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RELIABILITY-BASED OPTIMAL DESIGN DECISIONS IN THE PRESENCE OF SEISMIC RISK

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ABSTRACT

A systematic methodology is developed with the objective of incorporating seismic risk in an optimal design decision process for a structure. A general framework for multi-criteria optimal design is presented, extended to include the uncertainties in the seismic loads that a structure may experience during its lifetime, and demonstrated with a simple example.

KEYWORDS

Optimal design; reliability; seismic risk; seismic hazard; multi-criteria optimization; response spectrum.

INTRODUCTION

The decision-making process in the design of civil engineering systems requires the selection of the most promising choice for the design from a large design space, based on an evaluation using specified criteria reflecting the acceptability of a design. Such criteria usually include costs, structural engineering criteria, client preferences, social, political, legal and economic considerations, and liabilities from uncertain risks arising, for example, from engineering practice and environmental loads such as earthquakes and strong winds. The development of a computer-aided optimal design decision process would allow the designer to rapidly evaluate and improve a proposed design by taking into account the major factors of interest related to design, construction, and operation in the presence of risk. An AI-based software package (Smith *et al.*, 1995) entitled *Smart Optimal Design & Analysis* (SODA) has being developed to assist the design decision process by using new methodologies such as object-oriented programming, multi-criteria decision theory and stochastic optimization. Here, the existing SODA methodology is extended to incorporate uncertainties, especially those that arise due to seismic risk.

DESCRIPTION OF SODA METHODOLOGY

The design decision-making process is an iterative procedure which starts with a conceptual design and then iterates through stages of analysis, evaluation, and revision. In SODA, there is a separate module for each of these last three functions (see Figure 1): the ANALYZER uses finite-element analysis techniques, costing algorithms, etc. to compute performance parameter values corresponding to

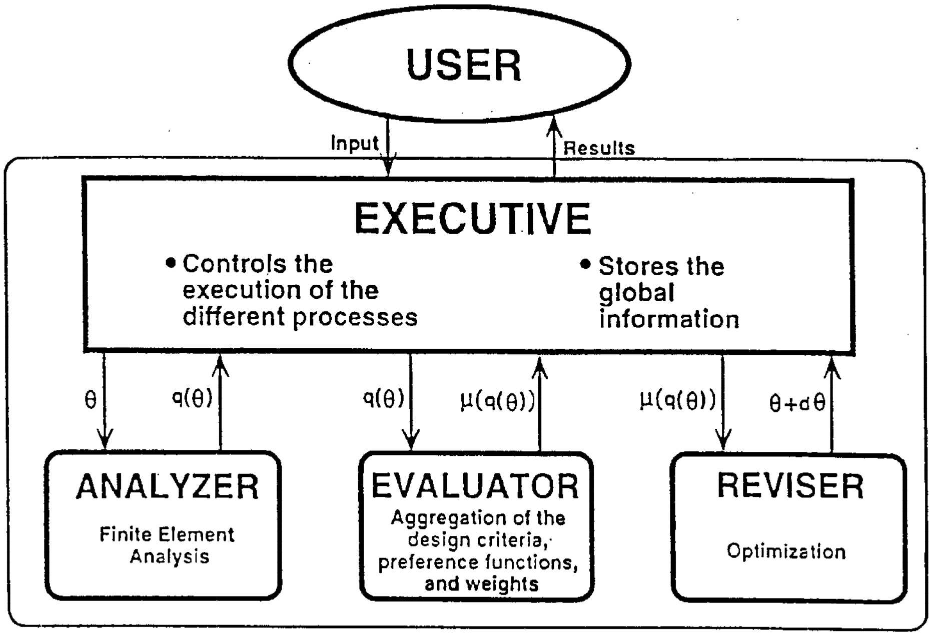

Fig. 1. Overall SODA system

structural response, cost, etc. for a structural configuration specified by the current values of the design parameters; the EVALUATOR then aggregates preference values for the current design, which are based on how well each of the individual design criteria are satisfied, in order to determine an overall evaluation measure for the design; and finally, the REVISER performs revisions of the design in order to find an optimal design based on maximization of the overall design evaluation measure. In addition, there is an EXECUTIVE module which acts as an interface between the original three modules and the user, and controls the execution of the different processes, performs error-checking, and stores the information associated with the analysis and design (see Figure 1).

