SEISMIC DAMAGE FORECASTING OF STRUCTURES

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SUMMARY

This paper reviews the different methodologies used in damage forecasting. Procedures to classify intensity and damage distribution are proposed. These procedures can be used to develop meaningful relationships between damage state (ratio) and intensity. An analytical damage-forecasting procedure under uncertainty of the loading and the structure resistance is presented. Design practice, construction quality and environmental factors are included in assessing the damage potential. The quality and quantity of available information are tentatively incorporated in the method with the use of the theory of probability and the fuzzy set theory.

INTRODUCTION

The two most important steps in seismic risk analysis are the hazard and vulnerability evaluations. While considerable work has been done in evaluating seismic hazard, relatively less research has been carried out on vulnerability analysis, due to an insufficient documented damage data base as well as a lack of understanding of the mechanism of damage in structures.

Present methods used in earthquake vulnerability analysis can be classified in two major groups: empirical and theoretical (Ref. 1). The empirical methods involve gathering and correlating ground-motion and damage information. They are based on statistical observations of the buildings damaged by the past earthquakes. Damage state (ratio) versus seismic intensity relations are then obtained. Although these methods are easy to apply, they have serious limitations. The data base is incomplete and the relations give an average value of the damage ratio for a group of buildings. Little is known about the uncertainty on this ratio except that it is large. The theoretical methods are usually used to forecast damage for a single structure and are based on mechanistic models that consider the dynamic characteristics of the structures under investigation. They usually correlate ground-loading characteristics such as peak ground acceleration, velocity, or spectral acceleration with the response characteristics of the structure (stress, strain, intensity drift, etc.). The advantage of these methods is that they correlate physical parameters used by engineers in seismic design; however, empirical relationships based on past damage data and engineering judgement are used to correlate the structural response parameters with the damage state (ratio). Empirical and theoretical damage-forecasting methods have statistical as well as model uncertainties. Many parameters such as quality of construction, type of material, level of engineering knowhow, and political and economical environments are known to be of importance but very difficult to quantify in a damage-forecasting procedure.

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This paper presents two methods of classifying seismic intensity and damage distribution and of deriving relationships between damage state and intensity. Damage ratio versus seismic intensity relations can then be developed. An analytical damage-forecasting model which incorporates available information from different sources such as from test data, analytical results, and engineering experience is developed.

EARTHQUAKE INTENSITY AND DAMAGE CLASSIFICATION

A problem of importance in the derivation of damage estimation and/or forecasting methods which correlate earthquake intensity with a damage severity index is a consistent estimation of the damage distribution of structures for any seismic intensity value. Intensity scales are not rigorously defined, particularly with respect to the damage distribution of modern structures. However, the intensity has been an important indicator in collecting past damage data. Hence it is desirable to develop a method by which consistent estimates of intensity and consequently damage curves can be made. The use of pattern recognition can deal with this problem when there is enough data (Ref. 2). In this method, the different damage states buildings suffer are used as the classification criteria. However, the extension to other factors is simple when data are available. All statistics needed are obtained from past investigations. The optimum classification of a damage distribution vector $\underline{x}$ in an intensity class ω_i^* is obtained through the Bayesian criterion which minimizes the expected error of misclassification, that is:

$$E[e/\omega_i^*] = \min_{1 \leq j \leq c} \{E(e/\omega_j)\} = 1 - \max_{1 \leq j \leq c} \{P(\omega_j/\underline{x})\}$$

where e is the classification error,
ω_j is the intensity class j,
$P(\omega_j/\underline{x})$ is the posterior probability that the damage distribution vector $\underline{x}$ belongs to a certain class ω_j defined as

$$P(\omega_j/\underline{x}) = \frac{Q_j \; f(\underline{x}/\omega_j)}{\sum_j Q_j \; f(\underline{x}/\omega_j)}$$

$f(\underline{x}/\omega_j)$ is the pdf of $\underline{x}$ given that it belongs to ω_j and Q_j are prior probabilities.

This method can be used for intensity identification after an earthquake and also for checking the past classification. Damage severity versus intensity relations consistent with the actual damage and intensity classification can then be derived.

In the preceding method, each vector $\underline{x}$ must belong to only one intensity class. This is not always possible, particularly when the intensity classes are ill defined. It is then useful to have a method which authorizes an element to belong simultaneously to several classes. Fuzzy clustering methods can solve this problem by obtaining the degree of belongingness ($\mu_i(\underline{x})$) of each damage distribution $\underline{x}$ for any intensity class ω_i. To this effect a classification function $C(\underline{x}) = \{\mu_1(\underline{x}),\ldots,\mu_c(\underline{x})\}$ can be found which minimizes the objective functional (Ref. 3):

$$J(C) = \sum_{\underline{x}} \sum_{\underline{y}} \{V(C(\underline{x}), C(\underline{y})) - F(\delta(\underline{x},\underline{y}))\}^2$$

where V(.) and δ(.) are metric distances.

