1 INTRODUCTION

1.1 Overview of seismic vulnerability analysis

We have learned from recent experience how earthquakes can seriously damage highway systems, even in those countries which are supposed to be prepared for such events. Many authors (see for example Ghasemi et al. 1996) report the example of the 1995 Kobe Earthquake, when at least 60% of the bridges in the Kobe area were damaged and the Hanshin Expressway, the major transportation route between Osaka and Kobe, collapsed.

Motivated by the potential vulnerability of road infrastructure, much research has been done on seismic risk assessment for bridges in recent years. Generally, this research can be divided into two areas: seismic assessment of individual bridges which is normally achieved by way of fragility curves and seismic assessment for the whole network based on the analysis results of individual bridges.

Used in the past by many researchers (e.g. Shinozuka et al. 2000a, Nielson 2005), fragility curves are conditional probability statements which give the likelihood of a bridge reaching or exceeding a particular damage level for an earthquake of a given intensity, this normally expressed as peak ground acceleration (PGA). According to the generating methodologies, there are two main kinds of fragility curves: empirical and analytical.

Empirical fragility curves are generated based on damage data of past earthquakes. Researchers started to develop fragility curves using actual bridge damage data after the 1989 Loma Prieta earthquake. Kiremidjian & Basoz (1997) developed empirical fragility curves based on bridge damage data in the Loma Prieta and Northridge earthquakes. First, the damage data were compiled into damage matrices, which contained the number of bridges for every defined damage state under different Peak Ground Acceleration (PGA) levels, and then empirical fragility curves were generated using logistic regression analysis based on damage matrices. Shinozuka et al. (2000b) proposed the maximum likelihood method to develop empirical fragility curves for the Hanshin Expressway Public Corporation’s bridges using bridge damage data from the 1995 Kobe earthquake. The median and log-standard deviation values are obtained by the maximum likelihood method. However, due to the infrequency of observed earthquakes, it is difficult to find enough actual damage data to generate empirical fragility curves. Analytical fragility curves are thus preferred by most researchers and engineers. Many researchers have developed analytical fragility curves for bridges using a variety of different methodologies.
and models. Hwang et al. (2000) developed fragility curves for several bridge types based on different models in Memphis. Shinozuka et al. (2000c) developed fragility curves of a bridge using two analytical methods: the time history analysis and the capacity spectrum method. The fragility curves of these two methods under different damage states are then compared. Nielson & DesRoches (2007) proposed a component level approach to generate seismic fragility curves for highway bridges: in this methodology, the overall fragility of a bridge is based on the performance of the major bridge components.

Compared with seismic assessment of individual bridges, network level seismic assessment normally involves network prioritization, which is always related to distributing limited financial, material and human resources to bridge maintenance, repair, and rehabilitation in an optimal manner. Many researchers used different criteria for network level assessment. For example, Basoz & Kiremidjian A.S (1995) used vulnerability and importance as criteria to rank bridges that need retrofitting. Nojima (1998) defined a performance measure based on the system flow capacity of road networks. Liu & Frangopol (2006) used maintenance cost, bridge failure cost, and user cost as objective functions to optimize bridge network maintenance management.

Recently, Bayesian Network (BN) has been used in risk assessment and management of infrastructural systems, because BN incorporates graph theory and probabilistic inference. Friis-Hansen (2000) and Bensi et al. (2009) have worked on the development of this issue.

1.2 Background of this research

Due to the political devolution process in Italy in the nineteen seventies, the number of bridges under APT’s responsibility doubled without an adequate transition period. (For more details of the APT stock, see Zonta et al. 2007). Currently, the APT manages approximately 2340 kilometers of roadways and 936 bridges. Most of the APT bridges were built or rebuilt after the Second World War, the age distribution diagram showing a peak in the 70’s. Based on this assumption, the probability of being in or exceeding a damage state in HAZUS (HAZUS-MH MR3, 2003) is modeled as:

\[ P_i(S_a) \] = \Phi\left[ \frac{1}{\beta} \ln\left( \frac{S_a}{A_i} \right) \right] \quad i = 1, 2, 3, 4 \tag{1} \]

Where \( \Phi \) is the standard log-normal cumulative distribution function; \( S_a \) is the spectral acceleration amplitude (for a period of \( T=1 \) sec); \( A_i \) is the median spectral acceleration that causes the \( \mu^i \) damage level (operational, damage control, life safety, collapse); \( \beta \) is the normalized composite log-normal standard deviation which takes account of uncertainty and randomness for both capacity and demand. Basöz & Mander (1999) recommend that \( \beta=0.6 \).

