A Novel Inference Model for Post-Earthquake Bridge Safety and Failure Probabilities Prediction-a Case Study in Taiwan

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Abstract -

Bridges are a vital and significant component of Taiwan's transportation infrastructure. Therefore, regular and comprehensive inspections of existing bridges are necessary to prevent damage and traffic disruption and reduce earthquake-related damage and casualties. However, due to the large number of bridges in Taiwan, the time and budget required to perform traditional structural analyses (preliminary assessment, detailed analysis) on every bridge to calculate yield acceleration (Ay) and collapse acceleration (Ac) values make doing so impractical. This paper integrates material degradation, pushover analysis, and artificial intelligence to create a new inference model as an alternative to traditional structural analysis. Historical cases are used to infer Ay and Ac values by mapping relationships between the preliminary assessment factors (input) of historical cases and detailed assessments of Ay and Ac values (output). Using the proposed inference model to predict Ay and Ac values, bridge maintenance planners can quickly and more cost effectively assess bridge earthquake damage probabilities as a guide to identifying priority bridge maintenance projects.

Keywords -

Seismic Assessment; Deterioration of Materials; Seismic Capacity; Evolutionary Support Vector Machine Inference Model

1 Introduction

Besides the functionality of crossing rivers and valleys to communicate with the outside world, bridges also play an important role in maintaining the economic arteries. In sparsely populated remote areas, bridges have become an important lifeline of living supplies and product output. Once bridges are damaged by natural disasters, it will generate far-reaching impacts on communication and transportation. It is also imaginable that life and property will be endangered, and social economy will be affected as well. At present, highway bridges in Taiwan are aged from newly built ones to the oldest ones aged more than eighty years. Accordingly, due to different seismic design specifications, as well as deterioration caused by environmental impact, some bridges do not meet the current seismic requirements and may result in damage.

Taiwan reinforced concrete bridges are the most widely used type (95%), and 75% bridge are used more than 20 years [1]. The old bridge will not meet the needs of seismic norms issued by the circumstances which led to destruction because different seismic design used or deterioration phenomenon caused by environmental influences. In other words, the current problems faced by the majority of Taiwan's bridges are old and deterioration. Taiwan belongs to many earthquakes, once large-scale natural disasters such as earthquakes, high probability of a bridge collapse or breakage. To avoid disaster, causing damage to the bridge leading to traffic disruption, or even residents trapped casualties and other incidents occur, the existing bridge is imperative to conduct a comprehensive inspection.

At present, the traditional structural analysis can be divided into three types, including: 1.brief investigation; 2. preliminary assessment; and 3. detailed assessment. The brief investigation table thus developed is mainly for relevant management personnel to identify buildings with seismic capacity-related problems. Professionals will then perform preliminary assessment of such problematic buildings. Regarding buildings of seismic capacity concerns after the brief investigation, civil engineers are hired to complete the preliminary assessment table to assess the buildings. Such investigation and assessment will result in large sum of precious data relating to the seismic capacity of buildings. Finally, according to the collected bridge data, professional and complex assessment methods, such as the pushover method, are applied to carry out the detailed assessment to obtain the highly accurate yielding acceleration (Ay) and complete damage acceleration (Ac).

However, there are more than forty thousand bridges in Taiwan. When applying the simple assessment method to carry out visual investigation, the results will be not accurate despite the fast speed of investigation. In the case of applying the detailed assessment, although the results are relatively accurate, it takes much more time and costs. In addition, detailed assessment can only be done by experienced professionals. To conduct detailed structural analysis of each bridge with limited funds and professional labor is impossible. If simple assessment factors and the mapping relation between Ay and Ac for detailed assessment of similar bridges can be identified to infer the Ay and Ac values of other bridges, it will save a great deal of manpower when acquiring Ay and Ac values within the tolerable error range.

