Multi-Objective Community-Level Seismic Retrofit Optimization for Resiliency using Engineering and Socioeconomic Variables

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ABSTRACT: A seismic loss estimation model is incorporated into a multi-objective community-level optimization for identifying the optimal retrofit plan for the woodframe building stock with the intention of improving a community's resiliency to earthquakes. The framework of the loss estimation model and multi-objective optimization considers five damage states based on potential morbidity rates, repair costs, relocation costs, and repair times. A community-level case study is conducted for Los Angeles County, California considering a maximum considered earthquake (MCE) seismic hazard using a simplified design space. The framework provides the pareto-optimal set of retrofit solutions for the community allowing for decision makers to apply community preferences in selecting the "optimal" resiliency plan.

1. INTRODUCTION

Thousands of earthquakes occur globally each year. To protect against seismic hazard, engineers have developed new performance-based seismic design methods, which have been implemented in some contexts but are still being refined. Traditionally, performance-based seismic design has been associated with performance objectives to meet the goals of building owners or other stakeholders. These goals often include collapse prevention, life safety, or immediate occupancy. Most recently, new ways to improve seismic resiliency have been introduced as part of a second generation of performance-based seismic design. In that case, the performance objectives often considered include: reducing economic loss, downtime, and casualties, while increasing quality of life indicators.

In the United States, the 1971 San Fernando earthquake, the 1989 Loma Prieta earthquake, and the 1994 Northridge earthquake are still widely considered the most destructive earthquake events in recent history. In all three cases, these earthquakes caused significant damage (on the order of billions of dollars) to woodframe structures. These historical losses are of concern because in the United States, approximately 90% of all residential buildings are of light-frame wood construction; and in California this estimate exceeds 98%. Therefore, improving the seismic resilience of the woodframe building stock would clearly have widespread economic and societal benefits.

The intention of a loss model is to predict and therefore prevent loss (economic and quality of life) and to identify the most vulnerable areas in order to improve immediate recovery effects. The present study incorporates a seismic loss estimation model into a community-level seismic retrofit optimization conducted over a community's woodframe building stock. The ultimate goal is to improve the community's disaster resiliency. Within the framework, traditional engineering variables were incorporated for predicting building damage and repair costs. Additionally, socioeconomic and community-level variables such as age, ethnicity, gender, family structure, and socioeconomic status were included. The socioeconomic variables were used to designate potential damage predictors such as the number of injuries and fatalities and rates of post-traumatic stress disorder (PTSD) diagnoses. These variables were used as proxies for the community's recovery time and loss in quality of life. The framework is demonstrated in a community-level case study on Los Angeles County, California.

2. RESILIENCY FRAMEWORK

The framework presented here was applied for determining retrofit techniques for woodframe buildings by taking a multi-disciplinary approach to disaster mitigation against large earthquakes at the community level. The community-level mitigation plan is developed by solving a multi-objective optimization problem via genetic algorithm. The genetic algorithm minimizes four objectives: initial cost, economic loss, number of morbidities, and recovery time. Within the algorithm, objective values were combined and taken as the fitness function. Genetic algorithms are used to identify the communities with a range of objective values. Several iterations are allowed until the solution converges. Along the way, the diverse solutions can be used to form the pareto-optimal set of solutions for decision makers to compare their preferences in order to select their community's optimal retrofit solution.

To use the framework, the community demographic information is uploaded from 2010 U.S. Census data, and the seismic hazard is defined. The genetic algorithm initializes the population and begins the computation of the damage states, damage measures, objectives, and population fitness. The following subsections provide additional detail on each of these computations.

2.1. Damage States

Five damage states were considered in this study based on five major damage categories identified for woodframe structures. These were identified based on experimental tests (e.g., Jennings et al. (2014)), and are consistent with the Hazus [DHS (2003)] damage states. Table 1 provides a description for each damage state with respect to the physical damage caused to woodframe structures. The damage states were centered on peak inter-story drift, which has been shown to be well-correlated with physical damage to woodframe structures [Filatrault and Folz (2002)].

Table 1: Damage State Descriptions.

Damage State	*Level*	*Description*
1	*No Damage*	*Structure can be immediately occupied, no repairs required.*
2	*Slight*	*Structure can be immediately occupied, minor drywall repairs required.*
3	*Moderate*	*Shelter-in-place allowed, drywall replacement required.*
4	*Severe*	*Shelter-in-place prohibited, structural damage incurred.*
5	*Collapse*	*Structure is not safe for entry, must be reconstructed.*

Within this framework, a set of archetypes are defined, modeled, and subjected to nonlinear time history analysis for obtaining the seismic performance for a range of earthquakes and seismic intensities. The peak inter-story drift values for each archetype are extracted from this data based on the inputted seismic hazard. These values are used to determine the probability of each archetype being in any damage state.

Lognormal cumulative distribution functions (CDFs) were developed for each damage state using the respective inter-story drift ranges and the damage states were modeled sequentially. The probability of each damage state given a specific inter-story drift was determined using the following relationship for sequential damage states and their respective CDFs.

$$P[DS = ds|ISD = x] = \begin{cases} 1 - P[DS] & ds = 1 \\ P[DS] - P[DS-1] & 2 \le ds \le 4 \\ P[DS] & ds = n_{ds} \end{cases} \quad (1)$$

where $n_{ds} = 5$ in this study,

$$P[DS] = P[DS \ge ds|ISD = x] \quad (2)$$

$$P[DS-1] = P[DS \ge ds - 1|ISD = x] \quad (3)$$

and

$$\sum_{ds=1}^{n_{ds}} P[DS = ds|ISD = x] = 1.0 \quad (4)$$

The damage states represent the connection between the damage measures (e.g., building performance, morbidity rates, repair costs, and repair times).

