted structural member, by utilizing data generated in Finite element Method (FEM) approach.

For FEM Fire analysis, Hwang's model (Hwang, 2018) was adopted for its high accuracy to fire experiment. Then to generate fire analysis data, 1770 RC columns were chosen and parametrized into 4 sectional variables as input features. The residual strength of RC column was expressed in P-M interaction diagram with 4 core points, from 0 min (before fire damage) to 190mins of fire exposure with 10 min time step each. In this research, 5 ML regression modellings (SVM, ANN, RF, XGB, LGBM) which is the most widely used were chosen and compared those performance under both accuracy and reliability of result.

2. FEM fire analysis of RC columns

Hwang's FEM approach fire analysis is consisted of 2 analysis phases. First one is heat transfer analysis of fire exposure RC column, which calculates the elevated temperature distribution of RC column. The second phase of fire analysis is behavior analysis of RC column, with the temperature distribution which was calculated in heat transfer analysis phase.

2.1 Heat transfer analysis

Once exposed to fire or high temperature of heated surrounding air, there has been temperature distribution change on structural member; so is RC column. Since the material properties and mechanical change occurs with temperature elevation, heat transfer analysis which reveals the temperature distribution needs to be preceded the behavior analysis.

$$\begin{aligned} \mathrm{k(T)}\left(\frac{\partial T}{\partial t}+\frac{\partial T}{\partial t}\right)\cdot n_i &= q_c+q_r = h\cdot(T_e-T_s)+\varepsilon\cdot\sigma\cdot(T_e^4-T_s^4) \\ &= (h+\varepsilon\cdot\sigma\cdot(T_e^2+T_s^2)\cdot(T_e+T_s))\cdot(T_e-T_s) = h_{eff}(\mathrm{T})\cdot(T_e-T_s) \end{aligned} \tag{1}$$

The RC column section was divided into 30×30 equally spaced grid along both width and depth span, resulting total 900 layers. The governing equation for heat transfer analysis is stated in Eq. (1) as result of solving heat transfer analysis. Related heat parameters were determined following Eurocode 1992-1-2(BSI, 2004).

2.2 Non-linear behavior analysis

Both concrete and steel experience change in material properties such as density, compressive/tensile strength, and also the non-mechanical strains such as thermal strain for heat expansion, creep strain for creep during exposed to extreme heat, and transient strain for additional chemical reactions in concrete, those not from mechanical reaction

For material properties change, Eurocode 1992-1-2(BSI, 2004) is adopted, and the compressive strength with elevated temperature is defined as Hertz (Hertz, 2005) suggested in his experimental work. And for those non-mechanical strain, Eurocode

1992-1-2, Harmathy's (Harmathy, 1967) model, Anderberg's (Anderberg, 1976) model were adopted for thermal strain for both concrete and steel, creep strain for concrete, and transient strain of concrete respectively.

With temperature distribution and material model determined as calculated in heat analysis for each 900 section layers, 2-dimensional non-linear behavior analysis was conducted where geometry nonlinearity was not counted in. The non-mechanical strain at each section layer was calculated and mechanical strain was taken together to solve equilibrium equation.

3. Data generation for fire damaged RC columns

The fire analysis data were generated on section sample set of 1770 RC sections, each of which is determined under Korean design practice to cover the practical range of RC column specs. To be applied to ML regressor, the fire analysis data should be parametrized with input features and output features. Hence each of 1770 RC sections were parametrized with 4 sectional variables, B(width), H(height), BN and HN (number or equally spaced steel Rebar along width and height span), as in the Fig. 1.

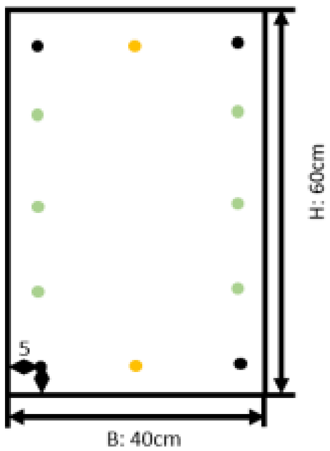

Fig. 1 RC column sectional variable

The fire analysis was conducted on each RC column to see if the RC column can endure at each fire exposure time, axial loading(P) and bending moment(M). A set of fire analysis reveals the P-M interaction diagram of RC column, which describes the residual strength of RC column at each fire exposure time on P-M coordinates. Each P-M interaction diagram was reduced to 4 core points(P1~4) as in AISC(AISC 2010), one for pure axial(P1), one for pure bending(P2), one for another strength point with same pure axial loading(P3), and the last one for balanced point(P4) as in the Fig. 2.

Thus, fire analysis data was reduced to 5 input features (B, H, BN, HN, t_var (fire exposure time)) with 4 output features (P1~4). This results total of (1,770×20×4 = 141,600) fire analysis data points with 80% and 20% divided for train and test set.