However, due to the large number of bridges in Taiwan, the time and budget required to perform traditional structural analyses (preliminary assessment, detailed analysis) on every bridge to calculate yield acceleration (Ay) and collapse acceleration (Ac) values make doing so impractical. This paper integrates material degradation, pushover analysis, and artificial intelligence to create a new inference model as an alternative to traditional structural analysis. Historical cases are used to infer Ay and Ac values by mapping relationships between the preliminary assessment factors (input) of historical cases and detailed assessments of Ay and Ac values (output). Using the proposed inference model to predict Ay and Ac values, bridge maintenance planners can quickly and more cost effectively assess bridge earthquake damage probabilities as a guide to identifying priority bridge maintenance projects.

2 Literature review

2.1 Seismic assessment of bridge

The static pushover analysis is becoming a popular tool for seismic performance evaluation of existing and new structures. The expectation is that the pushover analysis will provide adequate information on seismic demands imposed by the design ground motion on the structural system and its components [2]. Nonlinear static (pushover) analysis has become a popular tool during the last decade for the seismic assessment of buildings or bridges [3].

The static pushover analysis has no rigorous theoretical foundation. It is based on the assumption that the response of the structure can be related to the response of an equivalent single degree-of-freedom (SDOF) system. This implies that the response is controlled by a single mode, and that the shape of this mode remains constant throughout the time history response. Clearly, both assumptions are incorrect, but pilot studies carried out by several investigators have indicated that these assumptions lead to rather good predictions of the maximum seismic response of multi degree-of-freedom (MDOF) structures, provided their response is dominated by a single mode [2].

The purpose of the pushover analysis is to evaluate the expected performance of a structural system by estimating its strength and deformation demands in design earthquakes by means of a static inelastic analysis, and comparing these demands to available capacities at the performance levels of interest [2]. Large-scale simulations of transportation networks in urban regions have been the focus of numerous projects, such as HAZUS (1999). The goal of such simulations is to provide an economic impact analysis of damage caused by an earthquake event to a transportation network. Direct economic impact can be defined explicitly in terms of monetary losses due to damage to bridges and loss of function. Indirect damage can be defined in terms of damaged and failed links in the transportation network and link costs associated with traffic flow reduction, rerouting, and time delays that cause interruptions in the flow of goods and services.

Damage to bridges in the highway network contributes significantly to both direct and indirect losses. Bridge damage fragility curves, sometimes termed vulnerability curves, describe the conditional probability of exceeding a level of direct or indirect bridge damage, given a level of seismic hazard. The formulation of bridge fragility curves has historically transitioned from empirical to analytical methods [4].

2.2 Evolutionary Support Vector Machine Inference Model (ESIM)

Support vector machines and fast messy genetic algorithms represent recently developed AI paradigms. SVM was first suggested by Vapnik [5] and have recently been applied to a range of problems that include pattern recognition, bioinformatics, and text categorization. SVM classifies data with different class labels by determining a set of support vectors that are members of the set of training inputs that outline a hyper plane in a feature space. It provides a generic mechanism that uses a kernel function to fit the hyper plane surface to training data. The user may select the SVM kernel function (e.g. linear, polynomial, or sigmoid) during the training process, which identifies support vectors along the function surface. Using SVM presents users with the problem of how to set optimal kernel parameters. Therefore, SVM parameters must be obtained simultaneously. Proper parameter settings can improve SVM prediction accuracy, with parameters to be optimized including penalty parameter C and kernel function parameters such as the gamma of the radial basis function (RBF) kernel. In designing a SVM, one must choose a kernel function, set kernel parameters and determine a soft margin constant C (penalty parameter). The Grid algorithm is an alternative to finding the best C and gamma when using the RBF kernel function. However, this method is time consuming and does not perform well [6]. Fast messy genetic algorithms (fmGA) were developed by Goldberg et al [7]. Unlike the well-known simple genetic algorithm (sGA), which uses fixed length strings to represent possible solutions, fmGA applies messy chromosomes to form strings of various lengths. Its ability to identify efficiently optimal solutions for large-scale permutation problems gives fmGA the potential to generate SVM parameters C and gamma simultaneously. Considering the characteristics and merits of each, this paper combines the two to propose the Evolutionary Support Vector Machine Inference Model (ESIM).

The ESIM used here was developed by Cheng and Wu [8]. In the ESIM, the SVM is employed primarily to address learning and curve fitting, while fmGA addresses optimization. This model was developed to achieve the fittest C and gamma parameters with minimal prediction error. The structure of ESIM is shown in Figure 1.

