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OPTIMIZATION OF LIFE-CYCLE COST OF RETROFITTING SCHOOL BUILDINGS UNDER SEISMIC RISK USING EVOLUTIONARY SUPPORT VECTOR MACHINE

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Abstract. The assessment of the seismic performance of existing school buildings is especially important in seismic-disaster mitigation planning. Utilizing a support vector machine coupled with a fast messy genetic algorithm, this study developed two inference models, both using the same input variables: i.e., 18 building characteristics selected based on expert opinion. The first model was designed to judge whether a building needs to be retrofitted; and the second, to estimate the cost of retrofitting buildings to specific levels. The study proposes a life-cycle seismic risk framework that takes into account projections of the seismic risk a given building will confront over the course of its entire existence, and thus helps determine the economically optimal level of retrofitting. The results of a case study indicate that the higher upfront cost of retrofitting that is required to reach higher seismic performance levels could, depending on the level of predicted seismic risk, be offset by lower repair costs in the long run. It is hoped that this research will serve as a basis for further studies of the assessment of the life-cycle seismic risk of school buildings, with the wider aim of arriving at an economically optimal building-retrofit policy.

Keywords: life cycle cost, seismic risk, seismic retrofitting, support vector machine.

JEL Classification: R580.

Introduction and literature review

The seismic performance of school buildings is crucially important in disaster response, as they are expected to serve as temporary shelters after major earthquakes. However, such buildings' seismic resistance is often inadequate, due to poor seismic design and/or ongoing processes of aging and deterioration. Therefore, a rapid and reliable methodology for holisti-

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cally assessing the macroscale vulnerability buildings confronting seismic hazards has been of special importance to those tasked with seismic-disaster mitigation (N. Alam, M. S. Alam, & Tesfamariam, 2012). For example, Taiwan's National Center of Research on Earthquake Engineering (NCREE) has developed a framework for assessing the seismic performance of existing school buildings (Chen, Cheng, & Wu, 2012a). The methodology proposed by NCREE comprises three steps: (1) brief investigation, (2) preliminary assessment, and (3) detailed assessment (Kao, Chen, & Chou, 2011). The first step involves a field survey based merely on buildings' appearance, to identify structures whose seismic performance is potentially inadequate. Then, in the second step, professionals assess those buildings identified as possibly inadequate in the first step. Finally, those buildings that are still deemed inadequate after the completion of the second step undergo a detailed assessment to determine the amount and type of work that will be required to retrofit them to a particular required level of seismic resistance. The third step also includes a determination of buildings' seismic capability, including yielding acceleration and ultimate acceleration, using computational structural modeling, e.g., pushover analysis (Cheng, Wu, & Syu, 2014). Such modeling can serve as a practical means of evaluating the inelastic displacement response of structures in earthquakes, and thus has become a powerful tool for accurately assessing buildings' seismic performance. However, its computations require detailed information about the buildings being modeled, including their material strength, the original design of any concrete reinforcement, and their deterioration status, all of which require significant time, financial resources, and expert knowledge to determine accurately. As such, public bodies' implementation of such detailed assessments of large numbers of buildings has been rare. Likewise, due to limited financial resources, buildings that are found to have inadequate seismic resistance are often retrofitted only to the minimum requirements of current building codes. From the point of view of life-cycle risk assessment, however, the optimal retrofitting level can and should be arrived at not through present-day cost considerations alone, but by taking into account the seismic hazards a building is likely to confront throughout its existence.

