MACHINE LEARNING BASED REGIONAL SEISMIC RETROFIT DESIGN OPTIMIZATION FOR SOFT WEAK OPEN FROM WALLLINE BUILDINGS

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Abstract

Policies are often enacted to mandate the retrofit of seismically vulnerable buildings. A major challenge in specifying the design requirements for policy-based retrofits is ensuring that the desired performance enhancements are achieved across a portfolio of buildings that differ significantly in terms of structural characteristics and seismic hazard. To address this challenge, a machine-learning-based optimization framework is developed. The proposed methodology seeks to inform the development of prescriptive retrofit measures that maximize seismic performance enhancements at the portfolio scale under certain constraints. The initial framework is developed specifically for wood-frame buildings with soft, weak and open front (SWOF) wall lines (or soft-story buildings). There are three key elements to the overall methodology. First, machine-learning-based surrogate models are developed as compact statistical links between building structural characteristics (e.g. number of stories, story strengths, building configuration) and nonlinear response history analysis (including collapse simulation) and performance assessment (e.g. collapse, demolition, repair costs) outcomes. Second, objective functions are defined at the regional or portfolio scale (e.g. maximizing the total increase in collapse margin ratio for all buildings, minimizing total losses for a scenario earthquake) with appropriate constraints (e.g. minimum increase in collapse margin ratio for any single building, maximum cost of retrofit). Lastly, stochastic optimization is implemented to determine the retrofit enhancements (e.g. increase in strength and ductility) that would achieve the most desirable combined outcome for all buildings in the portfolio. The framework is demonstrated using the inventory of approximately 12,000 SWOF buildings that are under the purview of the Los Angeles Soft-Story Ordinance.

Keywords: machine learning, wood-frame building retrofit, regional building performance optimization

1. Background and introduction

For multi-unit residential woodframe buildings in the Los Angeles metropolitan area, it is common for the first story to be used for parking or commercial spaces such that a lower wall density is used relative to the upper stories. This can lead to substantial differences in the stiffness and strength of adjacent stories and the formation of a single-story mechanism during earthquake shaking. Numerous complete or partial woodframe building collapses have been attributed to soft-story damage in prior seismic events including the 1971 San Fernando, California [1], 1989 Loma Prieta, California [2] and 1994 Northridge, California earthquakes [3]. Several cities in California have established policies to address the seismic risk to soft-story woodframe buildings. For example, in Los Angeles, an ordinance was passed to mandate the retrofit of the approximately 12,060 soft, weak and open front (SWOF) wall line buildings in the city [4].

This paper develops a framework that incorporates machine learning and stochastic optimization to achieve the optimal retrofit strategy at the portfolio scale. An overview of the framework is shown in Fig. 1. The machine learning models enable a rapid estimation of performance outcomes conditioned on the building structural characteristics within the optimization algorithm. Portfolio-scale performance is evaluated for scenario earthquakes by aggregating the individual building performances. The stochastic optimization algorithm takes the structural properties as inputs and finds the optimal and most efficient retrofit strategy . The SWOF building inventory in Los Angeles and the Mw 7.1 Puente Hills earthquake are used to illustrate the methodology. The performance outcome and efficiency of the optimal retrofit scheme is compared to that of the basic retrofit guidelines developed for the ordinance [5].

