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ML Modelling on strength reduction of fire-damaged RC column via numerical data

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ABSTRACT

In this thesis, a dataset for strength reduction of fire-exposed RC column which is described in terms of P-M diagram downsize is built, and a Machine Learning (ML) based RC members mechanic analysis is proposed by making a model which predicts P-M reduction as fire exposure lasts. Since a fire exposed RC member experience physical property changes and non-mechanical deformation due to temperature increase and chemical reactions in it, it shows different mechanical behavior to the RC member before fire exposure. A dataset is consisted of numerical analysis of fire exposed RC column P-M diagram on sample set of 1770 RC section with different width, height, and reinforecd steel conditions. With this P-M diagram data, a model is built which predicts the P-M diagram reduction ratio given section input using several ML algorithms, kernel SVM, ANN, Random Forest, XGB and LGBM and each are compared. This model achieved stable result with Mean Absolute Percentage Error (MAPE) under 2%.

1. INTRODUCTION

According to statistics from Korean National Fire Agency, there are more than three-thousands of fire accidents annually regardless of place and time, which implies that there is non-negligible risk of fire. Especially in case of large fire, it decreases the strength of each element and causes collapse of total structure which makes it harder to rapid extinguish. Hence it requires fire analysis of higher accessibility for a rapid extinguish and prevention of extra losses. This paper is to propose a machine learning methodology to predict the reduction of RC column exposed to fire, with numerical data generated by FEM approach.

The concrete and steel, which is the most common modern construction materials, undergo several properties changes and non-mechanical strains such as thermal strain, creep strain, and transient strain when exposed to high temperature of 1000℃. The fire

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analysis on ground of these factors are proven to have high accuracy to the fire experiments.(Ju-Young and Hyo-Gyoung 2015)
To generate the fire analysis data for strength reduction modelling, parametrized RC column section set total of 1770 sections is introduced and analyzed its strength reduction on P-M interaction diagram.
In this paper, 5 machine learning modellings, Support Vector Machine (SVM), Artificial Neural Network (ANN), Random Forest (RF), eXtreme Gradient Boosting (XGB), and Light Gradient Boosting Machine (LGBM), were adopted and compared each other with respect of both accuracy and feasibility of results. Assumed that the P-M interaction strength of RC column section is given, each model achieved percentage error of under 3%

2. FEM fire analysis of RC element

Fire analysis of RC column in this paper is consisted of two sequential steps: heat transfer analysis of RC column exposed to fire, and then non-linear behavior analysis with temperature distribution of each section.

2.1 Heat transfer analysis

To consider the effects of being exposed to fire, the quantized heat distribution should be preceded. To acquire the elevated temperature map on RC column section according to length of fire exposure, each section is divided into 900 layers which is equally spaced along the width and height span. Solving heat transfer equation, the governing equations is stated as eqn(1).

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

2.1 Non-linear behavior analysis

Concrete and steel undergo change in properties and nonmechanical strains when exposed to elevated temperature. Harmathy’s model(Harmathy 1967) was adopted for compressive strength of concrete, and Lie’s model(Lie 1989) was used to describe the stress-strain curve of concrete. Thermal strain, creep strain, and transient strain of concrete is assumed to follow suggestion of Eurocode(EuroCode 1992.1.2 2004), Harmathy’s(Harmathy 1967), and Anderberg’s(Anderberg and Thelandersson 1976), respectively. And for the steel, stress-strain curve and thermal strain was constructed on basis of Eurocode.

This paper used 2-dimensional column element without geometry nonlinearity. The non-mechanical strain and physical properties change at each layers on RC section was taken together with mechanical strain to the equilibrium equation.

3. Data generation for fire damaged RC Columns

To generate dataset for strength reduction modelling for fire exposed RC columns, a parametrized RC column section set was organized. Following Korean design suggestion, RC section set total of 1770 sections were made as Fig.1.

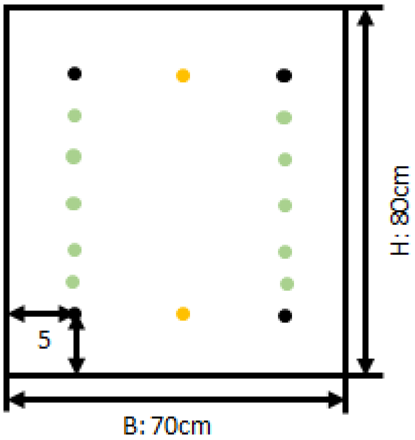

Fig. 1 example of parametrized RC section; B for width, H for height, yellow dots for width-span rebar, and green dots for height-span rebar

Then fire analysis was conducted on RC section set, and P-M interaction diagram was acquired in form of 4 core points reduction, following AISC suggestion. It was assumed that eccentricity of P-M interaction diagram was reserved regardless of fire exposure time. The description for 4 points reduced P-M interaction was shown in Fig. 2. The dataset for strength reduction modelling is concluded to have 5 input features, B,H,BN,HN, fire exposure time, and 4 outputs of $P_{1\sim4}$, each represents the 4 core points on P-M interaction.