The results show that, in the case of the APT stock, the direct seismic risk involving collapse or loss of life is moderate. In contrast, we expect a critical problem in network operation in a post-earthquake situation, when it will be necessary to identify the safest path between any two places in APT region. This problem is addressed by Dijkstra’s algorithm (Dijkstra, 1959) which is a graph search algorithm to find the shortest path between any source-destination pair for a non-directional and non-negative cost path graph. Compared with other shortest path algorithms such as Floyd-Warshall’s algorithm, Dijkstra’s algorithm is more efficient in developing a non-directional graph for a given start node graph, especially in a large transportation network.

1.3 Outline of the paper

We present first an overview of seismic assessment and of the background of the paper. In section 2, we introduce the HAZUS model and then use a typical bridge to show how fragility curves of bridges in APT stock are generated, based on the HAZUS model. This model is applied to all bridges in APT-BMS. The seismic vulnerability risk results are analyzed and the problem of network level operation is addressed. In section 3, the procedures of network simulation are explained first, and then Dijkstra’s algorithm is introduced and implemented in the simulated APT transportation network. Last, a case study is considered to illustrate the procedures.

2 SEISMIC VULNERABILITY OF INDIVIDUAL BRIDGES

2.1 HAZUS model

By definition, fragility curves are related to structural capacity (C) and ground motion demand (D). Normally, capacity and demand are modeled as log-normal probability distributions, so the quotient of C and D, statistically independent log-normal variables, is also a log-normal variable (Ang & Tang, 1975). Based on this assumption, the probability of being in or exceeding a damage state in HAZUS (HAZUS-MH MR3, 2003) is modeled as:

\[ P_i(S_a) = \Phi\left[ \frac{1}{\beta} \ln\left( \frac{S_a}{A_i} \right) \right] \quad i = 1, 2, 3, 4 \tag{1} \]
In equation (1), the only unknown parameter is $A_i$, which will be calculated using a capacity-spectrum approach. According to the Italian code (D.M. 14 Jan 2008), which in turn is largely based on Eurocode 8, the seismic demand is given by:

$$C_d = a_g \cdot S \cdot \eta \cdot F_0$$  \hspace{1cm} (2)

$$C_d = a_g \cdot S \cdot \eta \cdot F_0 \cdot \left( \frac{T_e}{T} \right)$$  \hspace{1cm} (3)

where $(C_d)_S$, $(C_d)_L$ are seismic demands of short and long period; $a_g$ is the design ground acceleration (normalized with respect to gravitational acceleration, $g$); $S$ is soil type; $\eta$ is the damping correction factor with a reference value of $\eta=1$ for 5% viscous damping; $F_0$ is the spectral amplification factor; $T_C$ is the upper limit of the period of the constant spectral acceleration branch; $T$ is the effective period given by:

$$T = 2\pi \cdot \sqrt{\frac{\Delta}{C_c \cdot g}}$$  \hspace{1cm} (4)

where $C_c$ is the capacity; $\Delta$ is maximum displacement response, which can be calculated using:

$$\Delta = \theta \cdot H$$  \hspace{1cm} (5)

where $\theta$ is the column drift, and $H$ is the column height (Basöz & Mander 1999). Under the capacity-spectrum approach, the capacity is assumed equal to the demand:

$$C_d = C_c$$  \hspace{1cm} (6)

Substituting equation (6) into equation (2) and equation (3), the required spectral accelerations can be obtained as the greater of $(A_i)_S$ and $(A_i)_L$:

$$(A_i)_S = \frac{C_c}{S \cdot \eta \cdot F_0}$$  \hspace{1cm} (7)

$$(A_i)_L = \frac{2\pi}{S \cdot \eta \cdot F_0} \cdot \sqrt{\frac{C_c \cdot \Delta}{g \cdot T_C} \cdot \frac{K_{3D}}{T_C}}$$  \hspace{1cm} (8)

where $K_{3D}$ is a factor accounting for the 3D arching action when displacements are sufficiently large, but omitted in equation (7) because the seismic displacements are small (Basöz & Mander 1999).

