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STRUCTURAL OPTIMIZATION FOR PERFORMANCE-BASED DESIGN IN EARTHQUAKE ENGINEERING: APPLICATION OF NEURAL NETWORKS

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ABSTRACT

In general, performance-based design implies finding design parameters which minimize a given objective (for example, total cost), while satisfying minimum reliability levels in each of several specified performance requirements or limit states. In the context of earthquake engineering, the problem involves consideration of random variables related to the ground motion as well as to the structure itself. The evaluation of structural responses involves the application of a nonlinear dynamic analysis. Responses of particular interest are maximum actions or maximum drifts or deformations, as well as the local or global damage accumulated during the earthquake. Since it is not possible to obtain explicit relationships between the intervening variables and the responses, a discrete response database is obtained deterministically for different combinations of the intervening random variables and design parameters. These results can then be conveniently represented with a response surface using neural networks. For each response, the variability resulting from different earthquake records is accommodated by implementing two networks: one for the mean response and another for the standard deviation of the response over the records. The input layers to these networks contain the remaining random variables and design parameters.

Using the mean and standard deviations, the variability of a given response over the records is assumed to follow a lognormal distribution. When the calculated response is a damage index with a collapse upper bound of 1.0, the corresponding distribution used is a beta distribution with a corresponding upper bound of 1.0. The evaluation of the reliability level achieved in each limit state can then be efficiently implemented trough Montecarlo simulation, using the neural networks as substitutes for the dynamic analysis corresponding to different combinations of the intervening variables. In the optimization, the minimization of the objective function is achieved by a gradient-free algorithm. First, design parameters are randomly selected within their respective bounds, and for each combination the achieved reliability is calculated. The objective function is calculated for those combinations that satisfy the minimum reliability targets, choosing the combination which results in the minimum objective. This provides an anchor around which other combinations are randomly chosen within a sphere. The objective is evaluated for each of

those which satisfy the reliability constraints, and the combination corresponding to the minimum is chosen as the new anchor. The process is repeated until all feasible combinations within the sphere result in objective functions greater than or equal to that of the corresponding anchor. In order to account for local minima, the process is repeated several cycles for different initial random choices, adopting as the final result the minimum among the minima.

As an application of the approach, this work considers the optimization of a portal reinforced concrete frame of 6 stories and 3 bays. Structural random variables include the mass per unit length of each story, the characteristic concrete strength, the steel reinforcement ratios, and the confinement pressure provided by the lateral reinforcement. Design parameters are: d_1: beam depth; d_2: depth of column cross-section; d_3: beam longitudinal steel reinforcement ratio; d_4: beam longitudinal steel reinforcement ratio at the supports; d_5: longitudinal steel reinforcement ratio for the columns. Random variables associated with the ground motion are the peak acceleration and the central frequency for the soil filter. The records used were artificially developed, but consistent with the seismicity of the city of Mendoza, Argentina. Using experimental design, a total of 900 combinations of the random variables were developed. For each combination, the nonlinear dynamic analysis was run for each of 20 records, obtaining the responses of interest to be represented by neural networks. The dispersion in each of the networks' regression was taken into account as an additional random variable, to account for the differences between the dynamic analyses and the networks' predictions. The objective function is the total structural cost, given by the original cost C_0 plus the cost of repairs C_1 following damage due to a future earthquake. $V(d_k)$ is the concrete volume (function of the design parameters d_k), with a unit cost C_c . Similarly, $P(d_k)$ is the steel weight, with a unit cost C_s. If DIG is the global damage index, also function of d_k, ν the arrival rate of the earthquakes, r the interest rate, $C_f\big|_{DIG}$ the repair cost given a damage DIG and $C_1\big|_{DIG}$ the corresponding present cost, then C_0 and C_1 are obtained from

$$C_0 = V(d_k)\, C_c + P(d_k)\, C_s$$

$$C_1\,|_{DIG} = C_f\big|_{DIG}\ \frac{\nu}{r+\nu} \quad\rightarrow\quad C_1 = \int_0^1 C_1\,|_{DIG} \cdot f_{DIG}(DIG)\cdot d(DIG)$$

in which $f_{DIG}(DIG)$ is the probability density function for the damage DIG. Three performance levels were considered, operational, life safety and collapse, with respective minimum annual failure probabilities of Pf_{anual} = 2x10^{-2}; Pf_{anual} = 2x10^{-3}; and Pf_{anual} = 7x10^{-3}. Each levels, in turn, was defined by limit states corresponding to limiting interstory drifts and damage indices. Optimization results are shown in the next Table.

Results	$\boldsymbol{d_1}$ **(cm)**	$\boldsymbol{d_2}$ **(cm)**	$\boldsymbol{d_3}$	$\boldsymbol{d_4}$	$\boldsymbol{d_5}$	$\boldsymbol{C_0}$ **(US$)**	**C$_1$(US$)**	***Total Cost* (US$)**
Cycle 1	59.18	53.73	0.01117	0.01211	0.02124	10199	1550	11749
Cycle 2	62.65	58.15	0.00904	0.01287	0.01747	10410	1415	11825
Cycle 3	59.95	50.13	0.01024	0.01145	0.02624	10238	1392	11631

The results for the different cycles show good agreement, and that the "optimum" total cost is relatively insensitive to small differences in the design parameters. However, accounting for the cost of damage repair results in the best solution not being that for the higher initial cost.