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Optimization of target safety levels based on community-level objectives

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ABSTRACT: Although buildings are designed in accordance with code provisions and local construction practices of the time, earthquakes have caused significant economic losses to communities. This is because of the fact that codes have focused on ensuring life safety of the buildings but not the socio-economic impact on communities from the damage or loss of functionality of the buildings. This study aims at developing a framework for optimizing the target safety levels of buildings based on community-level objectives. Target safety optimization process requires structural analyses of multiple possible designs of different buildings in a community. This task is computationally demanding if it is done for good accuracy. In lieu of such time-consuming structural analyses, neural networks are used for estimating the responses. The framework is demonstrated with a seismic safety target optimization for a class of mid-rise office buildings with steel moment-resisting frames located in Los Angeles, CA. The obtained optimal target reliability indices are compared with the code recommended values, which are found to be lower than the code recommended values.

1. INTRODUCTION

Seismic building design requirements represent the minimum standards to protect the public's safety. However, there is no emphasis on minimizing the functional loss of a building (Gebelein et al. 2017). Current studies (Kaveh et al. 2015, Fragiadakis et al. 2006) consider the functionality aspect in design at individual building level. Due to the interdependent nature of building functions in a community, considering the combined effects of functional losses of individual buildings leads to improved risk management of built environment.

Integrating the concept of functional loss into design codes by specifying target safety levels is challenging as it involves consideration of direct and indirect impacts of damage on a community and requires large computational effort for risk assessment of feasible designs. This makes it difficult to implement the optimization process into the determination of target safety levels in building design standards. In addition, for accurate estimation of structural responses in the reliability estimation, non-linear dynamic analysis should be performed. This increases the computational cost and time further.

Neural network has emerged as a potential alternative to approximate the structural response (Papadrakakis and Lagaros 2002, Moller et al. 2015) which can reduce the computational cost dramatically. Building upon the previous studies which developed neural network for only one building type, the current framework proposes a unified neural network that can be used for several building types that shares similar loading and failure characteristics. The unified neural network is essential for implementing optimization framework for target safety level determination since it can be used to estimate response of building types (e.g. different no. of floors and bays) that are not used in the training. A specified target safety level is realized into multiple building types which has numerous potential feasible designs. The impact of changing building target safety levels on the disaster risk to the corresponding building inventory can be assessed efficiently by using the unified neural network, which enables the target safety optimization based on community-level objectives.

In this paper, a framework is proposed for seismic design safety target optimization of group of buildings based on minimum total cost. To reduce the computation cost, a framework to develop a unified tool to predict the response of a group of buildings that share similar structural and functional characteristics and vary in height and width is presented. The study is novel for developing a unified neural network for a group of building types and its application to determine design target safety for a building class by considering a broader objective of minimizing the total cost to a community due to the building class. The developed framework is illustrated with the seismic safety target optimization for office buildings with steel moment resisting frame located in Los Angeles, California.

2. BUILDING CLASS SAFETY TARGET OPTIMIZATION FRAMEWORK

Optimizing safety target of a group of buildings requires consideration of the realizations of the safety target in the design of buildings of the group, proper measure of risk for the building inventory, and efficient risk assessment tool. The proposed framework for building class safety target optimization is shown in Figure 1. Target reliability index is used to represent safety target and the minimum total cost is used as the objective for the optimization. In this framework, building class is defined as the sub-group of buildings that are classified based on occupancy use and structural system (e.g. mid-rise office buildings with steel moment resisting frame). A building class comprises of several building types which can be defined by more specific characteristics such as size and kind of the lateral resisting system (e.g. four stories high and two bays wide moment-resisting system or 4x2 frame type). Feasible designs (code-compliant) are considered for each of the building types for varying target reliability index in the optimization.