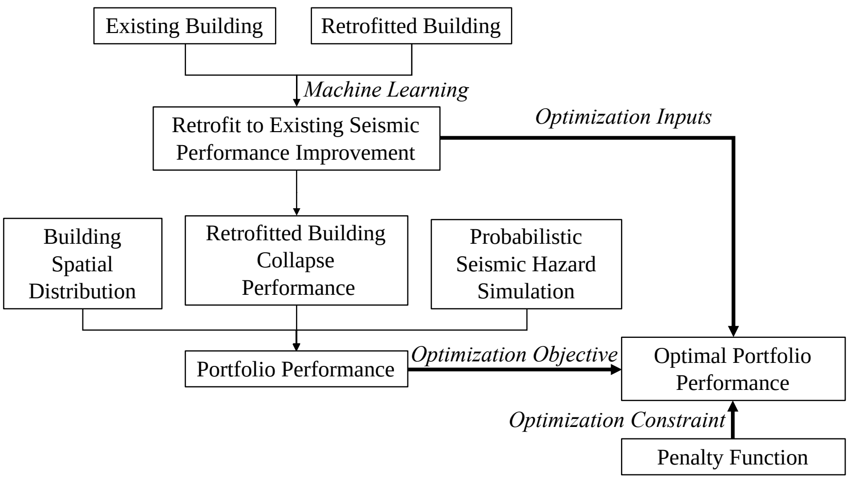

Fig. 1 Portfolio-scale seismic retrofit optimization framework

2. Woodframe building modeling and performance assessment

Four typical first story wall layouts (denoted L1 through L4) for the SWOF buildings are established through a survey of approximately 3,000 SWOF buildings (approximately 25% of the inventory) in Los Angeles shown in Fig. 2. Besides the differences in the first-story wall layouts, variations in the aspect ratio in plan, number of stories and the type of interior wall panels are considered. A total of 32 baseline archetypes are developed. The primary characteristics of the 32 archetypes can be found in Burton et al. [6].

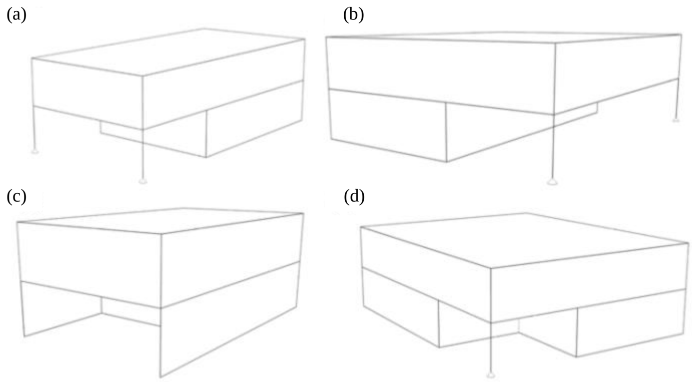

Fig. 2 Schematic isometric views highlighting different first story SWOF wall line layouts: (a) L1, (b) L2, (c) L3 and (d) L4

Nonlinear three-dimensional structural models of the studies buildings are constructed using the Open System of Earthquake Engineering Simulation (OpenSees) [7]. A two-node link element with a horizontal spring is used to model the wood panels. The Pinching4 material [8] is added to the horizontal spring in the two-node link to simulate the nonlinear behavior of the panels. Two springs in parallel, each with the associated model parameters, are used for panels with a different type of finish on each side (e.g. stucco on the exterior and horizontal wood siding on the interior). Residual strength of the wood panels is not considered since the results from sensitivity analyses showed that the performance benefit provided by the retrofit was the same with and without the consideration of residual strength. Additional details about the Pinching4 model and the calibration process are provided in Burton et al. [6].

Building peak strengths in the two principal directions are assessed using nonlinear static analysis. The pushover analyses are conducted using the load pattern from ASCE 7-16, Section 12.8-3 [9]. Building collapse safety is obtained by performing bi-directional nonlinear response history analyses using the 22 pairs of far-field ground motions specified in FEMA P695 [10]. For each structural model, incremental dynamic analyses (IDAs) are performed using increments corresponding to 10% of the first mode spectral acceleration level at the maximum considered earthquake (MCE) ($Sa_{T_1,MCE}$). A single scale factor is applied such that the median spectra for the ground motion set matches the target intensity. Additionally, the directions of the record-pairs are switched such that 44 analysis cases are conducted at each intensity. Collapse is defined as the condition where dynamic instability occurs, or the maximum story drift ratio exceeds 10% [11]. The median collapse intensity is computed by minimizing the squared loss in the empirical data and a single dispersion value of 0.6 is used for all existing and retrofitted archetypes. This value includes both record-to-record variation and model parameter uncertainty [10].

3. Development of Machine Learning-Based Surrogate Models for Rapid Performance Prediction of the Retrofitted and Existing SWOF Buildings

To obtain the portfolio-scale performance under different retrofit strategies, the performance of individual buildings, in this case, collapse safety, must first be assessed. To avoid the significant computational expense associated with iterative incremental dynamic analyses within the stochastic optimization environment, surrogate models are developed to provide a compact statistical between the key structural properties of the building and the collapse performance. Extreme Gradient Boosting (XGBoost) Model [12], which is an ensemble learning technique is adopted for this purpose. XGBoost combines the accuracy of ensemble learning, high efficiency and flexibility of the gradient boosting model, the suitability for parallel computing and low risk of overfitting. The superior performance of XGBoost on the datasets generated in the current study has been demonstrated through a preliminary comparative assessment with other types of machine learning algorithms (e.g. Kernel Ridge Regression, Gradient Boosting and Random Forest).