Machine learning (ML) techniques are powerful tools for solving immense multi-dimensional problems, insofar as they (1) require no assumptions to be made about data distributions and (2) have superior data-mining abilities when tackling highly multi-dimensional and large-scale data (Nakhaeizadeh & Taylor, 1998). As such, ML has been widely and effectively used to solve prioritization or selection problems (Khandekar, Antuchevičienė, & Chakraborty, 2015), economy prediction (Gupta, Ye, & Sako, 2013) and optimization problem (Koo, Hong, & Kim, 2015; Tsehayae & Fayek, 2016), by taking into account thousands to millions of multi-dimensional datasets. As one powerful inference model evolved from statistical-learning theory, the support vector machine (SVM) has been used to solve seismic-risk problems by mapping the underlying relationships among buildings' vulnerability levels and a wide range of their other attributes (Guéguen, Michel, & LeCorre, 2007; Kao, et al. 2011; Chen, Kao, & Tsai, 2012b; Riedel et al., 2015; Guettiche, Guéguen, & Mimoune, 2017). The results have demonstrated SVM's powerful ability to predict building vulnerability in the absence of the detailed data needed for computational modeling. Such SVM-based studies, however, have hitherto only addressed seismic performance under particular earthquake scenarios, and failed to take into account the future seismic risks that buildings will face over their entire life-cycles. Additionally, few if any studies have attempted to create frameworks for determining optimal retrofitting levels for existing school buildings based on consideration of seismic risks during their entire service lives. Accordingly, the present study proposes a novel evolutionary support vector machine (ESVM), in which SVM is coupled with a fast messy genetic algorithm (FMGA). The proposed ESVM model can efficiently search for the most appropriate model parameters with the help of FMGA, and then use SVM to map the relationship between inputs (basic building characteristics) and outputs (the costs of retrofitting to particular levels of seismic performance). Based on the proposed ESVM model, this study involved the development of two inference models: the first for judging whether or not a building needs to be retrofitted, and the second, for estimating the retrofit cost of given buildings to particular seismic-resistance levels. Both inference models utilize the same input variables, i.e., 18 building characteristics that were selected based on expert opinion.

To take into account the seismic risk a building may be exposed to during its entire service life, the present research also proposes a life-cycle seismic risk framework to help determine the economically optimal level of retrofit to school buildings. To validate it, case studies of a school building in Taiwan were conducted using the two proposed models and framework. It is hoped that this work will serve as a basis for further research on the assessment of school buildings' seismic performance and life-cycle seismic risk, with the wider aim of arriving at economically optimal building-retrofit policies.

1. Methodology

1.1. Building seismic-damage index

An effective seismic design is expected to protect human life by preventing a building from collapsing in a severe earthquake, while allowing limit structural and non-structural elements damage under low-to-moderate earthquakes. To aid the design process, several seismic-damage indices have been proposed (Ghosh, Datta, & Katakdhond, 2011). Generally, damage indices are dimensionless parameters ranging between 0 (for an undamaged structure) to 1 (for a collapsed structure). For instance, Park and Ang (1985) proposed an index ($D_{p\&A}$) that expresses damage to reinforced-concrete structures as a linear function of maximum deformation and the effect of repeated cyclic loading. This index combines ductility and cumulative hysteretic energy demand can be obtained by Eq. (1):

$$D_{p\&A} = \frac{\delta_M}{\delta_u} + \frac{\beta}{F_y \delta_u} \int dE, \tag{1}$$

where δ_u – ultimate deformation (capacity) under monotonic static loading; δ_M – maximum deformation (demand) under dynamic loading; dE – incremental hysteretic energy (demand); F_y – yield strength; and β – a non-negative non-dimensional parameter. The associated damage levels are illustrated in Table 1. The present study adopts the capacity-spectrum method (CSM) proposed by the Applied Technology Council (ATC) (ATC, 1996) to identify ultimate deformation capacity (δ_u), yielding the strength (F_y) of a single degree of freedom (SDOF) system for a building. It is worth noting that the key parameter in a CSM is the factor used to adjust equivalent hysteretic damping by measuring of how much the actual hysteretic behavior of the building differs from the theoretical elastic-plastic behavior (Cardone, 2007). The value of this factor was assigned by 1/3 by assuming poor hysteretic behaviors of the school buildings in the present study.