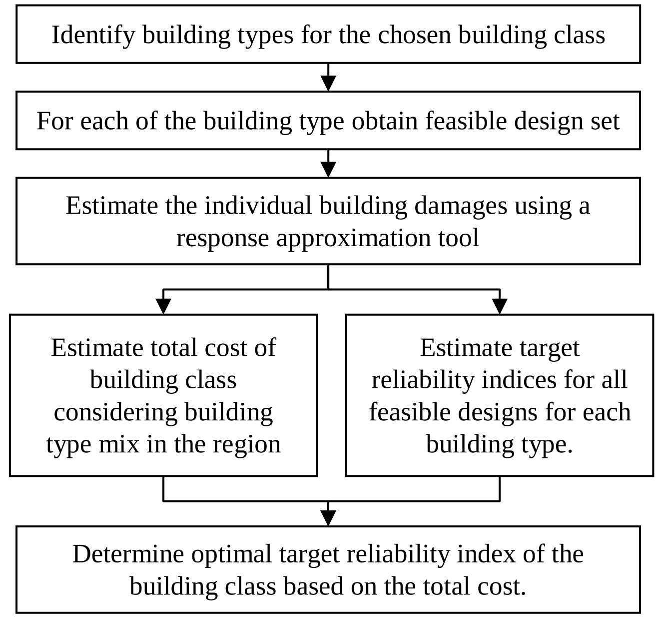

Figure 1: Building class safety target optimization framework

The total cost (TC) of a building class is determined by Eq. (1).

$$TC_{BC} = \sum_{i=1}^{N_{BT}} N_{B_i} \cdot E[LCC]_i \tag{1}$$

where $E[LCC]_i$ is the expected life-cycle cost (LCC) of a building type i, N_{Bi} is the number of buildings of type i and N_{BT} is the total number of building types. The concept of determining the optimal target reliability index for a building class is illustrated in Figure 2 and Figure 3. Figure 2 is a plot of $E[LCC]$ as a function of target reliability index for the feasible designs of a building type. For a given target reliability index, there exists multiple designs with varying LCC. The design of interest is the one with the least LCC for a given target reliability index, i.e. $LCC_{min}(\beta)$ curve in Figure 2.

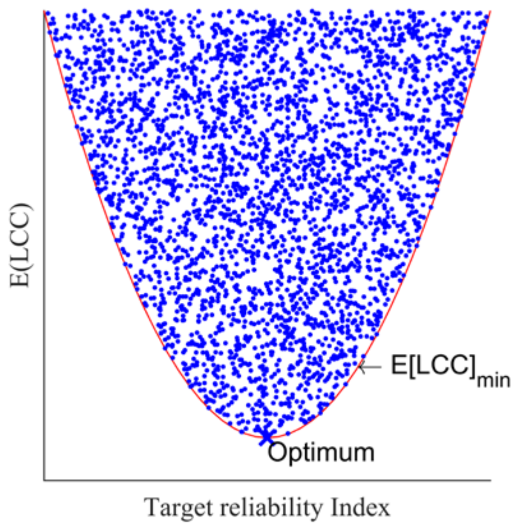

Figure 2:Optimal target reliability index for a building type

For a building class, total cost is determined by combining curves of all building types with considering building type mix in the region. The optimal target reliability index for a building class is then obtained at the minimum of the combined $LCC_{min}(\beta)$ curve. Figure 3 shows the plots of $LCC_{min}(\beta)$ curves for two different building types and $TC_{min}(\beta)$ as an illustration. As shown in Figure 3, the optimal target reliability index for building class is different from individual optimums.

In the optimization process, Monte-Carlo Simulation (MCS) is used for the estimation of reliability and cost. Artificial neural network is used for structural response prediction to reduce the computation time. A neural network represents an input-output relation which consists of several elements called nodes (neurons) arranged in three layers: input, hidden, and output layers. In this framework, design variables and ground motion intensity measures are the inputs while response variables are the outputs. The power to detect interactions among the input variables and complex non-linear relationships that exist between inputs and outputs is in the hidden layer (Tu 1996). Neural network development procedure for seismic response estimation is shown in Figure 4.