3.1 Introduction of XGBoost model

The XGBoost model predicts responses by combining a sequence of tree-based models as shown in Eq. (1).

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i) \tag{1}$$

where $\hat{y}_i$ is the prediction on the i^{th} data point, f_k is the k^{th} tree model computed by minimizing the objective function and x_i is a vector containing the feature of data point i. XGBoost is a boosting ensemble model, where a sub regression tree is developed on the basis of a previous tree, which adaptively boosts the performance of existing tree. In other words, the next subtree is grown to reduce the residuals of existing tree. However, a deep tree model can lead to overfitting, where high accuracy is achieved on the training set at the expense of the generalizability. To balance the model performance and risk of overfitting, the objective function of XGBoost model shown in Eq. (2) is used.

$$J = L(\theta) + \Omega(\theta) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \tag{2}$$

where $L(\theta)$ is the loss function used to evaluate the differences between prediction and responses, $\Omega(\theta)$ is the regularization function that penalizes deep and complex models and θ represents the model parameters. The loss function sums the differences between real response y_i and prediction $\hat{y}_i$ over n training samples. Common examples of loss functions used for regression include the mean squared error (MSE) and median absolute error (MAE). The regularization function sums the penalties for function f_i over a total of K models. Specifically, for the XGBoost model, the penalization on model complexity is defined in Eq. (3).

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} w_j^2 \tag{3}$$

where γ and λ are the regularization magnitude, which can be tuned. T and w_j are the number of leaves and the score of leave j in the tree-based model f, respectively. The model complexity and penalty increase with number of leaves and the scores.

XGBoost accumulates new trees by reducing the residual from previous step. At step t, the prediction can be computed using Eq. (4).

$$\hat{y}_i^t = \sum_{k=1}^{t} f_k(x_i) \tag{4}$$

To develop the model for step $t+1$, the residual from step t is minimized and the introduction of a new model f_{t+1} is penalized. The objective function for f_{t+1} is given by Eq. (5).

$$J_{t+1} = L_{t+1}(\theta) + \Omega_{t+1}(\theta) = \sum_{i=1}^{n} l\left(y_i, \hat{y}_i^t + f_{t+1}(x_i)\right) + \sum_{k=1}^{t} \Omega(f_k) + \Omega(f_{t+1}) \tag{5}$$

Considering the MSE loss function, the penalty term from the previous t steps is fixed when developing the model for step $t+1$ and the previous regularization term can be waived when minimizing the objective function. Eq. (5) can be furtherly simplified to Eq. (6).

$$J_{t+1} = \sum_{i=1}^{n} \left(y_i - (\hat{y}_i^t + f_{t+1}(x_i)\right)^2 + \Omega(f_{t+1}) = \sum_{i=1}^{n} 2(\hat{y}_i^t - y_i) f_{t+1}(x_i) + f_{t+1}(x_i)^2 + \Omega(f_{t+1}) \tag{6}$$

Eq. (6) can be estimated using the Taylor series expansion keeping the second order term. The analytical solution of f_{t+1} is computed by minimizing Eq. (7).

$$J_{t+1} = \sum_{i=1}^{n} \left[l\left(y_i, \hat{y}_i^t\right) + g_i f_{t+1}(x_i) + \frac{1}{2} h_i f_{t+1}^2(x_i) \right] + \Omega(f_{t+1}) \tag{7}$$

where g_i and h_i are the first and second order partial derivative of the loss with respect to the prediction for training i at step t, respectively. By removing the constant loss from the previous step, the finalized objective function for $f_{t+1}$is achieved through Eq. (8).

$$J_{t+1} = \sum_{i=1}^{n} \left[g_i f_{t+1}(x_i) + \frac{1}{2} h_i f_{t+1}^2(x_i) \right] + \Omega(f_{t+1}) \tag{8}$$