Table 1. Seismic-damage index (source: Chiu & Wang, 2012)

Damage index	Damage state	Description
0–0.2	No	Slight cracks in non-structural components
0.2–0.4	Slight	Slight cracks in structural components
0.4–0.6	Moderate	Flexure shear cracks in the top or bottom ends of columns; spalling of concrete cover; shear cracks in the middle part of columns connected with windowsills
0.6–0.9	Severe	Crushing of concrete in the core of columns; extensive loosing of stirrups; buckling of main bars
0.9	Collapse	Extensive crushing of the core concrete in columns without sufficient loading capacity

1.2. Modeling of earthquake events

It is assumed in the present study that the frequency of earthquakes $f(x)$ follows a Poisson process, as shown in Eq. (2),

$$f\left(x\right)=\frac{v^{x}}{x!}\exp\left(-v\right), \tag{2}$$

where x is the number of occurrences of earthquakes within a specified period (T_H), and v is the average number of earthquakes that occur in T_H.

In a Poisson process, the time interval between two occurrences follows an exponential distribution, and thus the time of occurrence of the t_{M+1} earthquake can be expressed using Eq. (3):

$$t_{M+1} = t_M + \Delta t, \tag{3}$$

where t_M is the time at which the M earthquake occurs, and Δt is the time interval between two earthquakes.

Now, assuming that the average number of earthquakes within a specified period (T_H) is known, the frequency of the earthquakes of a given magnitude within that period can be expressed using Eq. (4):

$$f\left(\Delta t\right)=\frac{v}{T_H}\exp\left(-\frac{v\Delta t}{T_H}\right). \tag{4}$$

For the purposes hereof, T_H is the number of years in a building's service lifetime, and $f(\Delta t)$ is calculated by the design earthquake return period.

1.3. Repair cost of seismic damage to buildings

The repair cost associated with seismic damage to a building has been found to correlate strongly with its cycle ductility ratio (Takahashi, Nakano, & Shiohara, 2006). Assuming that seismic-repair costs generally correspond to the maximum displacement response of reinforced-concrete buildings reaching a specific threshold, known as cracking displacement, (Chiu & Wang, 2012) proposed a repair-estimation index (I_{Rep}) that uses a convex curve to normalize the cost of replacing damaged buildings or restoring them to their original conditions, as shown in Eq. (5). Thus, the corresponding repair cost C_{Rep} to a given I_{Rep} can be obtained by the multiplication of I_{Rep} and the initial construction cost of buildings (C_c), as shown in Eq. (6).

$$I_{Rep} = \left[\left(\frac{1 - D_{P\&A}}{1 - \gamma} \right)^3 - 1 \right], \tag{5}$$

where $\gamma = \delta_c / \delta_u$, and δ_c is cracking displacement.

$$C_{Rep} = I_{Rep} \times C_c. \tag{6}$$

1.4. Evolutionary support vector machine inference model (ESIM)

SVM and FMGA have recently emerged as powerful ML techniques. SVMs were first proposed by Vapnik (Drucker, Burges, Kaufman, Smola, & Vapnik, 1996) and have recently been applied to a range of engineering problems including pattern recognition, bioinformatics, and text categorization. A SVM arranges data into different classes by determining a set of support vectors, each of which is a member of a set of training inputs that outline a hyperplane in a feature space. In a SVM model, one must choose a kernel function, set kernel parameters, and determine a penalty parameter. Penalty parameters must be obtained simultaneously based on users' proposed optimal kernel parameters. Therefore, proper settings of kernel parameters, such as the gamma of the radial basis function (RBF) kernel, can improve the prediction accuracy of the model.

Traditionally, a grid algorithm is used to determine the best penalty parameter and gamma of an RBF kernel function. However, such algorithms are vulnerable to the local-optimum problem (Huang & Wang, 2006). For this reason, Goldberg, Deb, & Korb (1991) developed the FMGA technique, by utilizing fixed-length strings to represent possible solutions, and applying messy chromosomes to form strings of various lengths. FMGA's ability to identify solutions of optimal efficiency to large-scale permutation problems gives it the potential to generate SVM-model penalty and gamma parameters simultaneously. Based on Goldberg et al.'s (1991) model, (Cheng & Wu, 2009) developed an ESVM inference model (ESIM) to arrive at the fittest penalty and gamma parameters with minimal prediction error. The ESIM, which the present study adopts, provide a generic mechanism that uses a kernel function to fit the hyperplane surface to training data, and allows users to select SVM kernel functions (e.g., linear or polynomial ones) during the training process, which identifies support vectors along the function surface. As shown in Figure 1, in the ESIM model, the SVM is employed primarily to address learning and curve fitting, while FMGA addresses optimization issues.