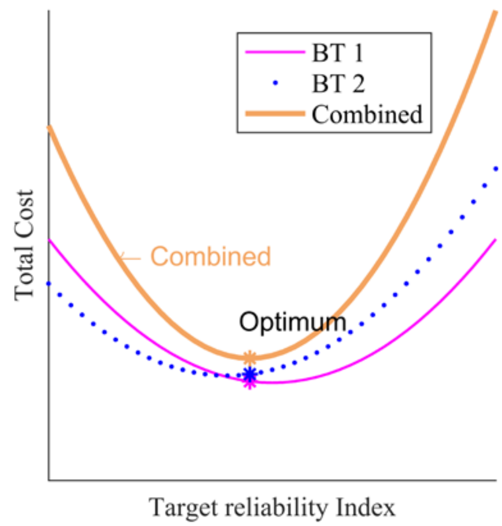

Figure 3: Optimal target reliability index for a building class

In this framework, reliability index (β) is used as the reliability estimate. For each design, the value of reliability index calculated is considered as the target reliability index that the design is based on. The target reliability index is then evaluated by Eq. (2).

$$\beta = \Phi^{-1}(1 - P_f) \qquad (2)$$

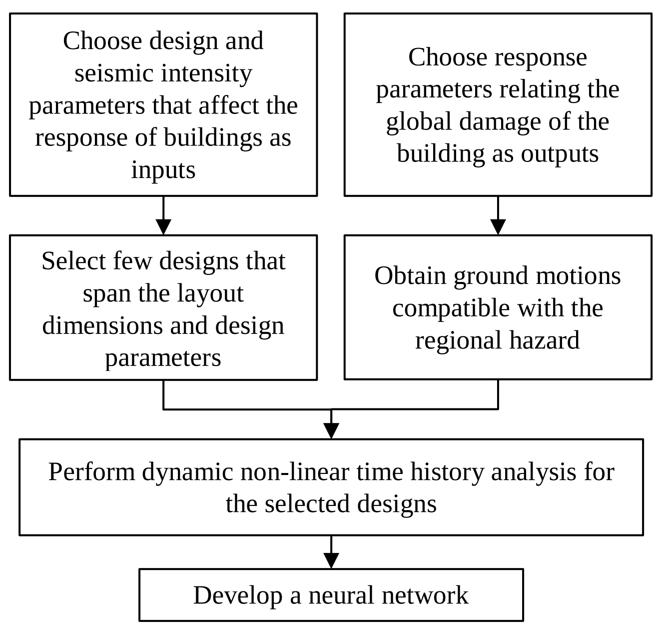

Figure 4: Input-output data generation for developing Neural network

3. CASE STUDY: OPTIMAL TARGET RELIABILITY INDEX FOR STEEL MOMENT-RESISTING FRAME OFFICE BUILDINGS SUBJECTED TO SEISMIC HAZARDS

Seismic safety target optimization framework is illustrated for a class of mid-rise office buildings with steel moment-resisting frames located in Los Angeles, CA. A neural network is developed by performing nonlinear dynamic analysis of only a handful of possible design alternatives of different building types. Four different building types are considered: (i) six stories with four bays (6x4) (ii) six stories with two bays (6x2) (iii) four stories with four bays (4x4) and (iv) four stories with two bays (4x2) as shown in Figure 5. The lateral force resisting system comprises of special steel moment-resisting frames with reduced beam sections. The beam size changes every two stories, every two bays and the column splicing locations are at mid height of story three and five as shown in Figure 5.