3.2 Training and testing dataset development

To develop a such XGBoost model, training and testing datasets are used to find the model parameters and evaluate its performance, respectively. 1,600 structural models are constructed and analyzed as described earlier and used for training and testing. 50 models are developed by adjusting the stiffness and ductility of the first story for each of the 32 archetypes. The adjustment of the first story structural properties proceeds as follows: 1. Generate 10 random samples from a uniform distribution between -10% and 10% for strength and drift Pinching4 parameter adjustment factors, 9ft and 12 ft for the story heights and 1% to 5% for the damping ratio to capture the model uncertainties for each existing archetype; 2. Generate 5 random samples from a uniform distribution between 0 and 40% for the Pinching4 strength parameter amplification to have stronger and stiffer first story after being retrofitted for each model generated by step 1. The models from step 2 can be regarded as the retrofitted models from step 1. Apart from the 1,600 generated models, another 128 models with real retrofit designs following the Ordinance Guideline, FEMA P807, ASCE 41 and IEBC 2012 are considered. The detailed designs can be found in Burton et al. Appendix B [6]. Since the model uses the peak strength ratio to predict the increase in the collapse safety, 32 edge cases without retrofit (peak strength ratio is 1 and increase in the median collapse intensity is 0) are added to the training dataset to improve the model performance near boundary condition. To boost the generalizability of the prediction model, the 1,600 generated models and 128 real design models are combined and split into 70% training and 30% testing dataset. The 32 edge cases are then incorporated in the training dataset without splitting.

3.3 Development of XGBoost Model

As shown in a previous study [6] in Fig. 3, the increase in pushover peak strength has an overall strong correlation with the improvement in collapse safety. Motivated by this result, XGBoost is constructed using the building information and retrofit to existing peak strength ratios as inputs to predict the improvement in collapse safety of the retrofitted SWOF building.

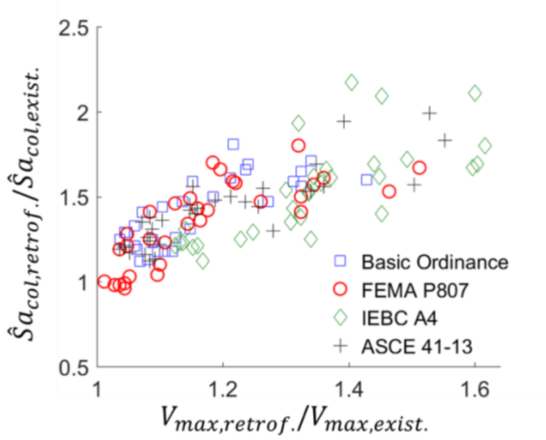

Fig. 3 Effect of $V_{max,retrof}/V_{max,exist}$ on CMR_{retrof}/CMR_{exist}

The response variable or model output is the collapse margin ratio of the retrofitted building normalized by that of the existing case (CMR_{retrof}/CMR_{exist}). The features or input variables include the number of stories, typical story height, building dimensions, floor area, total wall length, damping ratio and retrofit to existing pushover peak strength ratio in the two principal directions. The Huber loss, which is weighted average of MSE and MAE, is adopted in training prediction model to reduce model bias and variance. The mean absolute relative difference ($MARD$) computed using Eq. (9) is selected as metric to evaluate model performance.

$$MARD = \frac{1}{n}\sum_{i=1}^{n}\frac{|y_i - \hat{y}_i|}{y_i} \tag{9}$$

To reduce the risk of overfitting and find the optimal model parameters, cross-validation with random parameter search is implemented. By performing K-fold cross-validation, the training set is equally divided into K groups. In each iteration, a set of model parameters is independently sampled from a target range and used to formulate the model. The model is then trained using the $K-1$ data subsets and the validation score is computed using the remaining data. Taking the average score over K testing cases as the final cross-validation score, the parameter set with the highest score is selected.

Using the input parameters and cross-validation procedure described above, the predicted versus the actual CMR_{retrof}/CMR_{exist} is shown in Fig. 4. The data points are evenly clustered around a 45-degree angled straight line, which indicates low model bias. The training and testing $MARD$ of the model are 2.54% and 7.13%, respectively. In the testing set, the model, on average, over- or under-estimates the actual CMR_{retrof}/CMR_{exist} by 7%.

