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A resilience-based framework for design optimization of interdependent buildings

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ABSTRACT: In performance-based design, design targets are established based on the performance needs of the buildings. However, buildings are seen in isolation and their interactions are oftentimes neglected in the design. In order to reduce the impact from future disasters, a more comprehensive planning of the built environment on a community level is needed, which should address the aspects of hazard preparedness and recovery from the disaster. Optimizing seismic designs of the inventory of buildings in a region based on community resilience would be an example of such effort. This paper intends to provide a simple and viable framework for resilience-based design optimization of interdependent buildings. Regional economic loss is used as a community-level objective in this study, where the functional interdependencies between different buildings in a community is explicitly considered. Artificial neural networks are used to approximate the seismic response of buildings for reducing the computational time in the optimization process. The framework has been illustrated with a case study of the design optimization of office and hospital buildings.

1. INTRODUCTION

Exposure of the built environment to natural hazards such as earthquakes, can cause significant damage, which can impair the normal functionality of a community and makes it difficult to recover. Communities have incurred significant economic losses despite being designed according to the code provisions. An important reason for this consequence is that codes have focused on life safety aspect but not much on the socio-economic consequences from the damage. To lower the disaster impact, comprehensively planning of the built environment from a community perspective is needed. Hence, impact of damage should be considered both at an individual level and a community level. Such an approach can be called as resilience-based approach where the aspects of hazard preparedness and recovery from disaster are addressed (NIST 2015).

Estimating the community resilience involves careful consideration of losses from the hazard. Indirect losses in addition to direct losses due to building damage must be accounted for in the decision-making process. Indirect losses can be disproportionately high compared to the direct losses. It is therefore appropriate to mitigate such consequences by choosing a more resilient design. A crucial component in estimating community losses is to identify and account for interdependencies among different buildings in a community. While substantial effort has been invested to identify specific actions, policies or scenarios to lower the losses, very few methods exist in the literature that can quantify the losses including interdependencies among different buildings (Koliou et. al., 2018). A theoretical framework was developed by Mieler et al. (2015)

to obtain individual design targets based on community resilience goals. Lin et al. (2016) came up with the mathematical formulation of this framework and demonstrated to residential building inventory.

In this paper, we propose a framework to optimize building designs based on community-level objectives including the interdependencies. Computation issues in implementing the framework and tools to overcome them will be discussed. Finally, the proposed framework is illustrated with optimizing the design of hospital and office building in a community. The framework is explained for seismic hazards. However, the formulations and concepts are applicable to other types of hazards.

2. SEISMIC DESIGN OPTIMIZATION FRAMEWORK FOR INTERDEPENDENT BUILDINGS

To properly manage risk, design optimization should be performed for the buildings in a region simultaneously using a community-level objective like minimizing total loss of a region in a reference time period (Lin et. al. 2016, Feng et. al. 2017). As a result, limited financial resources can be allocated efficiently to meet the community goals. In this section, a framework to achieve community resilience goals by optimizing the seismic design of multiple buildings simultaneously is presented. For implementation of the developed framework, artificial neural networks for the structural response prediction and genetic algorithm for optimization are used.

2.1. Design optimization framework for interdependent buildings

The proposed optimization framework is outlined in Figure 1 and introduced below. An objective function at the regional level is chosen first. For the assessment of regional-level objective function, building inventory information is obtained. The asset portfolio is divided into two groups: first is the new buildings of which designs need to be optimized and second is the existing buildings in the region. The existing building portfolio can be obtained from government agencies or online databases administered by the county administration to classify the structures into categories considering key features like material type (steel, concrete) and occupancy type (residential, office). For each of the buildings that need to be optimized, structural responses should be calculated for evaluating the objective function. A neural network is developed for the response estimation for each building, using the input design variables and the input seismic intensity measures. For the rest of the buildings in the community, the responses are mapped with seismic fragility functions obtained from available databases such as HAZUS-MH database (FEMA, 2003), to support the analysis herein. The objective function is evaluated by integrating the probabilistic seismic hazard information with the damage consequences of the assets based on their