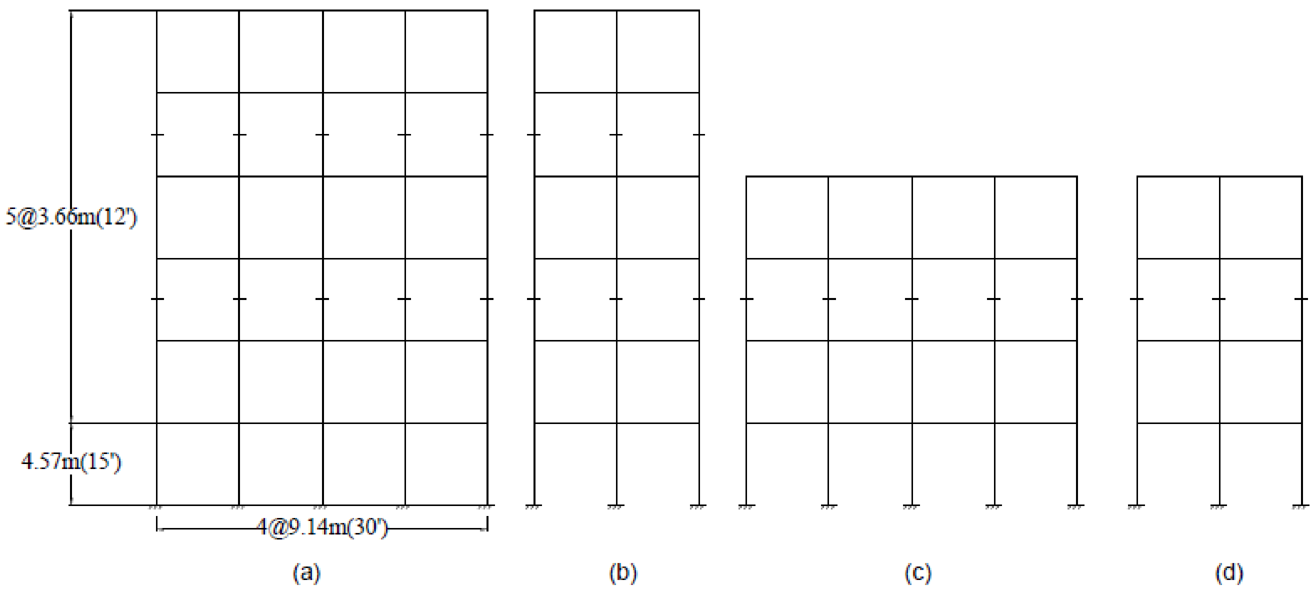

Figure 5: Elevation of the four building types of the mid-rise office building considered in the case study

3.1. Neural network inputs

The neural network inputs for response estimation include the number of stories, number of bays, moment of inertia of the resisting system members, yield strength and earthquake intensity parameters. A set of feasible design combinations are developed by varying member sections for each of the considered building type. Different members of the resisting system are selected from a commercially available database ranging from W4X13 to W44X335. The sections are chosen such that the design is code-compliant. Strong column-weak beam criteria of AISC 358, strength check in accordance with equivalent lateral force procedure of ASCE 7 and AISC 360 specification are used to obtain the feasible designs. In this way, several feasible designs are developed for each of the building type. Out of these, a small set of designs are used for the neural network development.

In developing the input data, the designs are chosen such that entire range of design vector and the output response vector are covered. The responses are measured in terms of interstory drift ratio which is used as a measure of the lateral strength of the resisting system. Drift responses are primarily governed by the flexural stiffness of the members for a moment-resisting frame. Therefore, the moment of inertia of various sections comprising the lateral resisting system are considered in this study as design variables. Another input variable considered is the yield strength of the members.

Furthermore, ground motion intensity is also used as an input data to the neural network for structural response estimation. Peak ground acceleration (PGA) has been considered as ground motion intensity measure. The ground motion time histories were chosen from the SAC steel research project (Somerville et al. 1997) for Los Angeles. 15 ground motion time histories with PGA ranging from 0.11g to 1.33g has been selected.

3.2. Neural network outputs

Maximum interstory drift ratio is used as output for the neural network model as it effectively captures the structural damage of the building system. The time history analyses are performed using Opensees software (PEER). The members are connected by rotational springs at the ends that account for the non-linear behavior and at each beam-column intersection panel zone shear deformations are also captured. Modified Ibarra-Krawinkler deterioration material model (Lignos and Krawinkler 2011) is used for modeling the rotational springs. Stiffness degradation, strength deterioration and pinching characteristics are included in this material model. Cyclic strength deterioration is ignored in the analysis. The rotational spring properties are obtained from an online database developed by Shawwa and Lignos (Shawwa and Lignos 2013). Additionally, the P-Delta effects are accounted by including a leaning column.

3.3. Neural network model

A single neural network is developed for predicting the response for the four building types. Table 1 shows the inputs for each building type. A total of sixteen input variables are considered: twelve inputs for the moment of inertia of the different members, number of stories, number of bays, the yield strength of steel and PGA. Number of members vary from building type and for the non-existing members for a building type, the corresponding inputs to the neural network are zero. As an example, a frame with 6 stories and 2 bays has only eight different members, the inputs for I_3, I_4, I_7, I_8, I_{11}, I_{12} are zero. The maximum interstory drift ratio is the only output. Bayesian regularization approach is used to train the neural network and the performance of various combinations of neurons and layers are compared. For the current study, network architecture with 20 neurons in two hidden layers is found to be appropriate.