In equations (7) and (8), the only parameter to be calculated is the normalized capacity $C_c$. Based on Dutta & Mander (1998), the normalized base shear capacity of a standard bridge can be expressed as:

$$C_c = \lambda_Q \cdot k_p \cdot \frac{D}{H}$$  \hspace{1cm} (9)

where $\lambda_Q$ is defined as a strength reduction factor that occurs due to cyclic loading; $k_p$ is a factor related to the reinforced concrete strength of the column; $D, H$ are column diameter and column height. As for single span bridges or bridges seated on weak bearings with strong piers, the capacity is assumed to arise from bearings only (Basöz & Mander 1999).

In this case, the capacity is given as:

$$C_c = \mu_i$$  \hspace{1cm} (10)

where $\mu_i$=coefficient of sliding friction of the bearings in the transverse direction.

Given the type of a bridge, the capacity can be calculated using equation (9) or (10), and then $A_i$ is obtained as the greater of equations (7) and (8). Once we have the cumulative probability, the probability of being in some specific damage state can be derived:

$$\text{prob}(D = DS_i | Sa) = 1 - \{P_f(Sa)\}_i$$  \hspace{1cm} (11)

$$\text{prob}(D = DS_i | Sa) = [P_f(Sa)]_i \cdot [P_f(Sa)]_i \cdot [P_f(Sa)]_{i+1}$$  \hspace{1cm} (12)

2.2 Example

Ponte Nogarè SP83 is a typical bridge in APT-BMS. It is a 3 spans prestressed reinforced concrete bridge with wall piers and non monolithic abutments. The column parameters are $D=5m$, $H=13.4m$. Its geographical location is Long=40.1025, Lat=11.2131, and the elastic spectra parameters are: $S=1, F_0=2.6835, T_C=0.33393$. The 3D arching factor is calculated as 1.21 based on models in Dutta & Mander (1998).

Since the bridge has wall piers, the capacity is assumed to arise from bearings only (Basöz & Mander 1999). Using equation (10), the seismic capacities $C_c$ in different damage states are obtained. Substituting $C_c$ into equations (7) and (8), the required median spectral acceleration $A_i$ is obtained. Table 1 gives the results. Given $A_i$, from equation (1), the fragility curves of Ponte Nogarè SP83 under different damage states are calculated as shown in Fig 2.

Assuming a spectral acceleration $S_a=0.071$, which is the earthquake intensity with a return period of 475 years, from equation (11) and (12), the seismic probabilities of Ponte Nogarè SP83 in every damage state are calculated as shown in table 2.

Figure 1. Ponte Nogarè SP83
Table 1. The required median spectral accelerations

<table>
<thead>
<tr>
<th>i</th>
<th>$\mu_t$</th>
<th>$\eta$</th>
<th>$\Delta$</th>
<th>$A_S$</th>
<th>$A_L$</th>
<th>$A$</th>
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<td>1</td>
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<td>0.6325</td>
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<tr>
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<td>0.6325</td>
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<td>1.5515</td>
<td>1.5515</td>
</tr>
<tr>
<td>4</td>
<td>0.75</td>
<td>0.6325</td>
<td>0.3</td>
<td>0.4419</td>
<td>2.0314</td>
<td>2.0314</td>
</tr>
</tbody>
</table>

Table 2. Seismic probability of Ponte Nogarè SP83

| i | $P[D>DS_i|Sa]$ | $P[D=DS_i|Sa]$ |
|---|---|---|
| 1 | 1.2885E-005 | 1E-00 |
| 2 | 1.4262E-006 | 1.1459E-005 |
| 3 | 1.3195E-007 | 1.2942E-006 |
| 4 | 1.0922E-008 | 1.2103E-007 |

Figure 2. Fragility curves of Ponte Nogarè SP8

2.3 Seismic vulnerability of APT stock

Using the above methods, the fragility curves for all the bridges in the APT stock are generated. Thus, given an earthquake scenario, seismic vulnerability for all damage states can be calculated. In APT-BMS, we consider 3 earthquake scenarios, with return periods of 72 years, 475 years, and 2475 years respectively. The probability of being in the 4 damage states, operational (OLS), damage control (DLS), life-safety (LLS), and collapse (CLS), are calculated.