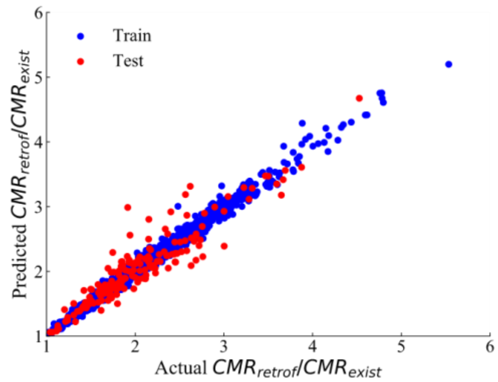

Fig. 4 Predicted versus actual CMR_{retrof}/CMR_{exist} obtained from XGBoost model

4. Portfolio-Scale Optimization

4.1 Problem formulation and constraints

The objective of this study is to develop a SWOF retrofit strategy that efficiently achieves the best performance for the entire building portfolio (in this case the 12,060 SWOF buildings in Los Angeles). The retrofit strategy is quantified as the percentage of "missing strength" – defined as the difference between the 2nd and 1st story strength – added to the peak strength. The optimization is performed for the M7.1 Puente Hills scenario and the total number of fatalities is used as the performance metric.

The total number of fatalities is computed using the FEMA P58 methodology [13]. The expected total number of fatalities F_{total} is computed using Eq. (10).

$$F_{total} = \frac{1}{N_{map}} \sum_{j=1}^{N_{maps}} \sum_{i=1}^{N_{sites}} \mathrm{P}\left(Collapse \middle| IM_{ji}\right) F_i \tag{10}$$

where, N_{maps} is the number of ground shaking maps generated for the scenario, N_{sites} is the number of considered building sites, $\mathrm{P}(Collapse|IM_{ji})$ is the probability of collapse at site i under shake map j, and F_i is the fatality rate of the building at site i given collapse. The fatality rate for a single building is a function of its use purpose, dimension and the time of day when the earthquake occurs. In this study, F_i is taken as a constant for a given archetype. The F_is are extracted from the loss assessment results using the *Seismic Performance Prediction Program (SP3)* for each archetype.

The probability of building collapse conditioned on the shaking intensity is computed using Eq. (11).

$$\Pr\left(collapse \middle| IM_{ji}\right) = \Phi\left(\frac{ln\left(IM_{ji}\right) - \ln\left(CM_i\right)}{\sigma}\right) \tag{11}$$

where, Φ is standard normal cumulative distribution function (CDF). CM_i is the median collapse intensity at location i, which can be predicted using the XGBoost model given the building features and increase in peak strength. σ is the lognormal standard deviation, which is set to 0.6 to account for record-to-record and model parameter uncertainties.

Certain constraints have to be considered to define the upper bound strength added during the retrofit. As observed from the nonlinear analysis results, the retrofit increases the strength and stiffness of the first story. As the missing strength between the first and second story decreases, damage is transferred to the second story and can lead to second story collapse. In such cases, there is very little benefit in terms of collapse safety. To capture the relationship between the missing strength and improvement in collapse safety, the percentage of missing strength added by the retrofit is taken as the parameter to be optimized. Naturally, the upper limit is taken as the addition of 100% of the missing strength, which means that the strength of the retrofitted building is the same in the first and upper stories. Also, one must consider that the improvement provided by the retrofit varies across different shaking intensities. Under extremely high intensities, both the existing and retrofitted building have equally high probabilities of collapse and therefore similar fatality rates. To consider this effect, eight shaking intensity bins are created, and the same missing strength is applied as part of the retrofit to all sites falling in the same intensity bin.

With only the above constraints, the algorithm would simply retrofit all buildings to achieve the maximum reduction in fatality i.e. 100% missing strength added. However, this may lead to an inefficient retrofit solution. To address this issue, a penalty term is added that is a function of the percentage of missing strength added as part of the retrofit. The penalty term can be interpreted as the cost of the retrofit. While penalty functions can take different forms, a second order inversion function as Eq. (12) is adopted herein.

$$P = \sum_{i=1}^{I} \frac{w}{(u_i - x_i + \varepsilon)^2} \tag{12}$$

where u_i is the upper limit for the optimization target x_i and w is penalty weight. In the current study, $w = 1$ is selected. To avoid numerical conversion problems, a small number ε is added to denominator.

Combining the fatality estimation, problem constraints and penalty function, the final objective of the optimization problem is to find the optimal percentage of missing strength x_k added to existing building to maximize Eq. (13).

$$J = -\frac{1}{N_{map}} \sum_{j=1}^{N_{map}} \sum_{i=1}^{N_{site}} \sum_{k=1}^{N_{bin}} \Phi\left(\frac{ln(IM_{ji}) - \ln(XGBoost(x_k))}{\sigma}\right) F_j I(IM_{ji} \in k) - P(x) \tag{13}$$

where N_{bin} is the number of shaking intensity bins. $I(IM_{ji} \in k)$ is an indicator function that yields 1 if the shaking intensity IM_{ji} falls in intensity bin k and 0 otherwise.