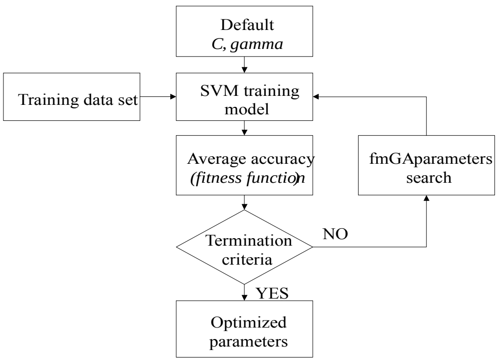

Figure 1. ESIM structure

3 Post-Earthquake Bridge Safety Assessment using Failure Probabilities Inference Model

The primary purpose of this study was to develop an earthquake seismic assessment of bridge diagnostic prediction model.

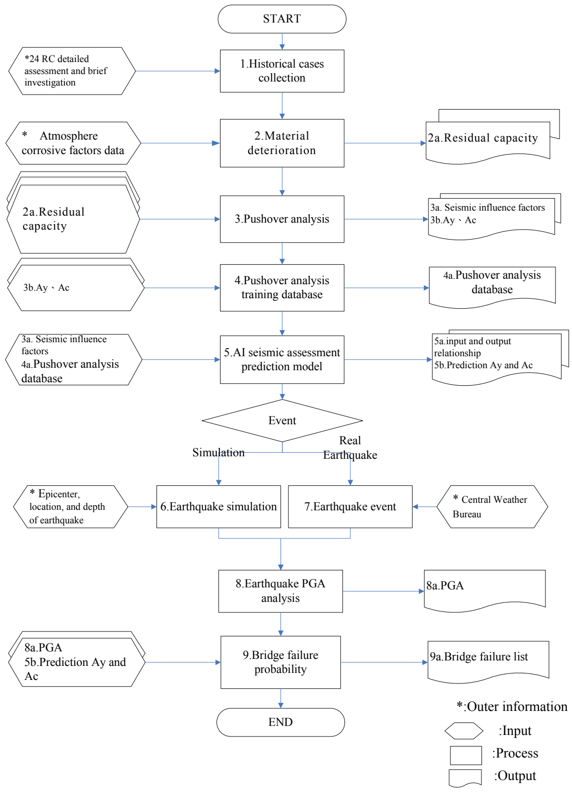

Figure 2. Bridge Failure Probabilities Inference Model

3.1 Historical cases collection

This paper adopted 24 RC bridges in Taiwan (as shown in Table 1).

Table 1. 24 RC bridge cases

No.	Length (m)	Design year	Design accelerate(g)	.	Structure type
1	50	1992	0.139	.	I beam
2	60	1992	0.139	.	T beam
.	.	.	.	.	.
24	150	1990	0.187	.	I beam

3.2 Material deterioration

The seismic performance of bridges can be evaluated using the capacity spectrum method suggested by ATC-40. This paper presents a model of deterioration due to carbonation taking into consideration uncertainty factors to estimate the initiation and the rate of corrosion and to analyze the structural capacity and serviceability of bridge. Then, it goes on to propose a method for evaluating the failure and severe cracking probability during earthquakes and the deterioration risk of members in specified years from construction (Figure 3).

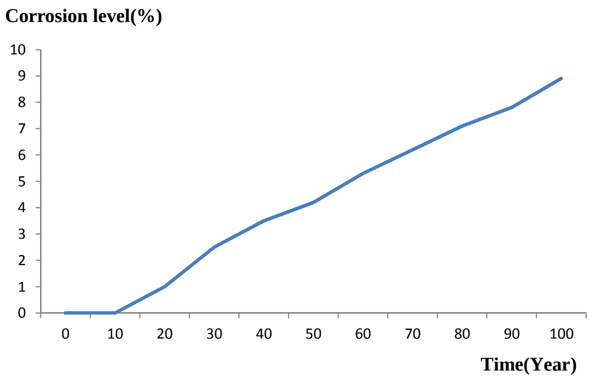

Figure 3. Steel corrosion level

3.3 Pushover analysis

This paper considers material corrosion level (0%, 5%, 10%, 20%, 35%; five degree corrosion) and bridge assessment analysis are applied to carry out the detailed assessment to obtain the yielding acceleration (Ay) and Damage acceleration (Ac). In the figure 4, bridges PGA with 5 corrosion levels are draw.