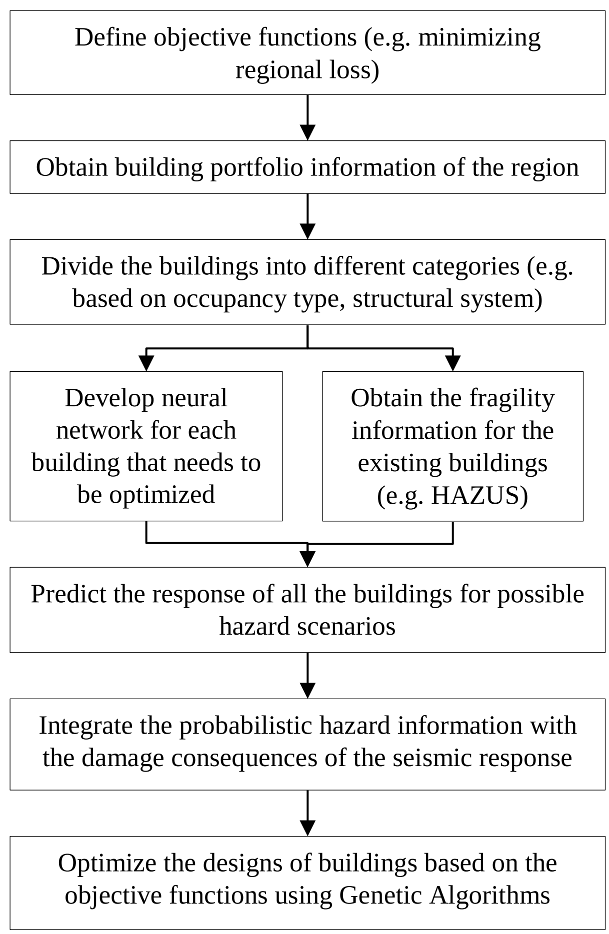

Figure 1: Flowchart of the design optimization framework

estimated responses. The damage consequences can include any functional dependencies. Finally, optimal member sizes for several buildings are obtained based on the objective functions using genetic algorithms.

2.2. Response Prediction using Neural Networks

Combined optimization of the designs of the multiple buildings toward a community resilience goal is a complex problem as several design options of multiple building structures should be considered and analyzed. Structural responses to potential hazards should be estimated in this process. To achieve a good accuracy, this task is computationally demanding, which makes it difficult to implement the optimization process into seismic design (Moller et al. 2015). Instead of such time-consuming structural analyses, it is useful to develop a tool for estimating the response and subsequently the damage to the structure.

Neural networks can model the complex non-linear relationship between the output and the input variables and has been used to predict maximum structural response such as interstory drift for moment-resisting frame buildings of steel buildings (Kaveh et al., 2015). A neural network consists of several elements called neurons arranged in three layers: input layer, hidden layers and output layer. Figure 2 shows the general procedure for developing the neural network for

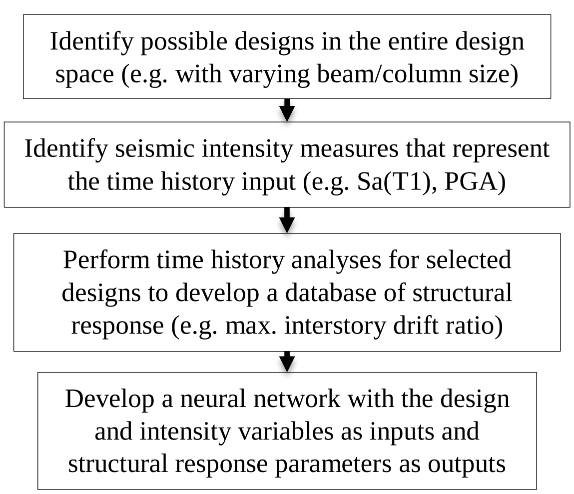

Figure 2: Neural network development procedure

each new building. Design variables and ground motion intensity measures form the inputs to the neural network while response variables form the outputs for this study. The neural network is trained through a small database of known input-output samples. An independent data set is used to test the generalization power of the trained network model. Details of the neural network development are provided elsewhere (Haykin 1999, Rumelhart, Hinton and Williams, 1986).