4.2 Scenario Description

The optimization is performed at the regional scale considering the approximately 12,060 SWOF buildings in the City of Los Angeles. The M7.1 Puente Hills event is used for this optimization. Fig. 5 shows the spatial distribution of median spectral acceleration at a period of 0.2 seconds ($Sa_{0.2s}$) for this scenario obtained from the Scenario ShakeMap Calculator application in OpenSHA [14]. The latitude and longitude of the earthquake epicenter, the boundary of the study region and several earthquake rupture parameters (e.g. rupture type, fault surface, magnitude) are the OpenSHA inputs. The median $Sa_{0.2s}$ map and residuals (inter-event and intra-event) are based on the Boore and Atkinson ground motion prediction equation [15]. The Jayaram and Baker model [16] is used to generate the spatially correlated shaking intensities. As shown in Fig. 5, the epicenter is located in East Los Angeles, the magnitude of the median simulated shaking intensities decays from the east to west.

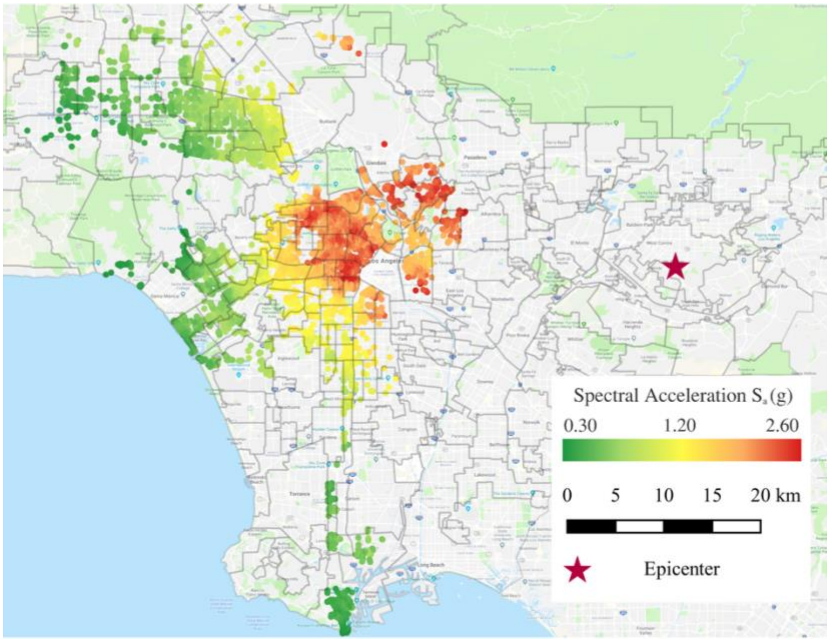

Fig. 5 Spatial distribution of median $Sa_{0.2s}$ values for the Mw 7.1 Puente Hills Scenario

4.3 Genetic Algorithm

Genetic algorithm is a heuristic search technique that mimics the process of natural selection on the fittest individuals to produce offspring. Each iteration in the search algorithm follows the flow chart shown in Fig. 6. First, a set of individuals forms an initial population. Each individual is a solution to the problem. An individual contains Genes, which represent the values of different parameters. For each individual in the initial population, the fitness is calculated to evaluate its performance. Then, a selection procedure is conducted to find the fittest individuals to pass their genes to the next generation. The selected 'parents' form a mating pool, where each pair can generate their offspring. The procedure of generating offspring involves crossover and mutation. By conducting crossover, new offspring is generated combining half Genes from both sides of parents. After a new offspring formed, some of their genes can be subjected to a mutation with a specified random probability to reflect the randomness. All offspring forms the new initial population for the next round of search.