The results are shown in Google Earth as Fig 3. According to their probability of exceeding the limit state, bridges are denoted by different color dots: green ($P<10^{-5}$), yellow ($10^{-5}<P<10^{-4}$), orange ($10^{-4}<P<10^{-3}$) and red ($P>10^{-3}$). This is a very straightforward way to show bridge managers and users the seismic risk of every bridge. The histogram of Fig 4 gives the number of bridges in each probability class.

The results show that the seismic risk in the APT stock is moderate. For limit states OLS and DLS, some bridges have relatively high failure probabilities as shown in Fig 3 (a) and Fig 3 (b). As for limit states LLS and CLS, 99% of the bridges in the APT stock have a very low probability as shown in Fig 3 (c) and Fig 3 (d). This can be explained by the seismic activity of the APT region. Fig 5 gives the PGA values of APT region in the 475 year return period. From fig 5, we can see that for the 475 year return period, PGA values in most areas of APT region are about 0.075g, which is a very low value. Only in the south east part of APT region, there is a higher PGA value. This region is classified as a low seismic zone.

Figure 3. Seismic vulnerability of APT stock in damage states (a), OLS (b), DLS (c), LLS (d), CLS
Although the direct seismic risk involving collapse or loss of life is moderate, system operation at network level is of concern in a post-earthquake situation. Approximately 15% of the bridges in the APT stock have a relatively high risk of suffering operational problems. It is therefore necessary to identify the safest path between any two given points after an earthquake. Here ‘the safest’ means the lowest risk of exposure to operational problems in a given earthquake scenario. After an earthquake, the ability to decide quickly is of great help to decision makers in best distributing the available human and material rescue resources to the disaster center. This problem is addressed in section 3 by Dijkstra’s algorithm (Dijkstra, 1959), which is a classic algorithm used to find the shortest path.

3 SEISMIC VULNERABILITY OF A SINGLE BRIDGE

3.1 Network simulation

There are 936 bridges in the APT stock. All these bridges are located along SP (province owned) roads and SS (state owned) roads. First, the whole APT network including all bridges and roads is simulated as a graph in Google Earth, and then the Dijkstra algorithm is performed on the graph to find the required path.

The key phase of network simulation is identifying all the nodes of the graph. The following points are defined as nodes: the intersections or endpoints of SP and SS roads. Each node has 3 variables: ID number, longitude, latitude. There are in total 558 nodes in the APT stock.

After identifying all the nodes, the next step is to identify all links. Not all connections between two nodes can be regarded as links; these must be along the SP or SS roads. There are 6 variables related to each link: ID number, start node ID, end node ID, ID of the road forming the link, the relative position of the start node on the road, the relative position of the end node on the road. In the APT stock, every node has a number to refer the position of the node along the road. This number is used to identify the relative position of the bridge on the road. Take SP3 for example, of length 20km; the position of the start node is 0, and the position of the end point is 20. If bridge A is on SP 3 at km 10, then clearly bridge A is at the midpoint of SP3. We note that the relative position is always related to a road, and one node can have two different relative positions if it is the intersection of two roads. After identifying all the links, the APT stock network is simulated as a graph in Google. There are 740 links in this graph.

3.2 Algorithm implementation

Dijkstra’s algorithm is a graph search algorithm that is used to solve the shortest path problem in a non-directional graph with non-negative path cost. It was proposed by Dutch computer scientist Edsger Dijkstra in 1959 (Dijkstra, 1959). This algorithm is often used in transportation routing.