The design parameters $\underline{\theta}$ are the parameters of the initial design which are selected to be varied during the search for an optimal design, that is, for the values of $\underline{\theta}$ which maximize the overall design evaluation measure $\mu(\underline{\theta})$. These parameters specify a particular design, so they relate to structural configuration, member sizes, choice of materials, etc. The first step in evaluating a design is to compute the performance parameters $\underline{q}(\underline{\theta})$ which are involved in user-specified design criteria. These may include structural response parameters (e.g. maximum member stresses or interstory drifts), construction costs, or even some of the design parameters, such as those specifying member sizes which must satisfy geometrical constraints. In a deterministic structural analysis, the role of the ANALYZER is to obtain the performance parameters $\underline{q}(\underline{\theta})$ as a function of the design parameters $\underline{\theta}$ for specified design loads.

The second step in evaluating a design is to determine how well each of the individual design criteria are satisfied by the current design. This step is performed in the EVALUATOR. An important ingredient in the SODA optimal design methodology is the introduction of preference functions $\mu_i(q_i)$ to implement the design criteria in a "soft" form. For the i-th design criterion, the preference of a particular design $\underline{\theta}$ is evaluated through a measure $\mu_i(q_i(\underline{\theta}))$ of the performance parameter $q_i(\underline{\theta})$, where values of μ_i range from 0 to 1. A larger value of μ_i implies that the designer prefers that design more, as judged by the i-th design criterion. Another way of looking at the preference functions is that they give a measure of the degree of satisfaction of each design criterion based on the calculated performance parameter values for a given design. For example, the extreme values $\mu_i(q_i(\underline{\theta})) = 0$ or $\mu_i(q_i(\underline{\theta})) = 1$ imply that the current design given by $\underline{\theta}$ is totally unacceptable or perfectly satisfactory, respectively. As an illustration, a possible preference function for the peak lifetime interstory drift is given in Figure 2 where it is

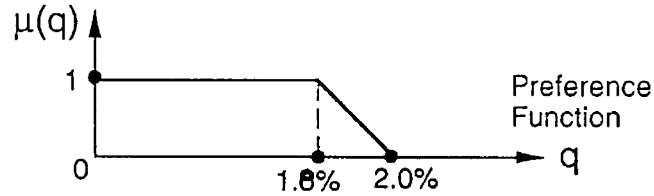

Fig. 2. Example of preference function: Interstory drift ratio

implied that an interstory drift ratio lower than 1.8% is perfectly acceptable while interstory drift ratios higher than 2% are completely unacceptable.

In the final step of the evaluation process, the overall evaluation measure $\mu(\underline{\theta})$ of the design specified by $\underline{\theta}$ is built up from the individual measures $\mu_i(q_i(\underline{\theta}))$ for each criterion through a preference aggregation rule which must satisfy certain consistency requirements. This task is performed by the EVALUATOR. A preference aggregation rule is simply a functional relationship between the overall design evaluation measure and the individual preference values for all of the design criteria: $\mu = f(\mu_1, \mu_2, ..., \mu_{N_c})$. An optimal design is therefore given by a design parameter vector $\underline{\theta}$ which maximizes:

$$\mu(\underline{\theta}) = f(\mu_1(\underline{q}(\underline{\theta})), \mu_2(\underline{q}(\underline{\theta})), ..., \mu_{N_c}(\underline{q}(\underline{\theta}))) \tag{1}$$

where it is understood, despite the notation here, that some of the preference functions μ_i may correspond to design parameter constraints in a "soft" form and, therefore, these μ_i will depend directly on the design parameter values. The optimization is performed by the REVISER.