K-fold cross-validation was used to ensure the reliability of the ESIM model adopted for the present research. This validation approach can discover whether a model generates adequate output only during the training process, and then fail to make reliable predictions based on new input data. It requires that K models be established for K tests, and model error is represented as the mean error of K testing subsets, as calculated by Eqs. (7) and (8). Generally, a model whose mean error is less than 10% is considered excellent; between 10% and 20%, fine; and less than 50%, acceptable. Accordingly, the accuracy rate (R_A) of a model can be established using Eq. (9).

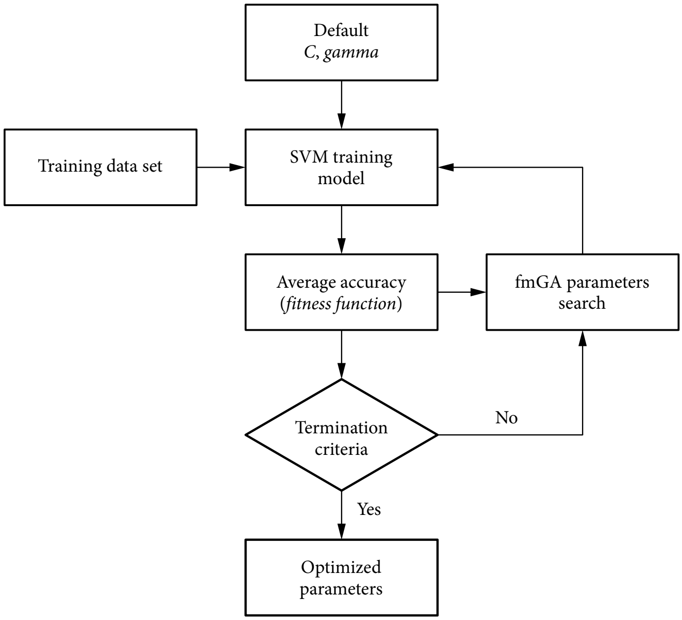

Figure 1. Evolutionary support vector machine inference model (source: Cheng & Wu, 2009)

$$Error_{model} = \frac{1}{K}\sum_{i=1}^{K}\left(RMSE\right)_i; \tag{7}$$

$$RMSE = \sqrt{n_e\sum_{i=1}^{n_e}\left(y_i - \hat{y}\right)^2 / \left(n_e - 1\right)\sum_{i=1}^{n_e} y_i^{\,2}}; \tag{8}$$

$$R_A = 1 - Error_{model} \tag{9}$$

root mean squared error (RMSE) is used in the proposed study to measure the performance of model prediction, by calculating the difference between inferred value ($\hat{y}$) and actual values (y) for a given number of samples (n_e).

1.5. Development of inference framework for life-cycle cost of school buildings under seismic risk

As shown in Figure 2, the present study's proposed framework for predicting school buildings' life-cycle seismic-repair cost comprises five steps: (1) defining critical factors in the cost of school-building retrofitting; (2) establishing a database of retrofitted school building cases and their associated building characteristics; (3) developing an ESIM model for judging whether a given school building requires retrofitting; (4) developing an ESIM model for estimating the cost of retrofitting that building to particular levels; and (5) determining the optimal retrofitting level from among all possible such levels, based on considerations of both life-cycle cost and seismic risk.