2.3. Multi-objective optimization

Objectives vary from community to community and defining them involves bringing together relevant stakeholders. To address various considerations of the decision makers, several objective functions need to be optimized (minimized or maximized) simultaneously, leading to a multi-objective problem. For instance, in community planning, apart from developing a resilient design which targets at minimizing the damage consequences, initial construction cost is also an important consideration in decision making due to limited availability of funds. These objectives are conflicting objectives that needs a tradeoff. Therefore, there is no single optimal design. Instead, there is a set of optimal designs known as Pareto optimal solutions. They represent a set of solutions that are non-dominant to each other but are superior to the rest of solutions in the search space (Safikhani et. al. 2011). Evolutionary algorithms such as genetic algorithms are especially applicable to multi-objective optimization problems with parameters that can only take discrete values. In this paper, a well-known non-domination-based genetic algorithm for multi-objective optimization, namely, NSGA II (Deb et. al. 2002) is used.

3. ILLUSTRATION OF THE FRAMEWORK

For illustrating the regional seismic design optimization framework described in the previous sections, the designs of a hospital and an office building located in a community in downtown Los Angeles, CA are optimized based on regional economic loss objective. The losses considered in this study includes direct damage costs (such as repair cost aftermath of earthquake and cost due to loss of contents), indirect damage cost (such as relocation cost, loss of income due to disruption of the building use, and loss of rent), and social loss (cost of injury and cost due to human fatality). The losses are initially evaluated for individual events, then aggregated together to obtain life time loss in present value. For this study, a life time of 50 years and an annual discount rate of 5% are used in calculating the losses. Initial construction cost is considered as another objective to account for a decision maker preferring a design with lower initial construction cost and be willing to accept a greater risk of future loss. The initial costs for different possible designs for both the office and hospital buildings were calculated per the building construction cost data by RS Means (2016).

3.1. Buildings description

The hospital and office buildings are four-stories each. The lateral force resisting frames of the hospital and office building comprises of special steel moment-resisting frames with reduced beam sections (RBS). For the office building, four different members constitute the resisting frame as shown in Figure 3. The beams of the 1st and 2nd story have same cross section; 3rd and 4th story beams have same sections; and the columns change at the splicing location on the third story as shown in Figure 3. In addition, both interior and exterior columns of the resisting frame in a story are assumed to be the same. The resisting frame of the hospital building is similar to the office building, except that the beams in the internal bay are different from the external bays, resulting in eight different member sections as shown in Figure 4. The lighter sections represent the gravity members.