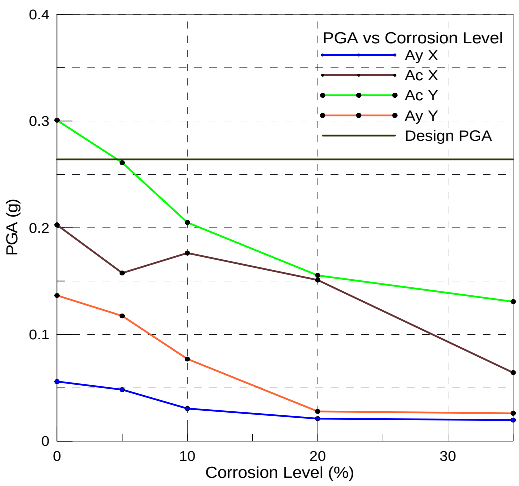

Figure 4. Bridge PGA with different corrosion level

3.4 Pushover analysis training database

After pushover analysis, 24 bridges detailed assessment are collected. This study analysed 5 degree corrosion levels (0%, 5%, 10%, 20%, 35%) for every bridge. Therefore, 120 training data are established in the Table 2.

Table 1. 120 pushover cases

no.	Corrosion (%)	Ay(g)	Ac(g)	Ay(g)	Ac(g)
		X dimension		Y dimension	
1	0	0.117	0.51	0.141	0.537
2	5	0.113	0.5	0.133	0.468
3	10	0.098	0.407	0.126	0.422
4	20	0.035	0.296	0.027	0.257
5	35	0.032	0.15	0.021	0.122
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119	20	0.113	0.17	1.86	2.33
120	35	0.11	0.15	1.56	1.91

3.5 AI seismic assessment prediction model

At present, the traditional structural analysis can be divided into three types, including: 1.brief investigation; 2. preliminary assessment; and 3. detailed assessment. The brief investigation table thus developed is mainly for relevant management personnel to identify buildings with seismic capacity-related problems. Professionals will then perform preliminary assessment of such problematic buildings. Regarding buildings of seismic capacity concerns after the brief investigation, civil engineers are hired to complete the preliminary assessment table to assess the buildings. Such investigation and assessment will result in large sum of precious data relating to the seismic capacity of buildings. Finally, according to the collected bridge data, professional and complex assessment methods, such as the pushover method, are applied to carry out the detailed assessment to obtain the highly accurate yielding acceleration (Ay) and complete damage acceleration (Ac). However, there are more than forty thousand bridges in Taiwan. When applying the simple assessment method to carry out visual investigation, the results will be not accurate despite the fast speed of investigation. In the case of applying the detailed assessment, although the results are relatively accurate, it takes much more time and costs. In addition, detailed assessment can only be done by experienced professionals. To conduct detailed structural analysis of each bridge with limited funds and professional labor is impossible. If simple assessment factors and the mapping relation between Ay and Ac for detailed assessment of similar bridges can be identified to infer the Ay and Ac values of other bridges, it will save a great deal of manpower when acquiring Ay and Ac values within the tolerable error range. Therefore, this study aimed to first use the bridge detailed assessment results of the "highway seismic capacity of bridge assessment and reinforcement project feasibility study" by the Directorate General of Highways, Ministry of Transportation and Communications, Taiwan. The artificial intelligence inference model was applied to find the mapping relation between inputs (brief investigation seismic capacity influence factor) and outputs (Ay and Ac) via cases (seismic capacity of bridge assessment results) learning. At present, artificial intelligence inference models mainly utilize learning models such as the artificial neural network, and support vector machine (SVM). However, such models have parameter setting and initialization problems. For considerations of the searching speed and inference accuracy, this study developed an "artificial intelligence mechanical learning inference model" by using fast and messy GA (fmGA) integrated with SVM. The model searched for the most appropriate model parameters by fmGA, and applied SVM to find the relationship between inputs (brief investigation seismic capacity influence factors) and outputs (detailed assessment of Ay and Ac), and further developed an optimal inference model. The advantage of such inference model was that it could improve the prediction accuracy by case database updating and increasing number of cases. To understand the accuracy of the model after training, this study employed the root mean square error (RMSE) in calculation equation to measure the model learning accuracy. The 10-folds testing results illustrate that the RMSE was 0.09 and 0.13 (as shown in the Table3).