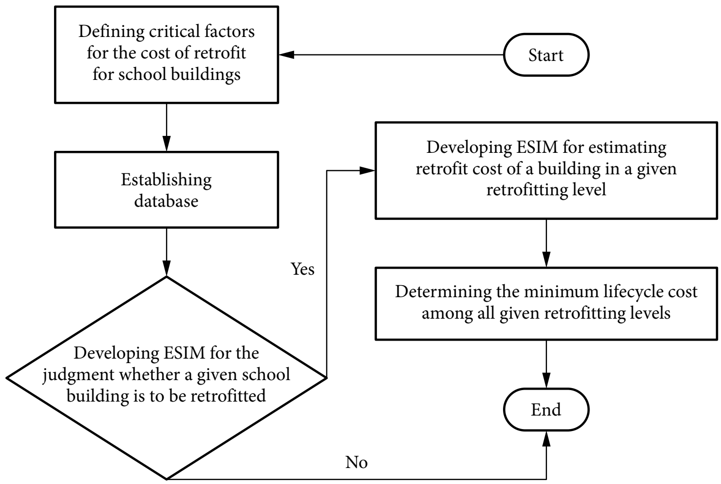

Figure 2. Inference framework for life-cycle cost of school buildings under seismic risk

Firstly, critical building characteristics need to be determined for use as input variables in the proposed ESIM models. The 27 basic items of building information that can be obtained from a field survey, as set forth by NCREE (Chung, Hwang, & Wu, 2012), include the sectional areas of columns, beams and shear walls, year built, and structural deficiencies. These 27 characteristics served as candidates for the input parameters of the proposed first ESIM model. Accordingly, the present study conducted a survey to determine the relative importance of each such characteristic to seismic performance, based on experts' professional judgements. The first section of the proposed expert questionnaire listed the 27 factors proposed by NCREE and asked the respondents to rate the importance of each to the seismic performance of buildings using a 5-point Likert scale (1 = least important and 5 = most important). As shown in Table 2, a total of 31 questionnaires were disseminated to engineers and other relevant professionals by means of email, phone calls and personal interviews. Table 3 shows, in descending order, the 18 factors that received average scores greater than three in the survey. In order to ensure the consistency of input units for the proposed ESIM models, the 18 factors (X) were then normalized to between 0 and 1 using Eq. (10):

$$X_n = \frac{X - X_{\min}}{X_{\max} - X_{\min}}, \tag{10}$$

where X_n is the normalized value, and $X_{\max}$ and $X_{\min}$ are the maximum and minimum values, respectively. A database containing the 18 normalized factors (X_n) for a total of 3,100 school buildings in Taiwan was then established.

In the proposed first ESIM model, developed to judge if a given school building needs to be retrofitted based on the above-mentioned 18 factors, the present study set 1 as the output in cases where the building needs to be retrofitted, and –1 as the output in cases where no retrofitting is needed. Once a given building's need for retrofitting is identified, the proposed second ESIM model estimates the cost of retrofitting it to a given level of seismic resistance

(C_R). The life-cycle cost (C_L) of a building that is retrofitted to a certain level of design peak ground acceleration (S_{aD}) is defined as the sum of the upfront cost of retrofit (C_R) and the repair cost (C_{Rep}) obtained from Eq. (6). Finally, in order to determine the minimum life-cycle cost of a building under a given level of seismic risk, the present study investigated the minimum value of all life-cycle costs associated with a range of S_{aD} from 0.28 to 0.40, in increments of 0.01: 0.28 of S_{aD} is determined as the minimum design peak ground acceleration for a 475-return-period earthquake; 0.40 represents a 2500-return-period earthquake by the current Taiwan Seismic Design Codes for Buildings (Chai & Teng, 2012).

Table 2. Characteristics of respondents to the expert survey

Organization type	Number of respondents	Education level	Average experience
Universities	5	B.S. 3; PhD 2	7.6 years
Consulting firms	10	B.S. 4; M.S. 6	
Governmental bodies	9	B.S 1; M.S. 7; PhD 1	
NCREE	4	M.S. 2; PhD 2	
Architectural firms	3	M.S. 3	

Table 3. Building-characteristic input factors (in descending order by seismic relevance)