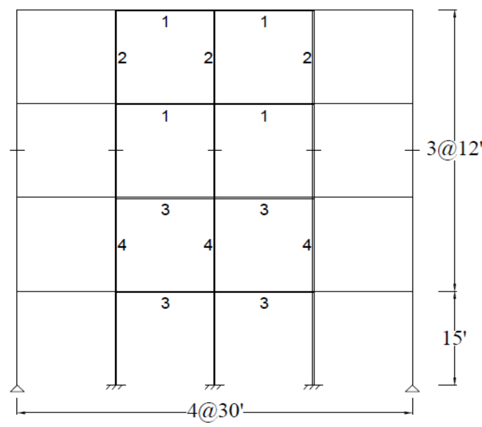

Figure 3:Office Building

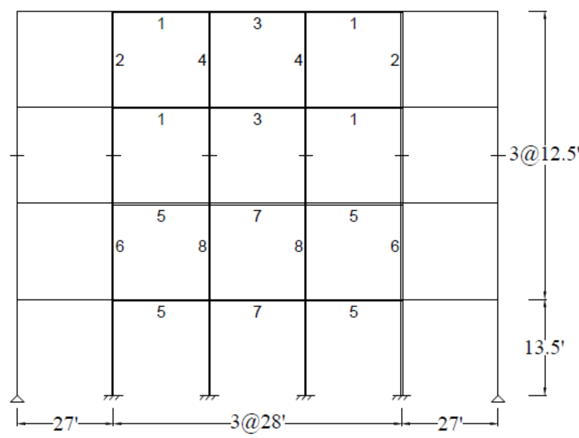

Figure 4: Hospital Building

3.2. Design options for each building

For the possible designs, the cross-section of each of the members of the lateral resisting frame is selected from a commercially available database of W-shape sections ranging from W4X13 to W44X335 with a total of 273 different sections. The sections are chosen such that the design is code-compliant (ASCE 7, AISC 341, AISC 358 and AISC 360). A total of about 10,000 and 35,000 such possible designs are obtained that satisfy the strength requirements for office and hospital buildings, respectively.

3.3. Input-output sample generation using non-linear time history analysis

For the neural network development, the input-output samples should be used. Since the neural network is to estimate dynamic responses of the buildings, input-output samples are generated by performing non-linear time history analysis for a selected design variables and seismic intensity measures. Only a small number of designs are selected for the non-linear time history analysis. Designs are chosen such that it adequately covers the entire range of design and intensity input variables. As a result, 141 designs for office building and 244 designs for hospital building are selected. The non-linear behavior of the steel moment-resisting frames of various designs is evaluated in terms of response such as maximum drift ratio.

For the structural analysis, a 2D finite element model in Opensees is considered, where the steel moment frames are modeled using elastic beam-column elements which are connected by rotational springs at the ends that account for the non-linear behavior of the members. Material model of the rotational springs are based on Modified Ibarra-Krawinkler Deterioration Model (Lignos and Krawinkler, 2011) with the backbone curve having a trilinear behavior. For simplicity, cyclic deterioration is ignored in the analysis. P-Delta effects are also accounted using leaning columns.

A suite of 25 ground motion time histories has been selected from the list of 60 ground motion time histories generated for the FEMA/SAC project (Somerville et al. 1997) for Los Angeles area. The records were chosen such that the PGA of the records was distributed throughout the entire range. A total of 25 earthquake records are used for the non-linear time history analysis of each design.

3.4. Neural network models

Maximum inter-story drift ratio is considered as the damage index in this study, which is used as output for a neural network model. Maximum floor acceleration is also included to account for modeling the damage of acceleration sensitive components such as HVAC system. For moment resisting frames, the drift is governed primarily by the stiffness of the members. So, a set of input variables considered are: moment of inertia of the different sections (4 for office building and 8 for hospital building), PGA of the ground motion record and the yield strength of steel. As such, the neural network model for office building has 6 input variables and another model for hospital building has 10 input variables.

Among all the data samples, 90% of the data is used for training the neural network and 10% for testing its generalization power. Several network architectures have been examined. Two hidden layers with 20 neurons in each layer had performance with reasonable accuracy as can be seen from the regression plots of Figure 5. The R^2 value for the training and testing data for both the models are above 0.95.

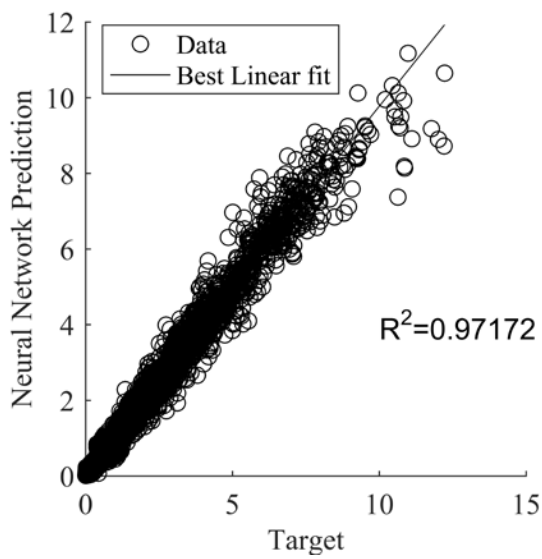

Figure 5: Regression plot between the predicted responses from neural network and the responses from time-history analyses for office building

3.5. Regional performance evaluation

Regional performance measures should encompass different dimensions of resilience such as economic, social, organizational and technical (Bruneau et al. 2003). An important aspect in the evaluation of a resilience is to account for the interdependencies among the buildings (Feng et. al. 2017). The resilience metrics considered in this study is the regional economic loss.