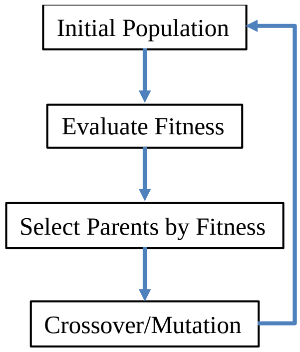

Fig. 6 Genetic algorithm flow chart

4.4 Results Discussion

The genetic algorithm is implemented to obtain the optimal percentage of missing strength added as part of the retrofit for each intensity bin, which by maximizes the reduction in the total number of fatalities under the M7.1 Puente Hills scenario and aforementioned constraints. Table 1 presents the optimal percentage of missing strength that must be added for each intensity bin. When the shaking intensity is between 1.0g and 1.5g, approximately 55% of the missing strength should be added. These intensities are in the vicinity of the median collapse intensities, where slight increases would significantly reduce the probability of collapse. For sites with shaking intensities lower than 0.25g or greater than 2g, no retrofitting is needed. In both cases, the probability of collapse is too low and high, respectively, such that the retrofit does not improve performance. As observed from the results, the algorithm provides the most efficient distribution of resources for the retrofits.

Table 1. Optimal percentage of missing strength to be added as part of the retrofit

Intensity Bin	Added Strength in Percentage of Missing Strength
0-0.25g	0.2%
0.25g-0.5g	23.9%
0.5g-0.75g	33.3%
0.75g-1.0g	32.1%
1.0g-1.5g	55.7%
1.5g-2g	34.3%
2g-2.5g	1.1%
> 2.5g	2.6%

From the perspective of the entire portfolio, the Ordinance retrofit reduces the total number of fatalities by 18.5%, while the algorithm only achieves a 11.4% reduction. However, total added strength by the algorithm is only 1.8% of that of Ordinance retrofit. In other words, the optimization algorithm achieves 61% of Ordinance retrofit reduction in fatality by adding only 1.8% of the strength used by the Ordinance retrofit.

Fig. 7 shows the spatial distribution of building-specific fatality for the existing case and the Ordinance and optimal retrofit schemes. Whereas Fig. 8 shows the reduction in the number of fatalities achieved by the Ordinance and optimal retrofit schemes. By comparing Fig. 7 (a), (b) and (a), (c), the Ordinance does achieve some reduction in the existing buildings with low fatality rates while the optimal solution does not. On the other hand, compared to the Ordinance, the optimal retrofit scheme achieves a greater reduction in the fatality in existing buildings with high fatality rates. This result is further highlighted in Fig. 8. By comparing Fig. 7(a) with Fig. 8(b), it is observed that the algorithm tends avoid retrofitted buildings with low fatality rates and focuses on the ones that have high fatality rates. From the perspective of individual buildings, the Ordinance and optimization algorithm reduces fatality rates within the range of 6% to 60% and 0 to 50%, respectively. The algorithm achieves a high level of efficiency because it balances the gain from reducing the fatality with the cost or penalty from adding more missing strength. Obviously, the selection of penalty function and penalty weight has significant impacts on the outcomes.

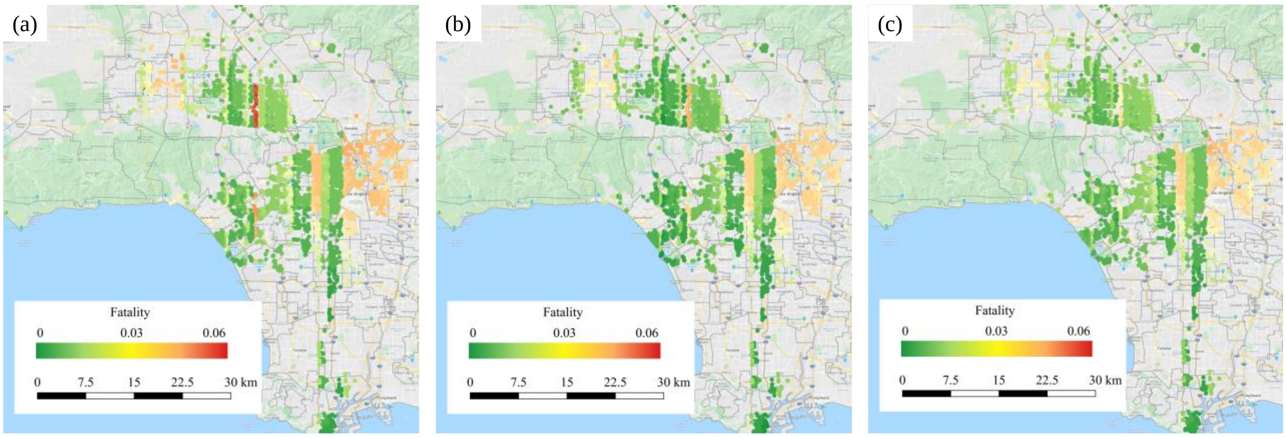

Fig. 7 Spatial distribution of individual building fatality: (a) existing buildings, (b) ordinance retrofit, (c) optimization algorithm outcome

