Active learning on ensemble machine-learning model to retrofit buildings under seismic mainshock-aftershock sequence

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Abstract. This research presents an efficient computational method for retrofitting of buildings by employing an active learning-based ensemble machine learning (AL-Ensemble ML) approach developed in OpenSees, Python and MATLAB. The results of the study shows that the AL-Ensemble ML model provides the most accurate estimations of interstory drift (ID) and residual interstory drift (RID) for steel structures using a dataset of 2-, to 9-story steel structures considering four soil type effects. To prepare the dataset, 3584 incremental dynamic analysis (IDA) were performed on 64 structures. The research employs 6-, and 8-story structures to validate the AL-Ensemble ML model's effectiveness, showing it achieves the highest accuracy among conventional ML models, with an R^2 of 98.4%. Specifically, it accurately predicts the RID of floor levels in a 6-story structure with an accuracy exceeding 96.6%. Additionally, the programming code identifies the specific damaged floor level in a building, facilitating targeted local retrofitting instead of retrofitting the entire structure promising a reduction in retrofitting costs while enhancing prediction accuracy.

Keywords: Computational Method, Active Learning, Ensemble Machine-Learning Model, Retrofitting Structures, Mainshock-Aftershock Sequence.

1 Introduction

The utilization of dissipation devices, such as viscous dampers, buckling-resisting braces (BRBs), and shape memory alloys (SMAs), constitutes an advanced and strategic approach in structural engineering and seismic retrofitting. Each of these dissipation devices serves a unique purpose in enhancing the resilience and performance of structures under dynamic loads, and avoiding intensive damages particularly in seismic-prone regions [1-3]. Viscous dampers are strategically placed within a structure or between structures to enhance its overall seismic performance and resilience [4-6], while knee braces and BRBs are implemented as bracing system [7]. By dissipating energy through controlled yielding or ductile behavior, BRBs contribute to the structure's resilience against seismic forces [8-10]. In addition, using infill walls also can be a reachable alternative for retrofitting of buildings [11, 12]. When incorporated into structural elements, SMAs contribute to damping vibrations and reducing the

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overall impact of seismic forces, enhancing the structure's performance and minimizing damage. Moreover, using SMA bolts can enhance the connections behavior and prevents large residual interstory drift (RID) that is crucial in the decision-making process for retrofitting procedures [13, 14]. Enhancing the safety and resilience of buildings in seismic challenges, this study aims to propose a novel retrofitting scheme.

Machine learning (ML) computational algorithms are widely used by researchers to provide prediction models on engineering problems such as seismic response and performance assessment [15-17], seismic risk assessment [18-20], and predicting concrete material strength [21] for steel and reinforced concrete (RC) structures. Meanwhile, there is still a gap for predicting the interstory drift (ID) and RID of floor levels of buildings for retrofitting purpose. Instead of relying on a single ML algorithm, ensemble methods combine predictions from several base models to make more robust and reliable predictions [22]. By iteratively selecting the most relevant data points for labeling, active learning can often achieve higher accuracy with fewer labeled instances compared to traditional supervised learning approaches. In addition, active learning allows retrofitting decisions to be based on the most informative data, optimizing the allocation of resources by strategically selecting dissipation devices that will benefit the most from retrofitting efforts.

This study aims to provide an active learning-based ensemble ML computational model to estimate the seismic response of ID and RID, which play a crucial role on illustrating the seismic behavior of building. Having these responses can help civil engineers to decide on retrofitting of building with recognizing the weak floor level and introduce it for retrofitting scheme. Moreover, by changing the structural members of the weak floor, it is possible to check the reliability of the retrofitted structure. This procedure can cut the complex modeling, time-consuming analysis, and need for a professional expert for modeling process. Since the structural conditions and seismic responses can vary widely among different buildings, active learning enables ensemble ML models to adaptively learn from the most relevant retrofitting cases (i.e., training dataset), allowing for the formulation of retrofitting strategies tailored to specific characteristics and vulnerabilities of each structure. Therefore, active learning can be a guidance to ensemble ML models to identify and prioritize the critical parameters influencing the effectiveness of retrofitting measures. Active learning helps reduce this uncertainty by iteratively refining the ensemble model based on the most relevant and informative data, leading to more robust retrofitting decisions that align with actual structural performance. Since the retrofitting of building after mainshock and before aftershock can be a challenging for its complex modeling of damaged building, the proposed method can be a useful strategy. It is noteworthy that using this procedure can widely reduce time of seismic evaluations and retrofitting of buildings.