Table 1: Neural network inputs for the four building types of the mid-rise office building

Building Type	**Neural Network Inputs**															
	Moment of inertia												**No. of stories**	**No. of bays**	**Yield Strength**	**PGA**
	I_1	**I_2**	**I_3**	**I_4**	**I_5**	**I_6**	**I_7**	**I_8**	**I_9**	**I_{10}**	**I_{11}**	**I_{12}**				
6x4 frame	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
6x2 frame	✓	✓	0	0	✓	✓	0	0	✓	✓	0	0	✓	✓	✓	✓
4x4 frame	✓	✓	✓	✓	✓	✓	✓	✓	0	0	0	0	✓	✓	✓	✓
4x2 frame	✓	✓	0	0	✓	✓	0	0	0	0	0	0	✓	✓	✓	✓

Performance of a prediction model is evaluated based on how close the predicted outputs are to the target values which is measured by R^2 value in this study. Table 2 shows the R^2 values for the training and testing sets for different number of designs of each building type considered for developing the neural network. 90% of the time history analysis data is used for training the neural network and 10% for testing.

Table 2: Neural network performance

Number of designs	R^2 Value	
	Training set	**Testing set**
10	0.902	0.757
20	0.905	0.793
30	0.947	0.849
40	0.973	0.877
50	0.966	0.885

Results from Table 2 indicate that only 30 designs of each building type are sufficient to develop the neural network to achieve an R^2 value of above 0.85 for the testing set.

To further improve the stability of the neural network prediction, an ensemble approach is used where average output of the several neural network models is considered. 10-fold cross validation is employed in this study to achieve this purpose. In a 10-fold cross validation, the whole data is randomly divided into 10 sets and the neural network model is built or trained using 9 sets, with the remaining set used as test data. This procedure is repeated 10 times by selecting different set as test data each time; thus, providing 10 different neural network models. The final ensemble model is obtained by combining the 10 neural network models.

3.4. Optimal target reliability index based on minimum total cost

For the seismic safety target optimization for the mid-rise office buildings, minimum total expected cost is used as an objective. Initial costs of construction and expected damage costs from future earthquakes during their lifetimes (50 years in this study) are considered for the total cost. The cost of construction is calculated per the building construction cost data by RS Means (2016).

The building damage depends on the seismicity of the region which is considered in terms of seismic hazard curves obtained from the USGS (2016). Damage costs 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), cost of injury and cost due to loss of life.

Initially, $LCC_{min}(\beta)$ curves for individual building frame types are first obtained as in Figure 2 and the optimal target reliability index for the mid-rise office buildings is obtained based on the total expected cost as in Figure 3. All the feasible design alternatives (Table 3) that are code-compliant are used to develop the $LCC_{min}(\beta)$ curve.

Latin hypercube sampling method is used for the estimation of *E[LCC]* and reliability index. The moment of inertia of each member is modeled as a normal distribution variable with mean to nominal ratio of 1 and a coefficient of variation of 0.05 (Zhang et al. 2016). Yield strength is assumed to follow lognormal distribution with a mean to nominal value of 1.05 and COV of 0.1 (Zhang et al. 2016). The building failure in this study is determined at the maximum interstory drift ratio exceeding 5% (Wen and Kang 2001). **Error! Reference source not found.** shows the plot of *E[LCC]* vs reliability index for the feasible designs for one of the frames. Similarly, the envelope curves are developed for other building types.