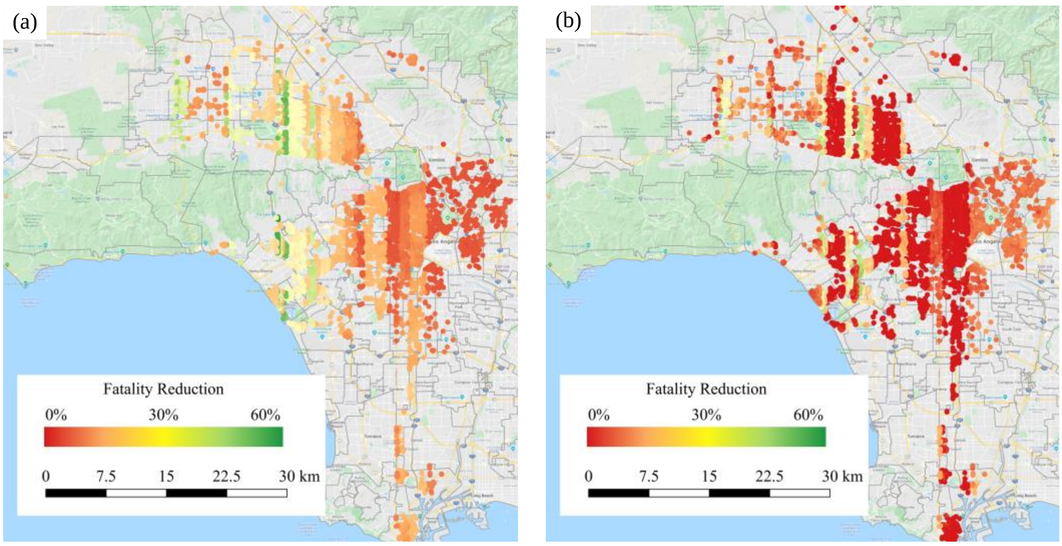

Fig. 8 Spatial distribution of reduction in fatality: (a) Ordinance retrofit, (b) optimization algorithm outcome

5. Conclusion

This study introduces a machine learning and stochastic optimization algorithm-based framework for developing optimal seismic retrofit schemes based on portfolio-scale performance. The methodology is demonstrated using the inventory of soft-weak and open front (SWOF) wall line buildings in the City of Los Angeles. The machine learning algorithms are used to provide rapid estimates of the performance improvement provided by the retrofit conditioned on key structural parameters. Objective functions that capture the reduction in the number of fatalities after retrofit along with other appropriate constraints, are then constructed. The stochastic optimization algorithm uses the key retrofit parameters as input to maximum the value of the objective function. The M7.1 Puente Hill scenario is considered in the application. The extreme gradient boosting model is selected to estimate the increase in the median collapse intensity achieved by adding strength to the peak strength. The total number of fatalities under the scenario earthquake is used as the portfolio-scale performance metric. The genetic algorithm is implemented to find the optimal retrofit scheme that minimizes the total number of fatalities in the presence of an upper limit of the added strength and the penalty function. Based on the considered constraints, the algorithm suggests that 56% of the missing strength (difference between upper and first story strengths) should be added to buildings located at sites with $Sa_{0.2s}$ between 1.0g and 1.5g. Also, buildings located at sites with $Sa_{0.2s}$ lower than 0.25g or greater than 2.0g should not be retrofitted. Comparing the optimal retrofit scheme produced by the algorithm with that of the Los Angeles Ordinance, the former uses only 1.8% of the strength added by the latter to achieve 61% of the reduction.

The case study presented in this paper is based on a single earthquake scenario. More events can be considered either separately or in aggregate to draw a more generalized conclusion. The penalty function plays an important role in suppressing too much added strength. Various penalty function options and weights can be investigated to inform the relationship between the magnitude of penalty and optimization outcomes. Additionally, other performance metrics such as the total economic loss and recovery time can be optimized within this framework.

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