The preference aggregation rule implemented in SODA, which satisfies desirable axioms of consistency (Otto, 1992), is the multiplicative trade-off strategy given by:

$$\mu = {\mu_1}^{m_1} {\mu_2}^{m_2} ... {\mu_{N_c}}^{m_{N_c}} \tag{2}$$

where $m_i = w_i / \sum_{j=1}^{N_c} w_j$, $i = 1, ..., N_c$, and w_i is a positive importance weight assigned to the i^{th} design criterion which can be used to control its trade-off relative to the other criteria. The user can give more influence to some design criteria than others by assigning them larger values of their importance weights. The choice of the values for these weights is subjective, but the user can gain experience in their selection in any design problem by investigating the influence that different values for the weights have on the final optimal design and on the corresponding preference values for each design criterion.

TREATMENT OF UNCERTAINTIES

In order to be able to trade-off reliability of performance and cost of a design in the design process, the uncertainties in the structural response performance parameters due to the uncertainties in the loads exciting the structure must be considered. These uncertainties, particularly for seismic loads, can be the most influential factors in the design decisions. A new methodology that incorporates both load and modeling uncertainties in the SODA framework is presented here.

In the stochastic case, there is no longer a function $\underline{q}(\underline{\theta})$ relating the design parameters $\underline{\theta}$ to all the performance parameters as assumed in the earlier description of the methodology. Some of the performance parameters will be uncertain because of the uncertain loads and modeling errors. For example, one of the q_i may be the peak interstory drift over the lifetime of the structure due to earthquakes, which is clearly a very uncertain quantity. Therefore, in the stochastic case, the principal role of the ANALYZER is to calculate a probability density function $p(\underline{q} \mid \underline{\theta})$. Of course, some of the q_i, such as the construction cost or structural performance parameters from code-based design loads, may be treated as deterministic functions of $\underline{\theta}$, but they can be interpreted in the general stochastic framework by simply viewing the corresponding marginal distributions $p(q_i \mid \underline{\theta})$ as delta functions centered at $q_i(\underline{\theta})$.

The first step in developing an expression for $p(\underline{q} \mid \underline{\theta})$ under earthquake loads is to characterize the seismic hazard at the construction site by a set of ground motion parameters $\underline{a}$ (for example, peak ground acceleration, response spectrum ordinates, duration of motion, frequency content, etc.). For most probabilistic hazard models in use, these parameters depend through appropriate "attenuation" relationships on a set of uncertain variables, designated by a vector $\underline{\phi}$, accounting for the uncertain regional seismic environment. For example, $\underline{\phi}$ may include variables such as earthquake magnitude, fault dimensions, source parameters, epicentral distance, propagation path properties, local site conditions, etc. The uncertain values of $\underline{\phi}$ are described by a probability density function $p(\underline{\phi})$ chosen to model the probability of occurrence of a given magnitude earthquake event, the probability of fault rupture at a specific location of a fault, etc. The attenuation relationships are often derived by an empirical fit to observed data. There is uncertainty associated with these attenuation models, even when $\underline{\phi}$ is known, which is reflected by the scatter of analyzed data about the mean or median model predictions. Therefore, the attenuation relationship actually gives a probabilistic description $p(\underline{a} \mid \underline{\phi})$ of the relation between the ground motion parameters $\underline{a}$ and the seismicity parameters $\underline{\phi}$.

Knowing the ground motion parameters $\underline{a}$ for a site does not completely specify the structural excitation. Furthermore, because of the presence of modeling errors, the structural model corresponding to a particular design $\underline{\theta}$ will not accurately predict the response of the structure should it be built. These uncertainties mean that a probability distribution $p(\underline{q} \mid \underline{a},\ \underline{\theta})$ must be set up for the performance parameters $\underline{q}$. This can be done using probabilistic analysis tools. For example, the effect of the uncertainty in the seismic excitation at the site can be treated using random vibration analysis if the ground motion is modeled as a stochastic process depending on the parameters $\underline{a}$. On the other hand, stochastic finite-elements could be used to treat the modeling uncertainties, for example. Finally, the uncertainties in the seismic environment, ground motion modeling and structural modeling can be combined using the total probability theorem to determine a probability density function for each stochastic (i.e. uncertain) performance parameter q_i:

$$p(q_i \mid \underline{\theta}) = \int\int p(q_i \mid \underline{a},\ \underline{\theta})\ p(\underline{a} \mid \underline{\phi})\ p(\underline{\phi})\ d\underline{a}\ d\underline{\phi} \tag{3}$$