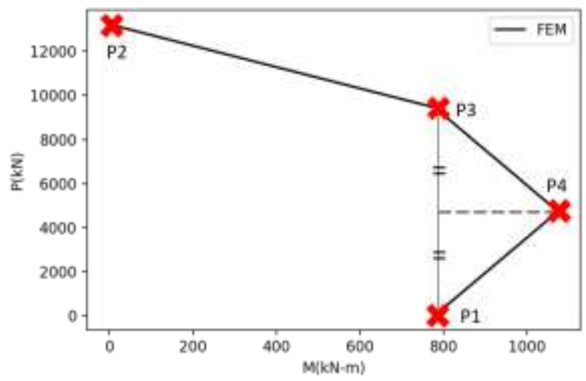

Fig. 2 P-M interaction reduction to 4 core points

4. Machine learning modelling

This study adopted 5 most widely accepted and used ML regressors, SVM, ANN, RF, XGB, and LGBM. Unlike the other typical ML algorithms, XGB and LGBM have advantage of built-in monotone constraints functions and each model with monotone constraints was named as XGBm, and LGBMm in this paper. XGB and LGBM with this feature was modelled along with non-featured 5 regressors, to meet the basic axiom that the longer fire exposure lasts, the less residual strength. Then each 7 regressors were tuned for optimal training with 5 CrossValidation (CV) with OPTUNA.

5. Results and discussion

This The performance of each 7 regressors was evaluated based on conventional scores such as MAPE, and also evaluated by one newly defined score in this paper, fitness error. Fitness error is defined as the percentage ratio of gap area of fire analysis P-M interaction diagram and model reconstructed P-M interaction diagram to the area of fire analysis P-M interaction diagram to measure the difference of reconstructed P-M interaction to fire analysis data one, P1~4 altogether, not separately.

Each of the 7 models showed considerable stable results, with less than 5% of MAPE for cases. For MAPE, LGBM showed the most accurate performance, and XGB, LGBMm, XGBm, ANN, SVM, and RF followed with mean MAPE of 1.12%, 1.27%, 1.58%, 1.76%, 2.14%, 2.58%, and 3.17% each. And for fitness error, the order slightly changed with best performance for LGBM, then XGB, ANN, LGBMm, XGBm, RF, and SVM followed after. This showed that XGBm, LGBMm, and SVM have high accuracy with respect to MAPE, however, they performed worse with fitness error when compared to MAPE, which implies that there is relatively larger deviation and incongruity in them.

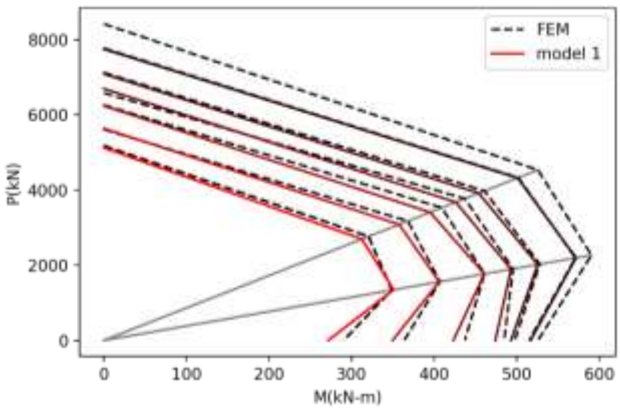

Fig. 3 example of LGBM reconstructed P-M interaction diagram (B=36, H=54, BN=2, HN=10)

However, it was discovered that reliable prediction is completely separate from accuracy alone. Based on the observation that longer exposed to fire, the less residual strength a RC element has, the trained model should give less residual strength prediction for the one with longer fire exposure time, but direct modelling didn't work in that way. They rather predicted reversed number, resulting overlapped P-M interaction diagram reconstruction over fire exposure time.

When it comes to the overlapped case, here overlapped case is defined as ratio of overlapped P-M interaction reconstructed RC sections to total (1770) in a model, SVM and ANN recorded 88.98% and 39.55% which implies that those are highly risky at possible overlapping reconstruction. And LGBM, XGB, and RF followed after with 27.95%, 16.95%, 10.45% each. Though those are overlapping reconstruction risky too, but certainly less risky to the ANN, SVM case. This is considered as the nature of decision tress based model, which ramify its nodes based on inequality, so naturally less overlapping cases. And for monotonic constraint regressors XGBm and LGBMm, which are featured with partial negative monotonicity for fire exposure time, it completely solved the overlapping case with 0% overlapped case.

6. Conclusion

In this study, ML regressor modelling which are highly effective was conducted on FEM approach fire analysis data. Fire analysis data were generated on RC column section set of 1770 sections, then 5 ML regressor(SVM, ANN, RF, XGB, LGBM) plus 2 regressor with constraint(XGBm and LGBMm) was modelled.

All the 7 regressor achieved considerable accuracy with less than 5% mean MAPE for all cases. The best performance was acquired from LGBM and XGBM in terms of MAPE. However, the order of performance in conventional scores MAPE is not always same as the order in fitness error. LGBMm, XGBm, and ANN showed relatively high fitness error compared to MAPE score. It is deduced that the percentage error is not only measure to see performance of model, and fitness error needs to be considered to get stable result.

However, it would be safe to say that LGBMm and XGBm is the most proper options to model the behavior of fire damaged RC column because it can completely solve the overlapped case, despite of the accuracy loss compared to non-constrained regressor. Despite of high time consumption when trained, those ML model on residual strength of RC column is expected to be a possible alternatives with better accessibility for FEM fire analysis, because of simplicity that this model does not require anything to determine, time saving to FEM fire analysis with considerable accuracy.

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