2 Structural modeling

For providing a dataset, buildings having 2-, to 9-story elevations have been designed according to ASCE 7-16 [23] (see also [15] for details of designing process) consider-

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ing four soil types (i.e., B, C, D, and E). It should be noted that to improve the modeling quality of the structure, IMK hinges have been used for beams [4], fiber section has been used for columns [5], and P-Δ effect has been considered in models using a leaning column [24, 25] modeled in OpenSees [26] software. The modeling procedure and dataset used in this research has been provided by Kazemi et al. [15] and 3584 incremental dynamic analysis (IDA) were done on selected 64 structures based on the $S_a(T_1)$ (i.e., intensity measure) and ID and RID (i.e., demanding thresholds) [27, 28]. In addition, the dataset has been improved by adding the floor labels of structures to have the ID of each floors as output of ML model. Moreover, the dataset has been changed to include the sections of beams and columns of each floor levels into account. Therefore, it will be possible to estimate the ID or RID of each floor level of structure; and then, check the sections of structural elements related to that floor level. This ability provides information regarding the weak floor level that can be useful for retrofitting purpose. Fig. 1 presents the IDA curves and median of IDA curves of the 6-, and 8-story structures subjected to pulse-like records.

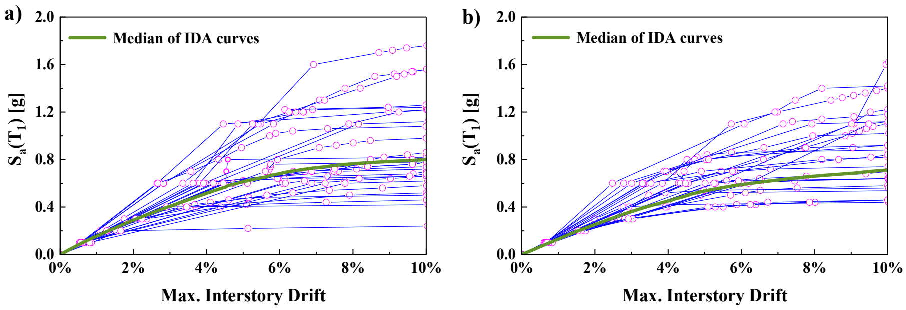

Fig. 1. IDA curves and median of IDA curves of the 6-, and 8-story structures subjected to pulse-like records.

3 Computational method

Literature review show that many studies used dissipation devices such as viscous dampers, knee braces, BRBs, and SMAs to improve the seismic behavior of building under seismic excitations. Meanwhile, they used dissipation devices as structural member in all floor levels rather than implementing on the floor level with high possibility of weakness. Therefore, as alternative retrofitting scheme, this study proposes dissipation devices to be implemented on the weak floor level to control the ID and RID, which this floor has been selected by active learning-based ensemble ML model. Fig. 2 illustrates the computational method based on active learning ensemble ML model for retrofitting of buildings. As it is presented, after modeling of structure in stage 1, the mainshock will be performed and ID and RID of the structure will be calculated in stage 2. According to the floor level with highest ID and RID, the designer can decide to use aforementioned dissipation devices as retrofitting scheme in stage 3. This process will be time-consuming since the modeling and performing the analysis need more complex modeling. To overcome this shortening, the active learn-

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ing ensemble ML model can use the structural characteristics to estimate the ID and RID of structure and corresponding floor level.

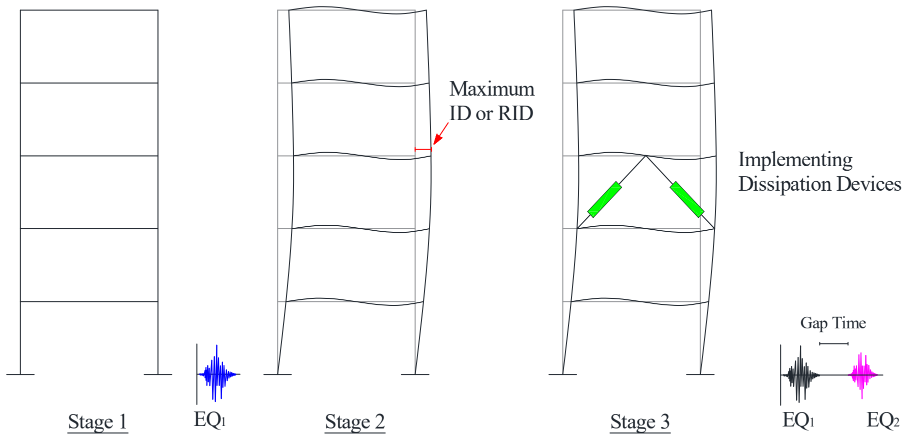

Fig. 2. Computational method based on active learning ensemble ML model for retrofitting of buildings.