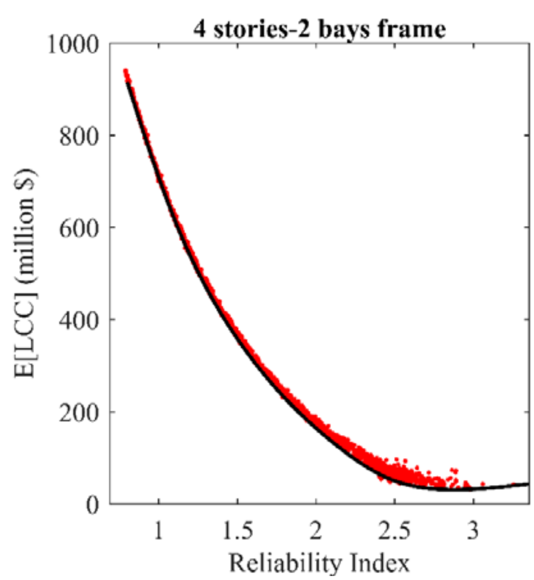

Figure 6: Plot of LCC as a function of target reliability index for the 4x2 building type

Table 3 lists the optimal target reliability index for each of the frames. Results show that the optimal target reliability index varies for all building types and ranges from 2.48 to 2.94. Optimal value reduces as the number of stories increase.

ASCE 7 (2016) specifies the conditional probability of failure based on risk targeted spectral acceleration for the maximum considered earthquake (MCE_R) as 10%. For downtown Los Angeles, the corresponding MCE_R in terms of PGA is 0.79g (ASCE 7, 2016). The conditional failure probabilities of the optimal designs are found to be above the ASCE-7 specified target reliabilities for most of the building types. This indicates that the codes are slightly stringent for the current case study building types at this location.

Table 3: Optimal safety levels for the four building types of mid-rise office building

Building Type	No. of feasible designs	Optimal Target reliability index	Conditional Probability of Failure by MCE_R (%)
6x4 frame	10200	2.48	12
4x4 frame	5000	2.94	21
6x2 frame	3800	2.74	4
4x2 frame	2300	2.88	17

The $LCC_{min}(\beta)$ curves for four building types are then used to evaluate the TC based on Eq. (1). Figure 7 shows the optimal target reliability index for the mid-rise office building class based on total expected cost objective. The building proportion of 1:3:10:20 has been considered as an example; i.e. one 6x4 frame office building, three 4x4 frame office buildings, ten 6x2 frame office buildings, twenty 4x2 frame office buildings. The contributions from each frame types are also plotted together with the *TC*. Optimal reliability index based on this formulation is 2.86 which is different from the optimal reliability indices of the four frame types in Table 3. It should be noted that the optimal value depends on the proportion of the buildings.

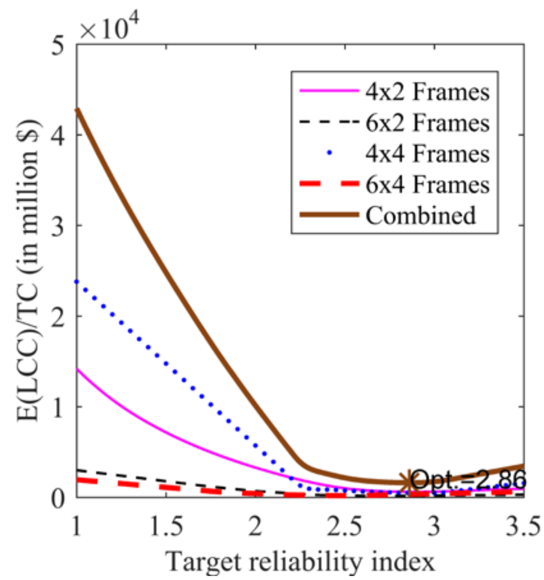

Figure 7: Optimal target reliability index of mid-rise office buildings

4. CONCLUSIONS

A framework for safety target optimization for a building class has been introduced. The neural network tool was used to reduce the computation time drastically and make possible of implementing optimization process in target reliability index determination. The framework can be extended to obtain optimal safety target for any group of buildings, such as buildings with same risk category, occupancy type, etc. The proposed framework was illustrated with a case study of determining optimal target reliability index for mid-rise office buildings in Los Angeles, CA based on minimum total cost. The optimization results are compared with the ASCE 7 target reliability for seismic hazards. The comparison suggested that the code requires higher reliability than the optimum based on the total cost. The framework should be applied to more groups of buildings and other locations to provide more comprehensive insight into the impact of community-level objectives on the target reliability index.

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