Regional economic loss is defined as the monetary loss for the whole community. It is widely used metrics for estimating the impact of a hazard at a community level. It depends on the damage to each building and their interdependent functionalities. Cascading effects of one building failure on the community can be modeled through these interdependencies, which are highly complex in nature (ATC-13 1985). For example, damage to a hospital building affects disaster relief efforts, leading to increased injury and fatalities. In this study, the expected regional economic loss (REL) in the event of an earthquake is computed as:

$$E\left[REL\right] = \sum_{r=1}^{N^c} E[EL_r] \tag{1}$$

where $E[.]$ is the expectation, EL_r is the economic loss from building category r and N^c is the total number of building categories. The economic loss in building category, r is evaluated by Eq. (2). The loss is split into several terms, to clearly account for the effect of interdependent losses.

$$EL_r = \sum_{i=1}^{N_r} E[EL^1_{i,r}] + \left\{ \begin{array}{l} \sum\limits_{\substack{i,j=1 \\ i\neq j}}^{N_r} \int EL^2_{i,r}(ds_{j,r}) \cdot f_{DS_{j,r}} \cdot d(ds_{j,r}) + \\ \sum\limits_{\substack{i;j=1 \\ s=1 \\ r\neq s}}^{\substack{N^c \\ N_r;N_s}} \int EL^2_{i,r}(ds_{j,s}) \cdot f_{DS_{j,s}} \cdot d(ds_{j,s}) \end{array} \right\} + .. \tag{2}$$

where $EL^1_{i,r}$ is the component of economic loss to a community from damage of building i in isolation which corresponds to the building loss without considering any interdependencies with other buildings; $EL^2_{i,r}$ is the component of economic loss from damage of building i which is dependent on the DS of building j and is attributed to interdependency on 1 building; $f_{DS_{j,r}}$ is the PDF of DS of building j, and N^r is the number of buildings in building category, r. The interdependency component, EL^2, is divided into two terms, the first corresponding to the interdependent losses in the same category and the second term corresponds to interdependent losses among different categories.

In many loss assessment studies (e.g. Wen and Kang, 2001; Liu et. al.,2003), injuries from building damage in a community are assumed to be timely treated with the underlying assumption that the hospital is fully operational which is not necessarily the case. The advantage of the proposed framework is that the dependency effects such as the reduction in operational efficiency due to damage to a hospital building can be considered through the dependency term EL^2 of Eq. 2. In the current study EL^2 is modeled through increase in the injury level as a function of the damage to the hospital building. For illustration purposes, a simple quadratic model is assumed to relate this increased injury rate to that of damage ratio in this study. However, complicated models to accurately model such interdependencies can also be incorporated such as a metamodel which includes the arrival rate of the patients at the hospital and the percentage of number of patients requiring an operating room developed by Paul et. al. (2006).

3.6. Optimization results

In order to investigate the optimal designs for the office and hospital buildings, conflicting objective of initial cost and regional loss are considered. NSGA II genetic algorithm is used to accomplish the evolutionary process of the multi-objective optimization. Figure 6 depicts the obtained non-dominated optimum design points as a Pareto front. Each of the points in Figure 6 corresponds to cost and loss evaluation from a combination of designs for office and hospital buildings. For illustration purpose, four of the optimal design points, namely, P1, P2, P3 and P4 are chosen as indicated in Figure 6. The designs for these points are listed in Table 1. Points P1 and P4 are the extremes with the maximum losses for point P1 estimated to be about \$130 million and minimum losses for point P4 to be around \$33 million. Among designs P1 and P2, although P1 has a lower initial cost it may not be very appealing to a decision maker to choose P1 because of the huge difference in the potential losses of about $67 million compared to P2 and very little gain from savings in initial costs of about $35,000. Pareto plot like that of Figure 6 can assist decision makers to choose an appropriate insurance policy for the buildings based on the expected losses.