It should be noted that modeling local damages of structural members and a damaged building is not an easy task due to differences in strength of each elements and different damage limitations. Therefore, total structural evaluations can ease the way of retrofitting by reducing modeling process and structure can be retrofitted before aftershock. To automate the procedure, a Tcl code has been developed in OpenSees [26] to model structure and provide a mainshock-aftershock analysis [29], then, the procedure has been controlled by MATLAB software to achieve results of analysis and prepare the dataset of each structures. Python programming code has been developed for labeling of dataset and performing active learning process on ensemble ML model. The results of ID and RID for floor levels have been illustrated on text file and can be used as source of retrofitting scheme. Although this study explores the procedure for steel structures, the procedure can be used for RC structures by providing related dataset.

4 Retrofitting of building with ML method

The application of active learning in ensemble ML models is a systematic and strategic approach to optimizing model performance through iterative data selection and labeling. A pool of unlabeled data serves as the starting point. The ensemble actively selects instances from this pool for labeling based on their perceived potential to improve model performance. Various active learning query strategies guide the ensemble ML model in selecting instances for labeling. Common strategies include uncertainty sampling, query by committee, expected model change, and other metrics that quantify the model's confidence or uncertainty in its predictions.

The active learning process unfolds iteratively, and then, in each iteration, the ensemble model makes predictions on the unlabeled instances, selects a subset based on the

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chosen query strategy, and queries a user for labels. After each iteration, the predictions of the individual base models are aggregated to form a collective prediction. Ensemble techniques such as bagging, boosting, or stacking may be employed to combine the strengths of the diverse models within the ensemble. In this research, the gradient boosting machine (GBM), extreme gradient boosting (XGBoost), and extra trees regressor (ETR) were used for ensemble ML model [15-20]. The results of estimating the maximum ID in floor levels of the 6-story structure are compared for individual ML algorithms and active learning-based ensemble ML model (AL-Ensemble ML) composed from those three ML algorithms presented in Fig. 3.

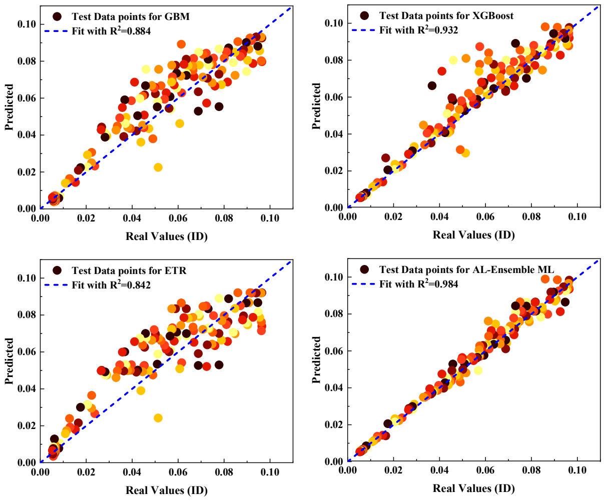

Fig. 3. Scatter results of the 6-story structure assuming soil D considering the conventional and AL-Ensemble ML models.

It can be seen that the conventional ML models has less ability to estimate the maximum ID of 6-story structure by large dispersion on x=y line. For instance, the XGBoost model achieved the accuracy of 93.2% and the result show that it has good ability to estimate the ID less than 0.04. Although using ensemble modeling can widely improve the performance of estimation model, active learning can enhance it further. The result confirm that AL-Ensemble ML is the best prediction model with accuracy of 98.4%. For brevity, only result of the 6-story structure has been plotted, while similar results has been achieved. Since the AL-Ensemble ML model has the best prediction among other models, it has been used to estimate RID of the 6-story structure and the results has been presented in Fig. 4. It is clear that having accuracy more than 96.6% allows the AL-Ensemble ML model to estimate the RID of floor levels of the 6-story structure that can be used for retrofitting scheme. According to results, maximum RID has been determined in the first and second floor levels of the 6-, and 8-story structures and these floors are introduced for retrofitting with viscous dampers. By adding dissipations devices, the RID of the structures has been compared to non-retrofitted structures in Fig. 5. It can be concluded that the precise predictions made by AL-Ensemble ML model helped to find those weak floor levels and reduce

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maximum RID of structures and the cost of retrofitting accordingly. Therefore, the procedure can be a useful tool for retrofitting structures under seismic sequences.