When there is a lack of historical data, expert opinions play a key role in the derivation of damage-intensity relations. Delphi and/or Bayesian statistical approaches can be used to integrate different sources of information (Ref. 4). However, the information obtained from experts is imprecise and difficult to quantify. Also, the complexity of the problem increases dramatically when we try to reduce the imprecision to an acceptable level. Hence, simplified probabilistic models with idealized assumptions have to be used in order to carry on the mathematical manipulations. Fuzzy inference rules seem to be suitable for this type of problems.

Fuzzy set theory initiated by Zadeh (Ref. 5) has been considerably developed in the past few years and applied in a wide variety of scientific areas. Brown and Yao (Ref. 6) reviewed the applications of this theory in structural engineering and Chinese researchers have done considerable work in developing this theory in the field of earthquake engineering. For example, a damage prediction model for masonry buildings based on fuzzy logic and approximate reasoning is suggested by Liu and Dong (Ref. 7). Feng et al. (Ref. 8) introduced the approaching degree concept for evaluating seismic intensity when damage distribution and intensity definitions are ill defined. This method can be extended to the determination of the intensity after a rapid survey of the damage to structures and to an estimation of losses from consistent damage versus intensity relations derived from past data with one of the above methodologies (Ref. 4). A quick estimation of damage can then be obtained after an earthquake for public policy makers. More refined techniques can be applied over a longer period of time.

Very often, experts use linguistic variables to define the damage of a structure. However, for practical purposes, a numerical damage scale is preferred. The transition from one scale to another is complex and approximation has to be done. This problem can be tentatively solved by use of fuzzy rules (Ref. 9).

ANALYTICAL DAMAGE-FORECASTING MODELS

The assessment of the damageability of a structure under seismic loading involves many uncertainties. The uncertitude can be classified into two types (Ref. 10): "Natural randomness which causes uncertainty and imprecision which causes fuzziness." Randomness comes from the imperfect information on the loading, material strength, model used, and alike. Imprecision is present at any stage of a damage-forecasting method. For example, the meaning of "light damage" is quite imprecise. However it conveys useful information. The incorporation of qualitative factors such as the quality of design and construction which are known to be of importance is very difficult to make, if not impossible, in a conventional procedure. The importance of these factors cannot be precisely assessed and depends on professional subjective judgement.

Uncertainty can be treated by the theory of probability while fuzziness has been proposed to be handled by the theory of fuzzy sets. Several recent applications (Refs. 10-12) combine those two types of uncertainty in a general framework. A similar procedure can be applied for an analytical damage forecasting model.

An analysis is performed on the structure and structural components are investigated. Then the variables which govern the failure for a particular component are defined. Let x and y be the demand and capacity of a critical variable and $S = x/y$. Randomness is represented by the pdf of x and y. The pdf $P_1(S)$ of S can then be obtained. The incorporation of qualitative information like the importance of quality control, model used, and alike, can be done as defined by Pugsley and reformulated by Brown (Ref. 10). The parameters considered to be of importance in the estimation of S are assessed linguistically in terms of gravity (G_k) and consequences (E_k). The total effect (P) is derived by fuzzy intersection and union operations:

$$P = \bigcup_k (G_k \cap E_k)$$

Then a fuzzy conditional relationship (R) links the consequences to the estimation of S (C) through the fuzzy cartesian products,

$$R = \bigcup_k (E_k \times C_k)$$

The fuzzy set F defined by the composite relation

$$F = P \circ R$$

is used to obtain the membership function of S, m(S). (m(S = s) can be represented as the possibility that S is equal to s)

The pdf of S can then be updated as, for example:

$$P(S) = \frac{m(S)\; P_1(S)}{\int_{-\infty}^{\infty} m(S_1)\; P_1(S_1)\; dS_1}$$

A relation between the variable S and the damage of the component can be assessed from damage tests (Ref. 13), past earthquakes, and professional knowledge (Ref. 14). Because the uncertainty in the data and the difficulty for an engineer to estimate the damageability of an element on a numerical scale, it is preferable to obtain a relation between damage states defined linguistically and S through membership functions (Fig. 1). The probabilistic information on various damage states for a given critical variable is then obtained, for example, as

$$P(DS_j) = \int \mu_{DS_j}(S)\; P(S)\; dS \quad \left(\sum_j P(DS_j) = 1\right)$$

where DS_j is the j^{th} damage state.

Since failure due to seismic loading involves several modes of failure, there will be several critical variables and several pdf associated with each damage state. The overall pdf of each damage state can be obtained with consideration of the probability of occurrence of the damage state for any failure mode.