A rational approach to achieve the best tradeoff point from the Pareto front is through the weighted sum method where the values of each of the objective functions of the Pareto front can be normalized using Eq. (3).

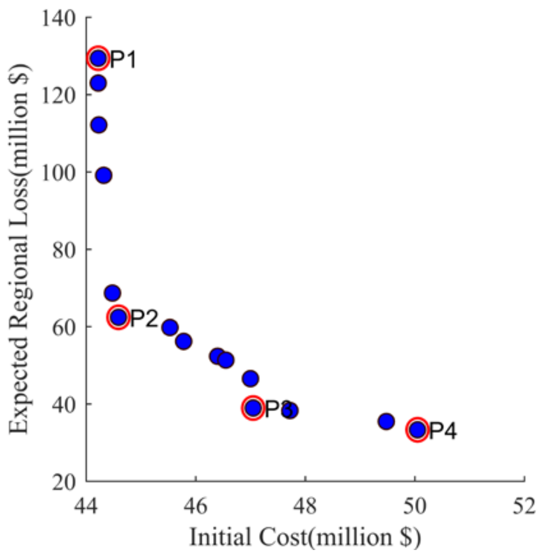

Figure 6: Regional loss versus initial cost optimal points at the Pareto front

Table 1: Members of representative designs

Building	Design P1	Design P2	Design P3	Design P4
Office Building	W14X109	W21X93	W24X117	W33X118
	W21X93	W18X283	W14X665	W24X279
	W18X130	W24X131	W24X192	W36X170
	W24X131	W33X201	W36X302	W36X231
Hospital Building	W24X68	W21X132	W30X124	W30X124
	W18X158	W30X148	W36X170	W36X170
	W27X94	W24X162	W30X191	W30X191
	W24X162	W36X182	W33X263	W33X263
	W27X114	W33X130	W30X235	W33X201
	W14X283	W24X250	W27X307	W14X665
	W33X141	W36X194	W36X262	W36X262
	W18X311	W30X292	W36X330	W36X330

$$O_{normalized} = \frac{O - O_{\text{min.}}}{O_{\text{max.}} - O_{\text{min.}}} \quad (3)$$

where O is the objective value, $O_{\text{max.}}$ and $O_{\text{min.}}$, are the maximum and minimum values of the objective function for the Pareto optimal set. Depending on the weights assigned to each objective and a multitude of tradeoff points could be obtained. The weighted sums are presented in Table 2 for a case with 75% weight to the initial cost objective and 25% weight to the loss objective. Design point P2 is found to be the most desirable point in this case. Note that compared to the case when Total Cost (IC + RL) is used as the objective, the optimal design for hospital remained the same but for the office building it resulted in a stronger and costly design.

Table 2: Values of objective functions and normalized weighted sum

Point	Initial Cost (million $)	Regional Loss (million $)	$0.75 * IC_{norm} + 0.25 * RL_{norm}$
P1	44.22	129.37	0.25
P2	44.59	62.39	**0.12**
P3	47.04	38.93	0.38
P4	50.04	33.30	0.75

On a computer with Intel Core i7 @ 3.4GHz processor and 8 GB of RAM, without the neural network and genetic algorithm tools, approximate computation time for evaluating all the possible design alternatives would be approximately 2000 days. This makes it impractical to achieve an optimal design. On the contrary, the computational time for 25-time history analyses of 141 office designs and 244 hospital designs, required to develop the neural networks is around 90 hrs each and for optimization using the neural network is 2hrs, which is a substantial reduction of the computation time.

4. CONCLUSIONS

In the recent years, the aspect of community resilience has attracted great attention in the risk management community. In the near future, it is most likely that the community resilience or other community-level objectives would become an integral part of the design codes and regulations. To advocate such a change, this paper presented a simple and viable framework for resilience-based design optimization of multiple buildings subjected to seismic hazard. A key aspect of this framework is the comprehensive and efficient assessment of disaster impact in a region. The framework was illustrated with a simple example of determining optimal seismic designs of two interdependent buildings simultaneously based on the regional loss and construction cost. The general framework can be used for other building types and hazard types and with other community-level objectives.

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