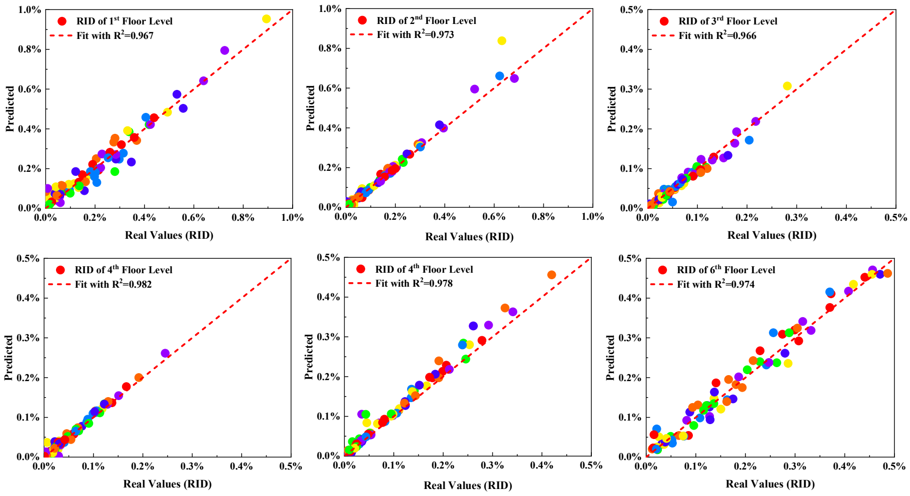

Fig. 4. Scatter RID prediction results of the 6-story structure assuming soil D considering the conventional and AL-Ensemble ML models.

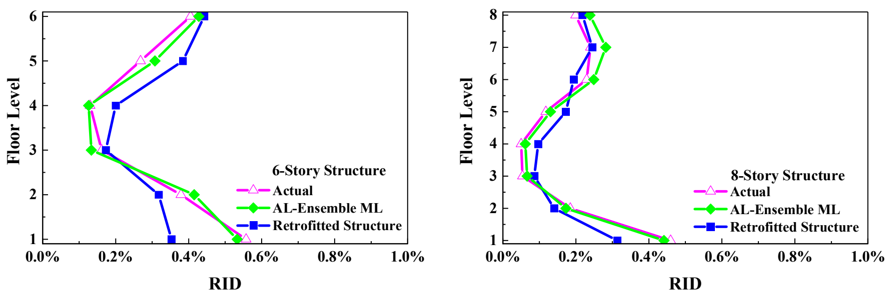

Fig. 5. Retrofitting first and second floor levels of the 6-, and 8-story structures according to prediction results of AL-Ensemble ML model.

5 Conclusions

This study introduces an efficient computational approach aimed at retrofitting of buildings affected by seismic mainshock-aftershock sequences using active learning-based ensemble ML method. The proposed method is versatile, capable of retrofitting both steel and reinforced concrete structures while accommodating various intensity measures and engineering requirements. It allows for the application of diverse retrofitting devices, including viscous dampers and BRBs. Results confirm that the AL-Ensemble ML model has the best estimations of ID and RID of steel structures that can be used for retrofitting of structures by implementing dissipation devices at floor levels with highest values of RID and ID. The proposed procedure introduces a novel ML-based retrofitting scheme that can reduce the computational time, cost of retrofit-

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ting, and improve the accuracy of predictions that are useful for preliminary assessment of structures. For this purpose, the 6-, and 8-story structures have been used. AL-Ensemble ML model had the highest accuracy among conventional ML models with R^2=98.4%, and predicting the RID of floor levels of 6-story structure by accuracy more than 96.6%. Furthermore, the programming code identifies the specific damaged floor level of a building, enabling targeted local retrofitting rather than the retrofitting of the entire structure.

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