This multi-dimensional integral can be evaluated numerically if the dimension is not too high (say, less than 6). Otherwise, efficient importance sampling simulation methods or asymptotic methods can be used (Papadimitriou *et al.*, 1995).

A measure of the reliability of the design $\underline{\theta}$, as judged by the i-th design criterion, is the probability that this criterion is satisfied. Since the preference function $\mu_i(q_i)$ for the i-th design criterion can also be viewed as a membership function for the fuzzy set "acceptable performance" based on this criterion, the desired reliability is the probability that q_i lies in this fuzzy set:

$$\overline{\mu}_i(\underline{\theta}) = \int_0^\infty \mu_i(q_i)\ p(q_i \mid \underline{\theta})\ dq_i \tag{4}$$

This measure is also seen to be equivalent to the mean preference value for the i-th design criterion. In the special case of no uncertainties, for which $p(q_i \mid \underline{\theta})$ is taken as a delta function, $\overline{\mu}_i(\underline{\theta}) = \mu_i(q_i(\underline{\theta}))$, and so the deterministic case described earlier is recovered. Using integration by parts, equation (4) gives

$$\overline{\mu}_i(\underline{\theta}) = -\int_0^\infty d\mu_i(q_i)/dq_i\ F_i(q_i \mid \underline{\theta}) dq_i \tag{5}$$

where $F_i(\widehat{q} \mid \underline{\theta}) = \ P(q_i \leq \widehat{q} \mid \underline{\theta}) = \int_0^{\widehat{q}} p(q_i \mid \underline{\theta})\ dq_i$ is the classical reliability function for the performance parameter q_i given $\underline{\theta}$. Using, for example, the preference function for the peak lifetime interstory drift shown in Figure 2, denoting $\ell_i = 1.8\%$ and $u_i = 2\%$, equation (5) yields

$$\overline{\mu}_i(\underline{\theta}) = \frac{1}{u_i - \ell_i} \int_{\ell_i}^{u_i} F_i(q_i \mid \underline{\theta}) dq_i \tag{6}$$

which is the average value of the classical reliability over the interval $[\ell_i, u_i]$. Clearly, a high mean preference value $\overline{\mu}_i(\underline{\theta})$ means that the design $\underline{\theta}$ has a high fuzzy reliability. or, equivalently, a high average classical reliability, as judged by the i-th design criterion.

To generalize the deterministic optimal design methodology described earlier, all that remains is to replace each $\mu_i(\underline{\theta})$ corresponding to a stochastic design criterion by $\overline{\mu}_i(\underline{\theta})$ in the preference aggregation rule (2). The evaluation of $\overline{\mu}_i(\underline{\theta})$ depends on the choice of the user-supplied preference function $\mu_i(q_i)$ for the i-th design criterion, and the reliability function $F_i(\widehat{q} \mid \underline{\theta})$. The reliability function depends on the degree of sophistication of the seismic hazard and structural models, as well as the accuracy of the probabilistic analysis tools for calculating $F_i(\widehat{q} \mid \underline{\theta})$.

APPLICATION

A particular choice of the structural model and seismic hazard model is next made and used to illustrate the methodology. A three-story, single-bay frame is considered. The frame members are taken as steel I-beams with the length of the floor beams fixed at 240 in. and the height of the story columns fixed at 120 in. For simplicity, the sections for the columns and beams are taken to be identical. The design parameters $\underline{\theta}$ are the member flange width b and web depth d, i.e. $\underline{\theta} = (b, d)^T$, since the flange and web plate thickness are held fixed at 0.5 in. The objective is to determine $\underline{\theta}$ so that the frame design is optimized according to the following design criteria:

1. Flange Width: The flange width b of the members in the frame must be greater than 4 in. and less than 16 in., with greatest preference ($\mu = 1$) given to widths between 5 in. and 15 in., and with a linear fall-off at each end to $\mu = 0$ at 4 in. and 16 in.