The probability distribution of each damage state being obtained for each element, the estimation of damage to the overall structure can be obtained with probability techniques. Fuzzy inference rules can also be used as described in the simple example shown in Fig. 2. The probability that each element is in a given damage state is given in Table 1 and for each exhaustive combination of damage states $DS_{\ell j}$ (ℓ = element number, j = damage state), the possibilities of damage for the structure are given in Table 2. These possibilities are obtained after consideration of qualitative factors that an experienced engineer feels are of importance in the damage assessment. For example, if element 1 is in damage state 1 (DS_{11}) and element 2 is in damage state 3 (DS_{23}), then the degrees of possibility that the structure is in damage states 1, 2, and 3 are 0.1, 0.5, and 0.4, respectively. Also in this table, the probability that a combination of two damage states occur for two elements is given. In this example, the independence between the damage states is assumed for simplification.

The probability that the structure is in a given damage state is obtained, for example from the following rule (Ref. 10):

$$P(DS_j) = \frac{\sum_n \omega_{nm} P_n}{\sum_n \sum_m \omega_{nm} P_n}$$

where ω_{nm} is the $(nm)^{th}$ element of the matrix of membership values given in Table 2. Hence,

$$P(DS_1) = 0.03; \quad P(DS_2) = 0.352; \quad P(DS_3) = 0.618$$

CONCLUSIONS

Many uncertainties exist in a damage-forecasting methodology because of a paucity of data and the poor understanding of the damage mechanisms. Hence all available information must be incorporated in a consistent and rational manner. Pattern recognition methods can eliminate biases and inconsistency in the acquisition of data and the formulation of empirical damage relationships. New theories such as the fuzzy sets can incorporate statistical observations and/or knowledge in an integrated method. Rule-based systems for damage assessment (Ref. 15) can be modified to integrate different sources of information.

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Table 1. Damage Probabilities

Element	Damage States		
	DS_1	DS_2	DS_3
1	0.08	0.37	0.55
2	0.05	0.30	0.65

Table 2. Relationship of Global Damage - Local Damage

Combination of Damage States	$Prob(DS_{ij} \cap DS_{k\ell})$	Membership Values		
	P_n	DS_1	DS_2	DS_3
$DS_{11} \cap DS_{21}$	0.004	1	0	0
$DS_{11} \cap DS_{22}$	0.024	0.7	0.5	0
$DS_{11} \cap DS_{23}$	0.052	0.1	0.5	0.4
$DS_{12} \cap DS_{21}$	0.019	0.3	0.8	0
$DS_{12} \cap DS_{22}$	0.111	0	1	0
$DS_{12} \cap DS_{23}$	0.241	0	0.7	0.5
$DS_{13} \cap DS_{21}$	0.028	0	0.5	0.7
$DS_{13} \cap DS_{22}$	0.165	0	0.2	0.9
$DS_{13} \cap DS_{23}$	0.358	0	0	1

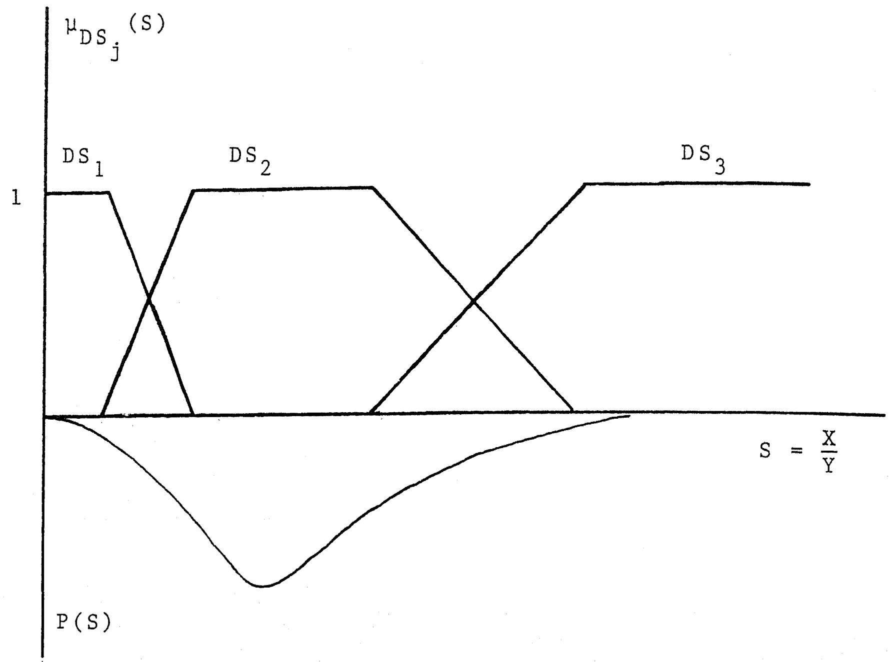

Figure 1. Probability and fuzzy distributions.

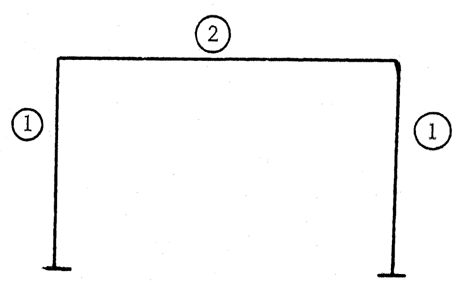

Figure 2. Example.