1. Design peak ground acceleration (S_{aD})	10. Total sectional area of brick walls on first floor
2. Number of stories above-ground of building	11. Effective strength of walls
3. Number of stories underground of building	12. Seismic performance index
4. Area of second floor	13. Vertical irregularity
5. Total number of floors	14. Soft story
6. Sectional area of exterior columns on first floor	15. Deterioration
7. Sectional area of interior columns on first floor	16. Plan irregularity
8. Effective strength of columns	17. Short column
9. Total sectional area of reinforced-concrete walls on first floor	18. Year built

2. Model validation and application

2.1. Model for judging whether or not a building needs to be retrofitted

The 3.100 school buildings in the NCREE database were used for testing and training the proposed models. The 18 building characteristics affecting the need for retrofit, as set forth in Table 3, served as the input variables of the model. All output variables were either 1 or –1, representing "yes" and "no" to retrofit, respectively. The 3.100 buildings were randomly grouped into 10 sets of 310 buildings each. One of these 10 sets was then sequentially selected to serve as the model's testing case, and the remaining nine sets were used as training cases. Such will guarantee that every subset will serve as a testing case once, nine times as a training case. The accuracy rate (R_A) of a model – defined as the difference between its target output values and the inferred output values of the training and testing cases – can be obtained using Eq. (8). As shown in Table 4, the model achieved average accuracy rates for training and testing of 93.57% and 92.9%, respectively, clearly indicating its validity. The kernel (γ) and penalty (C) parameters for each group of testing and training cases are shown in Table 5.

Table 4. Accuracy rates (R_A) for testing and training cases (%)

Group	Training	Testing
0	93.06	93.87
1	93.31	94.52
2	94.21	92.58
3	92.78	95.81
4	93.24	90.97
5	94.10	92.26
6	93.42	92.58
7	93.78	92.90
8	94.21	91.29
9	93.60	92.26
Average	93.57	92.90

Table 5. Kernel (γ) and penalty (C) parameters

Group	γ	C
0	0.1842	20
1	0.8417	10
2	0.9469	30
3	0.1579	45
4	0.1842	145
5	0.9732	35
6	0.9091	6
7	0.4849	66
8	0.5152	156
9	0.8821	10

2.2. Model for estimating the cost of retrofitting buildings to a given level of seismic performance

Of the 3.100 school buildings in the sample of the proposed model, 543 had detailed retrofit costs included in the NCREE database, and these buildings were therefore used as the proposed model-testing and model-training cases. The 18 factors in Table 3 served as the input variables of the model, and the output variables were the costs of retrofitting the buildings to given levels of seismic performance. The 543 buildings were randomly divided into three groups of 181. One of the three groups was then selected sequentially to serve as the model's testing cases, and the remaining two groups became the training cases. To validate the proposed model, RMSE of the difference between target output values and inferred output values for the training and testing cases were both calculated using Eq. (8). As shown in Table 6, the model was found to be valid: with RMSE averages for training and testing of 0.105782 and 0.102538, respectively. The kernel (γ) and penalty (C) parameters for each group are shown in Table 7.

Table 6. RMSE for testing and training sets (%)

Group	Training	Testing
1	0.127321	0.122545
2	0.073151	0.072235
3	0.116875	0.112844
Average	0.105782	0.102538

Table 7. Kernel (γ) and penalty (C) parameters

Group	γ	C
1	0.8417	10
2	0.9469	30
3	0.1579	45

2.3. Inference framework for life-cycle cost of school buildings under seismic risk

One school building was randomly selected from the NCREE database for a case study aimed at determining its optimal seismic retrofit level using the proposed framework. Following the procedure of the proposed framework (Fig. 2), the repair cost (C_{Rep}) for seismic damage within an S_{aD} range of 0.28 to 0.40 (in increments of 0.01) were calculated using Eq. (6). After the building was identified as needing retrofitting via the first proposed model, the cost of retrofitting it (C_R) to a given level (S_{aD}) was estimated using the second proposed model. The life-cycle cost (C_L) of a building that is retrofitted to S_{aD} can be obtained by summing the upfront cost of retrofit (C_R) and the repair cost (C_{Rep}). As shown in Table 8, the life-cycle cost of the case building, if retrofitted to the minimum seismic resistance required by current building codes (S_{aD} = 0.28), is NT$6,839,118. However, its optimal life-cycle cost (NT$6,512,147) was attained when S_{aD} = 0.33. This result indicates that a higher cost of retrofit (C_R) aimed at achieving a higher level of seismic performance may be more than offset by lower repair costs (C_{Rep}), if seismic risk to the building during its entire service life is taken into consideration.