2. Web Depth: The web depth d of the members in the frame must be greater than 5 in. and less than 30 in., with greatest preference ($\mu = 1$) given to depths between 6 in. and 29 in., and with a linear fall-off at each end to $\mu = 0$ at 5 in. and 30 in.

3. Steel Volume: The smallest possible steel volume is desired since steel volume is assumed to be directly related to cost. A linearly decreasing function is used to specify the preference values in the steel volume, with $\mu = 1$ at the minimum possible volume of 8640 in^3 allowed by the geometric constraints (i.e. $b = 4$ in, $d = 5$ in), and $\mu = 0$ at the maximum possible volume of 43920 in^3 corresponding to $b = 16$ in, $d = 30$ in.

4. Peak Lifetime Interstory Drift : The interstory drift is required to be less than 2.0% of the story height, with greatest preference $\mu = 1$ given to drifts which are less than 1.8%. The preference function decreases linearly from $\mu = 1$ to $\mu = 0$ for drifts between 1.8% and 2.0%, and $\mu = 0$ is assigned to drift values that exceed 2.0% (see Figure 2).

Notice that the first two design criteria involve only the design parameters and their preference values can be directly computed and incorporated in the preference combination rule (2). The last two design criteria are a deterministic one relating to material cost and a stochastic one relating to structural response. For the peak interstory drift, a probabilistic seismic hazard model is considered in order to derive the probabilistic description of the drift needed to evaluate equation (6). In contrast, the steel volume is easily computed from the member dimensions for a given $\underline{\theta}$. The importance weight for each design criterion is set to 1.0 for the aggregation of preference values, unless otherwise noted.

In the probabilistic seismic hazard model considered, ground motion is characterized by the pseudo-velocity response spectrum $S_v(T, \zeta)$ where T is the period and ζ is the damping ratio of a single degree-of-freedom linear oscillator. Thus, a response spectrum analysis is used to compute the peak interstory drift d of the first story. For this, available modal combination rules may be used to estimate d from the maximum modal drifts d_j (e.g. Der Kiureghian, 1981). Assuming well separated structural modal frequencies, this gives $d = (d_1^2 + \cdots + d_n^2)^{1/2}$, where $d_j = \alpha_j \ S_v(T_j, \zeta_j)$, T_j is the modal period, ζ_j is the modal damping ratio, and α_j is the corresponding effective modal participation factor for the first floor, which depends on the j-th modal properties. These properties are obtained by an eigenvalue analysis of the structure corresponding to a particular $\underline{\theta}$. Structural modeling errors and the uncertainty in the estimate for d given by the modal combination rule are ignored in this example.

Attenuation formulas (e.g. Lee, 1993; Boore *et al.*, 1994) can be used to model the $S_v(T, \zeta)$ in terms of earthquake magnitude and epicentral distance. For this example, the formula by Lee (1993) is used:

$$\log_{10}(S_v(T,\zeta)) = \log_{10}(\hat{S}_v(T,\zeta)) + \varepsilon(T,\zeta) \tag{7}$$

where

$$\log_{10}(\hat{S}_v(T,\zeta)) = M_< + \mathrm{Att}(D,M,T) + \hat{b}_1 \ M_{<>} + \hat{b}_2 \ h + \hat{b}_5 + \hat{b}_6 \ M_{<>}^2 + \hat{b}_7 \ S_L \tag{8}$$

Here $M_<$ and $M_{<>}$ depend on the earthquake magnitude M, T and ζ; h is the sediment depth; S_L is a soil type parameter; $\mathrm{Att}(D, M, T)$ is a frequency dependent attenuation function; D is the representative source-to-site distance depending on epicentral distance R, focal depth H, magnitude M and $S_0 = C_sT/2$, the coherence radius of the source, where C_s is the shear wave velocity. For a compete description of all variables appearing in the attenuation formula (8), the reader is referred to Lee (1993). For the example, $h = 1$km, $H = 13$km, $S_L = 2$ and $C_S = 0.5$km/s.

