Explaining Seismic Response and Fragility of RC Frames Through Machine Learning

Structural engineering and design are key research areas that facilitate construction of safe buildings. Some of the important variables involved in design and assessment of RC buildings are loading conditions, soil type, building typology, material properties, ground motion characteristics, codal provisions, dynamic characteristics including the fundamental period, base shear, fragility curve parameters, in-structure acceleration amplification factor, and spectral acceleration amplification function. Researchers have developed several techniques to simplify different stages of structural analysis to rapidly obtain these design variables. These techniques are based on experimental observations and computationally complex simulations. Because of the development of machine learning models and their applications in structural engineering, researchers have been able to predict static and dynamic response of RC buildings.

However, there exist certain limitations with respect to the use of these models. Due to complexity of machine learning models, they behave as black-box and hence the model predictions are not explainable. Further, the existing works consider only structural and ground motion characteristics as input for training the machine learning models. Hence, there exist the need to incorporate different input features like properties of construction materials, wide range of ground motion characteristics, structural characteristics including fundamental period, level of inelasticity in building to obtain desired predictions for RC frames. The machine learning model explanation method should also be used to provide insights into the effect of input features on model predictions.

In this work, explainable machine learning models are developed for four tasks: fundamental period prediction, seismic fragility curve parameter prediction, in-storey acceleration amplification factor prediction, and spectral acceleration amplification function at fundamental and second mode vibration period. The dataset for training fundamental period prediction model is prepared by eigen value analysis of 4, 8, and 12 storey buildings modelled in OpenSees by considering 200 sets of material modelling parameters of concrete and reinforcing steel. Overall, 6 parameters (2 for modelling concrete, i.e., unconfined concrete's peak compressive strength and strain, and 4 for modelling reinforcing steel, i.e., yield strength, Elastic modulus, post-yield strain hardening ratio, and curvature variation parameter of Bauschinger curve after each strain reversal) are used to generate 200 sets through Latin hypercube sampling method by considering the appropriate probability distributions as obtained from the literature. The machine learning models trained to predict fundamental period are neural networks and extreme gradient boosting trees, both of which yielded equally good results. SHAP analysis which was performed to explain the effect of input feature on model predictions revealed that fundamental period is governed by unconfined concrete's strength and strain in addition to number of storeys in the RC buildings.

The second aspect of the study investigated the effect of the material properties (same as taken in case of fundamental period prediction) on the fragility curve parameters of RC frames. The fragility curves are an effective tool to evaluate the seismic performance of buildings as the entire structural state can be represented by their two parameters. In this study, 4, 8, and 12 storey RC buildings were subjected to 184 pulse type ground motions to develop fragility curves corresponding to three intensity measures, i.e., peak ground acceleration, 5%-damped spectral acceleration at fundamental period ($Sa(T_1)$), and average spectral acceleration (Sa_{avg} $[T_2, 2T_1]$). The ground motions were scaled from 0.1 g to 1.5 g at a step of 0.1 g to perform nonlinear dynamic analysis. The XGBoost models performed significantly better than the neural network models in predicting the fragility curve parameters. The model predictions were explained using SHAP analysis, revealing that fundamental period, and modelling parameters of unconfined concrete played important role at all limit states. The importance of material properties of reinforcing steel was lower than other input features like properties of concrete and fundamental period and increased with increase in the severity of limit state.

The third and fourth aspect of this study deals with understanding the effect of 16 input features which comprises of 6 material, 6 ground motion, and 4 structural characteristics on the in-structure acceleration amplification factor (IAAF) and spectral acceleration amplification factors corresponding to fundamental (A_1) and second mode (A_2) period of RC buildings. The 4, 8, and 12 storey buildings with 50 sets of material properties were subjected to 30 ground motions at different levels of inelasticity to obtain IAAF, A_1 and A_2 at each floor. Using this dataset, separate machine learning models were trained to predict IAAF and SAAF where the XGBoost models significantly outperformed neural networks. Through SHAP analysis, it was revealed that structural features are most important followed by ground motion characteristics and then material properties while predicting IAAF, A_1 and A_2.

Finally, the methodology to train machine learning models was applied to predict fundamental period of bare and infilled RC frames using an existing dataset of more than 4000 buildings. The model predictions were explained through three different model explanation methods like partial dependency plots, additive local explanations, and SHAP analysis. The trained ML models were used as surrogate while optimizing the geometrical and mechanical properties of the frames while targeting desired fundamental periods. Interactive dashboards are developed for providing access to all the ML models developed in this work.