Table 8. Life-cycle cost of a retrofitted school building under seismic risk (NTD)

S_{aD}	C_{Rep}	C_R	C_L
0.28	1,479,398	5,359,720	6,839,118
0.29	1,220,241	5,477,785	6,698,026
0.30	1,005,270	5,596,169	6,601,440
0.31	827,350	5,714,853	6,542,203
0.32	680,366	5,833,813	6,514,178
0.33	559,120	5,953,027	6,512,147
0.34	459,228	6,072,475	6,531,703
0.35	377,013	6,192,134	6,569,147
0.36	309,402	6,311,982	6,621,384
0.37	253,839	6,431,997	6,685,836
0.38	208,203	6,552,158	6,760,361
0.39	170,736	6,672,442	6,843,178
0.40	139,988	6,792,827	6,932,815

Conclusions

School buildings are expected to serve as public shelters after major earthquakes. Unfortunately, like all other buildings, they continuously deteriorate as they age, and this negatively affects their seismic resistance. Therefore, assessment and enhancement of the seismic performance of existing school buildings has been of special importance in seismic-disaster planning. Existing approaches to the assessment of the seismic performance of buildings, such as pushover analysis, are expensive and time-consuming, and tend to ignore the seismic risks a building may confront over its entire service life. Utilizing a support vector machine coupled with a fast messy genetic algorithm, this study developed two inference models: the first model to judge whether or not a building needs to be retrofitted, and the second, to estimate the cost of retrofitted it to specified levels. Both models used the same set of input variables, i.e., 18 building characteristics selected based on a survey of experts. Additionally, by taking into account the seismic risk during a building's entire life, a life-cycle seismic risk framework was proposed to help determine the economically optimal level of retrofit to school buildings.

The first proposed model was applied to a sample of 3.100 school buildings that were randomly grouped into 10 sets, of which nine were sequentially chosen as model training cases and one as the testing case. The 18 building characteristics pertaining to seismic performance, selected based on a questionnaire survey of 31 engineers and other professionals, served as input variables, while the output variable was whether or not a given building needed to be retrofitted. The first model was valid, with average accuracy rates of 93.57% and 92.9% for the training and testing cases, respectively. The second proposed model was applied to a sample of 543 school buildings randomly grouped into three sets, of which two were sequentially chosen as model-training cases and one as the testing case. The same 18 selected building characteristics again served as input variables, and retrofit cost as the output variable. The second model was also valid, with average RMSE values for the training and testing cases being 0.105782 and 0.102538, respectively. Finally, a school building was randomly selected from the NCREE database to serve as a case study for the determination of its optimal seismic-retrofitting level/cost using the proposed framework. The results show that the minimum requirements of the current building code in Taiwan were not optimal in terms of life-cycle cost. Instead, this building's optimal life-cycle cost was found to occur if it was retrofitted to a somewhat higher level of seismic performance (S_{aD} = 0.33 rather than 0.28). In other words, the higher upfront cost of doing more than the minimum was more than offset by lower repair costs in the long run.

The proposed models and framework appear to be a powerful tool for effectively and efficiently determining optimal building-retrofit levels. Despite this advantage, the proposed methodology can be improved in the future study by taking into account a repair loss threshold. For better and practical estimation of repair cost, a repair loss threshold should be incorporated into a seismic loss model, in order to recognize that a threshold beyond which replacing the building is more convenient than repairing always exist for stakeholders like building owners or relevant public agencies (Cardone & Perrone, 2017; Cardone, Sullivan, Gesualdi, & Perrone, 2017). It is hoped that this research will serve as a basis for further studies of the assessment of seismic performance and life-cycle seismic risk to school buildings, with the wider aim of arriving at an economically optimal building-retrofit policy.

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