The best estimates of the parameters $\hat{b}_i \equiv \hat{b}_i(T,\zeta)$ appearing in the model for $\hat{S}_v(T,\zeta)$ have been determined by regression analysis of a large database of accelerograms and are reported in Lee (1993) for 5 damping values and 12 periods. Values of these model parameters at other periods are obtained herein using linear interpolation. The function $\varepsilon(T,\zeta)$ in (7) represents the uncertain model error in the actual spectral amplitutes $S_v(T,\zeta)$ compared with the estimated model amplitudes $\hat{S}_v(T,\zeta)$. The probability density function for $\varepsilon(T,\zeta)$ was assumed by Lee to follow an extreme value distribution over the range of periods analyzed. In this study, it is replaced by the simpler Gaussian distribution which was found to be acceptable for periods up to 4.4 seconds. Moreover, it was found that the dependence of ε on the period T is small and was neglected. The mean and the standard deviation $\sigma(\zeta)$ of the Gaussian distribution were obtained by fitting the data for different damping ratios and for periods up to 4.4 seconds. The mean values were found to be very small and so they were set equal to zero. For $\zeta = 5\%$ used herein, it was found that $\sigma(\zeta) = 0.2821$.

The epicentral distance R and the earthquake magnitude M are considered to be uncertain in this study. The probabilistic distribution of these seismicity parameters are derived by assuming a simple seismicity model as follows. The earthquake sources are point sources located in a circular area with a radius of $R_{\max}$ centered at the site where the building is located. It is assumed that an earthquake is equally likely to occur at any point inside this circular source region, so the probability $p(R)dR$ is simply the ratio of the area of a strip of width dr located R distance away from the center to the area of the circle with radius $R_{\max}$, yielding the probability density function:

$$p(R) = 2R \ / \ R_{\max}^2 \tag{9}$$

The probability density function $p(M)$ for the earthquake magnitude, based on a truncated Gutenberg-Richter relationship (Gutenberg and Richter, 1958), is

$$p(M) = b' \ \exp(-b' \ M) \ / \ [\exp(-b' \ M_{\min}) - \exp(-b' \ M_{\max})] \tag{10}$$

where $M_{\min}$ and $M_{\max}$ are the lower and upper regional bounds for the earthquake magnitude, and $b' = b \ \log_e(10)$. The expected number of events per annum falling into the magnitude range considered is $\nu = 10^{a-bM_{\min}} - 10^{a-bM_{\max}}$. The following data are taken for the parameters of the seismicity model: $R_{\max} = 50$ km, $M_{\min} = 4.0$, $M_{\max} = 6.5$, $a = 3.5$ and $b = 1.0$.

The uncertain parameter set $\underline{\phi}$ for the ground motion model describing $S_v(T, \zeta)$ consists of the magnitude M and the epicentral distance R. The probability density function corresponding to $p(\underline{a} \mid \underline{\phi})$ in the general theory is $p(\underline{S}_v \mid M, R)$ where $\underline{S}_v = [S_v(T_1, \zeta_1), \ldots, S_v(T_n, \zeta_n)]^T$. Using a probability model which assumes stochastic independence of the spectral ordinates:

$$p(\underline{S}_v \mid M, R) = \prod_{j=1}^{n} p(S_v(T_j, \zeta_j) \mid M, R) \tag{11}$$