The input of this algorithm is a diagonal \( n \times n \) matrix; \( n \) is the number of nodes in the graph. Each element of the matrix is the distance value between two nodes. For example, \( M_{ij} \) is the edge cost of link between node \( i \) and node \( j \). Given a start node, Dijkstra’s algorithm will assign some initial distance value and try to improve this step by step until the shortest path is found between two given nodes. Given the simulated network, the input matrix is obtained under these rules:

1. For each link, a safety value is assigned to it as the edge cost, which is the sum of probabilities of being in operational damage state for all bridges located along the link.
2. If there is no bridge on a link, then the edge cost of this link is zero.
3. The distance between the node and itself is zero so all the diagonal elements \( M_{ii} \) equal zero.
4. If node \( i \) and node \( j \) are not connected in the graph, the matrix element \( M_{ij} \) is assigned as infinite.

After creating the input matrix, given any two nodes, this algorithm can find the shortest path.
which represents here the safest path between these two nodes.

3.3 Results

Lavazè Pass and Riccomassimo are two remote places in Trentino Province, located at the north and south path of APT region, respectively. Given the start node as Riccomassimo and the end node as Lavazè Pass, MATLAB program can generate the KML file automatically, which can then be loaded in Google Earth to show the simulated network and the outlined safest path. Fig. 6 shows the results in Google Earth map. The red lines represent the simulated network, while the white lines represent the safest path between Lavazè Pass and Riccomassimo. In the same way, all the safest paths between any two given places can be identified in Google Earth. These results are very helpful for bridge managers and government officials in understanding the network status and can assist them in making rapid decisions in near-real time, under post earthquake conditions.

3.4 Case study

Based on the previous analysis, we follow with an implementation of the algorithm on the graph from Trento to Ala. Trento is the capital of the APT region, while Ala is an important town in the south of the APT, near the high risk seismic zones in Northern Italy. In this case, the availability of the path is vital for the distribution of human and material resources to disaster areas after an earthquake.

Fig 7 is the simulation graph from Trento to Ala. There are 40 bridges that have different probabilities of being in operational limit state, as represented by the colored circles. SS12 and SP90 are two main roads connecting Trento and Ala. The Adige River and A22 highway are between SS12 and SP90.

First we identify all the nodes in the network. Only the intersection and the endpoints of SS12 and SP90 can be identified as nodes. Based on this definition, there are 16 nodes in this graph. After identifying all the nodes, it is easy to find that there are 22 links in this graph. After finding all the nodes and links, based on the previous assumptions in network simulation, the input matrix can be calculated, and is a $16 \times 16$ diagonal matrix. Last, the safest path between start node and end node is found by the algorithm based on the input matrix. The result is shown as a white line in Fig 8.

4 CONCLUSION AND FUTURE WORK

Seismic risk assessment of APT-BMS is performed on both component and network levels. At component level, results show that most bridges in the APT stock have very low risk of collapse and loss of life. As for the network level, the safest path between any two given places is identified using Dijkstra’s algorithm.

Given any two places, this method can show the optimal path rapidly and clearly on Google Earth. It is of great help to government officers and non-professionals in understanding research results.
However, it is important to keep in mind the limits of this type of analysis. The first limitation is the simplicity of the HAZUS model, which is a rough approximation and does not take account of all the structural details of a bridge. Secondly, in the network simulation, only the seismic risk of bridges is considered, while there are other infrastructure elements, such as tunnels and roads that contribute to network performance. In this paper we have proposed the basic framework for the seismic assessment of a medium-sized regional road network. However, before applying this model to reality there are issues that need to be addressed. These include:

1. A more refined model in network simulation. Transportation infrastructure is a complex combination of elements, among which bridges are only a part, even if very important. To apply the approach presented to a real case would need a more sophisticated model including the response of all the elements within the roadway network. As a next step,
we must examine the seismic vulnerability of other important elements, such as tunnels and retaining walls.

(2) A more refined model for decision making. In this paper, only the objective of safest path is addressed. In real-life, in a post-earthquake situation, the decision makers need to take decisions on a variety of issues, not only on problems of safest path. Also, the information they have will be changing all the time. In this case, a dynamic model is required to assist them in reaching flexible and rapid decisions. Bayesian Networks is a very good choice. It is the incorporation of graph theory and probabilistic inference. It can account for the evolving nature of available information in the post-event period (Bensi et al. 2009), so has great potential in post earthquake response.

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