Table 3. AI prediction results

Fold no.	Ay(g) RMSE	Ac(g) RMSE
1	0.085	0.17
2	0.144	0.194
3	0.058	0.065
4	0.066	0.059
5	0.071	0.071
6	0.143	0.189
7	0.09	0.084
8	0.071	0.11
9	0.054	0.144
10	0.117	0.214
Avg.	0.09	0.13

3.6 Earthquake simulation

User can assign the epicenter, location, and depth of earthquake. For example, 921 Chi-Chi earthquakes can be simulated in the system.

3.7 Earthquake event

According to Central Weather Bureau earthquake alert information collected by agent system, the model can evaluate the PGA of bridge automatically.

3.8 Earthquake PGA analysis

Taiwan is divided into several grids in order to evaluate the PGA of every zone. Distances, site and other parameters are input of seismic attenuation equation. The output is accelerating of every zone**.**

3.9 Bridge failure probability

Finally, according to bridge's location, PGA of every bridge can be calculated. If the accelerate is higher than Ay or Ac. The bridge failure probability will be high (as shown in Figure 5). In the Figure 6, 921 Chi-chi earthquake event is simulated in the system. High failure probability bridges will be listed. Therefore, alert message will send to manager's phone by SMS (Short message service) automatically.

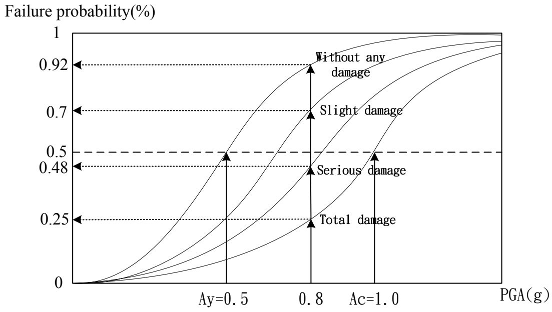

Figure 5. Bridge failure probability curve

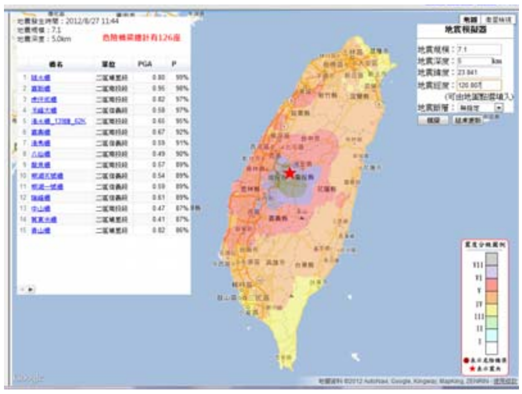

Figure 6. 921 chichi earthquake simulation results

4 Conclusion

This study collected relevant literature on bridge inspection, and selected by filtering bridge seismic capacity influence factors. The on-site investigation and detailed assessment data of 24 bridges were summarized to establish the historical case database.

Taking seismic capacity of bridge prediction as an example, this study collected historical cases and applied SVM (SVM) and fmGA to creatively build a "seismic capacity of bridge prediction model". After integrating with material deterioration, the case training learning was started to obtain the mapping relationship between bridge seismic capacity influence factors (input variable) and the values of Ay and Ac(output variable) to build the seismic capacity of bridge diagnostic model.

The highly efficient and accurate bridge seismic capacity prediction model proposed in this study can effectively improve the inability to assess the bridge seismic capacity in real time by traditional calculation approach, and hence considerably reduce time and costs. The prediction results can be a reference for relevant management personnel when doing maintenance.

Acknowledgements

The authors thank the support from Harbor and Marine Technology Center in Taiwan, MOTC.

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