where each probability density function in the product is a log normal distribution implied by equation (7) together with the assumption that $\varepsilon(T_j, \zeta_j)$ is Gaussian with zero mean and variance $\sigma^2(\zeta_j)$. The reliability function $F_i(q \mid \underline{\theta})$, required in the evaluation of $\overline{\mu}(\underline{\theta})$ given by (6), is computed using a probabilistic structural analysis as follows. Assuming that the occurences of earthquake events follow a Poisson arrival process, the reliability function $F_i(q \mid \underline{\theta}) = P(d \leq q|\underline{\theta})$, denoting the probability that the level q is not exceeded during the lifetime t of the structure (t is taken as 50 years), is given by:

$$F_i(q \mid \underline{\theta}) = \exp[-\lambda(q \mid \underline{\theta})\ t] \tag{12}$$

where $\lambda(q|\underline{\theta})$ is the expected number of events per annum in which the drift exceeds the level q:

$$\lambda(q|\underline{\theta}) = \nu \int\int\int P(d > q|\ \underline{S}_v,\ \underline{\theta})\ p(\underline{S}_v \mid M, R)\ p(M)\ p(R)\ d\underline{S}_v\ dM\ dR \tag{13}$$

Under the previous assumption that d is known once $\underline{S}_v$ and $\underline{\theta}$ are given, it is clear that $P(d > q|\ \underline{S}_v,\ \underline{\theta})$ is either 1 or 0, depending on whether $d(\ \underline{S}_v,\ \underline{\theta}) > q$ or not, so

$$\lambda(q|\underline{\theta}) = \nu \int\int_{d(\ \underline{S}_v,\ \underline{\theta})>q} p(\underline{S}_v \mid M, R)\ p(M)\ p(R)\ d\underline{S}_v\ dM\ dR \tag{14}$$

The integration involved in computing $\lambda(q|\underline{\theta})$ can be a time consuming operation. Second-order reliability methods (Madsen *et al.*, 1986) provide a convenient tool for performing this integration efficiently.

Results are presented by assuming that the fundamental mode of vibration (with $\zeta_1 = 0.05$) controls the maximum first story drift. In this case, the one-dimensional integration over $\underline{S}_v$ in (14) can be carried out analytically, resulting in a two dimensional integral over M and R, which can then be evaluated numerically. The importance weights for the first three design criteria are fixed to 1.0. Table 1 gives results obtained by the SODA software for three values of the importance factor w_4 for the drift. It is worth noting that cost (i.e. steel volume) increases as drift reliability increases due to increasing importance being given to the drift criterion. This shows how trade-off of design criteria can be influenced by the user. The optimum design was also computed using SODA by replacing the drift criterion with the UBC (Uniform Building Code) drift criterion and replacing the seismic hazard model by the deterministic UBC response spectrum. All importance factors were set equal to unity. The SODA system was then used for a single-step evaluation of this code-based optimum design using the reliability drift criterion. The results are reported in Table 1. It can be seen that the code-based design is equivalent to the reliability-based design when very high importance ($w_4 = 50$) is given to the drift reliability. Of course, the reliability of approximately 0.9987 over 50 years is only for getting acceptable drift and ignores other limit states of the structure. Furthermore, for simplicity, linear dynamics have been used even though for large drifts the structural response would involve inelastic behavior.

Table 1. Results from SODA system for the three story, single bay frame

Drift	Reliability Based Design						Code Design	
	weight = 1		weight = 10		weight = 50		weight = 1	
	value	mu	value	mu	value	mu	value	mu
b (in)	5.32	1.0	5.00	1.0	5.00	1.0	5.22	1.0
d (in)	6.00	1.0	10.94	1.0	15.55	1.0	15.97	1.0
Volume	11258	0.926	14354	0.838	17676	0.744	19180	0.726
Drift		0.9655		0.9931		0.9987		0.9990
Period	T = 1.588 s		T = 0.805 s		T = 0.528 s		T = 0.504 s	
Overall	mu = 0.9723		mu = 0.9812		mu = 0.9902		mu = 0.9229	

CONCLUSIONS

The general methodology proposed provides a rational basis for incorporating seismic load uncertainties in the decision process and for making reliability-based optimal design decisions that meet specified multiple criteria. The methodology is readily extended to include loading uncertainties due to wind, as well as structural model uncertainties.

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