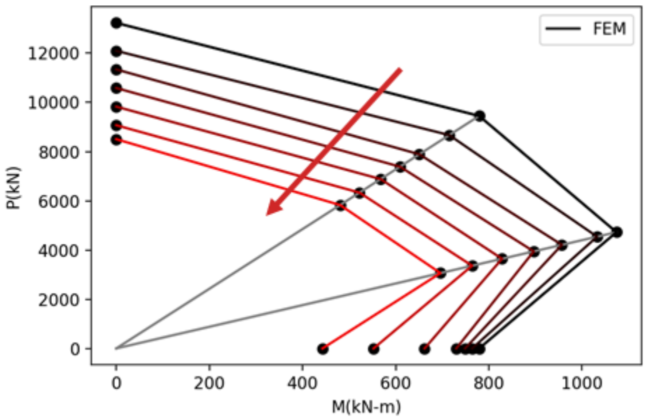

Fig. 2 Description for 4 points reduced P-M interaction diagram of a RC section with varying fire exposure time.

4. Machine learning modelling

In this study, the five most widely used machine learning modellings, SVM, ANN, RF, XGB, and LGBM were chosen to be applied. Different from other modellings, XGB and LGBM has in-built partial monotonicity constraints. To reflect the basic observation that the longer the fire exposure is, the weaker the RC element is, XGB and LGBM with partial monotone constraints on fire exposure time along with non-constraint XGB and LGBM. Then each model was tuned to have optimal training by 5-CV with OPTUNA.

5. Results

The performance of each modelling was evaluated on the basis on score functions MAPE, NRMSE, RMSE, and fitness error. Here fitness error was newly introduced to see how different the reconstructed P-M interaction diagram of machine learning modelling to the FEM P-M interaction diagram.

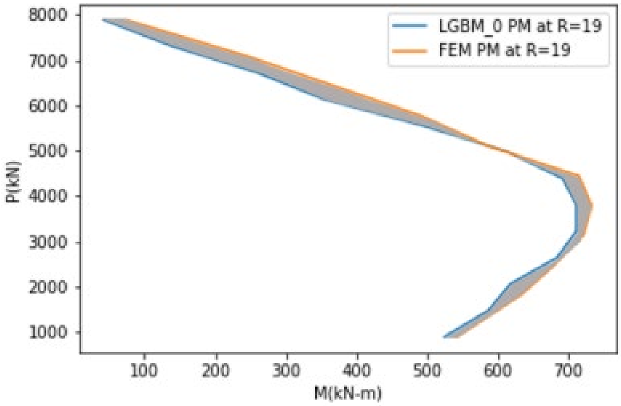

Fig. 3 concept of fitness error

Each modelling achieved MAPE and NRMSE lower than 3% and 6% respectively, showing that each of them has possibility to be applied to model FEM results. All the five models achieved stable results also with respect to fitness error. Together with conventional scores such as MAPE and newly introduced score, fitness error, LGBM scored the first and XGB, ANN, SVM, and RF followed after.

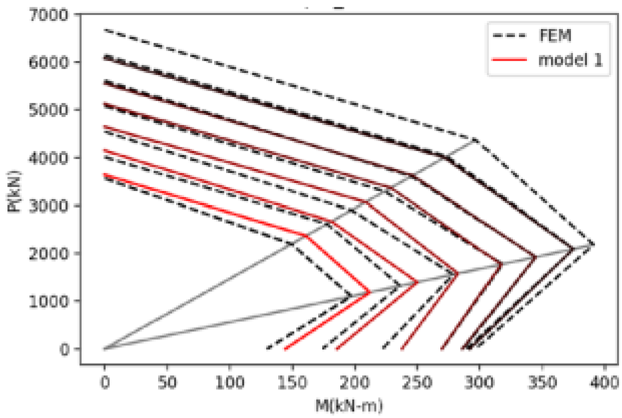

Fig. 4 example of P-M interaction diagram reconstructed (B=40, H=40, BN=6, HN=2)

However, some bad prediction was observed, that the reconstructed P-M diagram was overlapped each other for different fire exposure time. Each reconstructed P-M interaction diagram was proven to have high accuracy to the FEM one by the numerical scorers, but in total there are some crushes between different fire exposure time, which violates the basic rule of fire analysis. This trouble was solved by the introduction of partial monotonicity constraints of XGB and LGBM.

6. Conclusions

In this study, machine learning modelling was conducted on the dataset which is generated via finite element analysis approach fire analysis. All the chosen five machine learning modellings showed high accuracy to the FEM results, and especially high accuracy in case of LGBM and XGB. And the introduction of partial monotonicity constraints even gave physically more feasible results.

Fire analysis so far was mainly conducted by finite element analysis. Though it has advantages that it has clear theoretical backgrounds and was proven to simulate closely to the experiments, it has a lot of models and constrains to determine which makes it hard to access and use it.

The modelling introduced in this paper is so basic that would rarely used in real structure analysis, However, it showed the possibility for a machine learning modelling to be applied in structural analysis field and calculation dimension reduction.

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