2.2. Damage Measures

Four damage measures were considered in this study: morbidity rates, repair costs, relocation costs, and repair times.

2.2.1. Morbidity Rates

The preservation of life is the central goal in any structural design. In this study it is proposed that preserving quality of life should also be considered as a design goal using the population's mental health as a metric. The morbidity rates include rates for five injury levels, including fatalities, injuries, and a rate for PTSD diagnoses. Table 2 provides a description of the five injury severity levels. The morbidity rates were determined as a function of the damage states and adjusted based on the demographics of the population. The morbidity rates for the injury severity levels were computed as

$$MR_{is,ds} = (F_{age,MR} \cdot F_{env,MR} \cdot F_{gen,MR} \cdot F_{ses,MR}) \cdot IS_{is,ds} \quad (5)$$

and the morbidity rate for PTSD was computed as

$$MR_{pr,ds} = (F_{age,MR} \cdot F_{env,MR} \cdot F_{eth,MR} \cdot F_{fam,MR} \cdot F_{gen,MR} \cdot F_{ses,MR}) \cdot PR_{ds} \quad (6)$$

where F_{age}, F_{env}, F_{eth}, F_{fam}, F_{gen}, and F_{ses} are the socioeconomic factors for age, age, quality and density of the built environment, ethnicity, family, gender, and socioeconomic status, respectively, and where the *MR* subscript refers to the factor value for either injury severity or PTSD rate. $IS_{is,ds}$ and PR_{ds} are the probability of injury severity level *is* and PTSD rate for damage state *ds*, respectively. These variables are not derived here for brevity, but were modeled as random variables. The mean values were selected as the Hazus values for the injury severity rates. The PTSD rate was set as the same rate as severe injuries. The standard deviation for each of the morbidity rates was set as one-third of the mean and used in fitting the lognormal distributions. The morbidity rates were then used in the computation of three objectives: economic loss, number of morbidities, and time to recovery.

Table 2: Description of Injury Severity Levels.

Injury Severity Level	*Description*
Minor	*Self-treatable*
Moderate	*Basic medical care required*
Severe	*Hospitalization required*
Critical	*Life threatening*
Fatal	*Non-survivable*

The economic loss due to morbidity was determined as the sum of the economic loss caused by the number of persons in each morbidity category (five injury severity levels, including death, and PTSD).

$$EL_M = \sum_{is=1}^{5} EL_{Inj,is} + EL_{PTSD} \quad (7)$$

where $EL_{Inj,is}$ is the economic loss due to injury for injury severity level *is*, and EL_{PTSD} is the economic loss due to PTSD. The community economic losses due to each injury severity level were modeled as random variables by multiplying the particular cost value associated with each injury severity level by the respective mean value of the injury severity rate distribution. The standard deviation was determined by taking one-third of the particular cost value. The cost values for each injury severity level were set as the values the U.S. government assigns to each injury severity level, including fatality [FHWA (1994)]. These values are comprehensive costs covering pain, lost quality of life, medical costs, legal costs, lost earnings, lost household productivity, etc.

The economic loss due to PTSD, EL_{PTSD}, was modeled as the sum of economic losses due to treatment cost of PTSD, $EL_{PTSD,T}$ and work downtime due to PTSD considering absenteeism, $EL_{PTSD,A}$, and presenteeism, $EL_{PTSD,P}$.

$$EL_{PTSD} = EL_{PTSD,T} + EL_{PTSD,A} + EL_{PTSD,P} \quad (8)$$

To model the economic loss due to PTSD as a random variable, the process above was similarly repeated. The equations used for determining the annual rate of absenteeism and presenteeism based on the number of work loss days and work cut back days were obtained from Goetzel et al. (2004) and Kessler and Frank (1997), and again are not presented here for brevity.

2.2.2. Repair Cost

Repair costs were represented as random variables with mean values provided at the subassembly level for five subassemblies [Reitherman and Cobeen (2003)]. To determine the repair costs for archetype *i* the number of units for each of the five subassemblies was determined. To compute the total archetype repair cost, $RC_{ds,i}$, for each damage state, the lognormal inverse CDF, $\phi^{-1}(RC_{ds,k})$, for the subassembly repair costs was multiplied by the number of subassembly units, $n_{units,k}$, and summed together for all subassemblies *k*.

$$RC_{ds,i} = \sum_{k=1}^{5} n_{unit,k} \cdot \Phi^{-1}(RC_{ds,k}) \quad (9)$$

To compute the economic loss due to all archetypes in the community for all damage states, the archetype *i* repair cost for damage state *ds*, $RC_{ds,i}$, was multiplied by the total number of archetypes n_i in the community and summed together.

$$EL_{RC} = \sum_{ds=1}^{n_{ds}} \sum_{i=1}^{n_{arch}} RC_{ds,i} \cdot n_i \quad (10)$$

2.2.3. Relocation Cost

Following the input scenario earthquake, if a building reached DS4 or DS5, then temporary relocation of the building occupants would be required. The ability for building occupants to shelter in place is important to decision makers and community leaders since it could lead to permanent relocation of residents to another community which will have significant impact on the community both financially and culturally. The number of relocated persons, n_{rel}, was computed as the number of buildings reaching damage states 4, $n_i(DS4)$, and damage state 5, $n_i(DS5)$ multiplied by the specific building's occupancy, occ_i.

$$n_{rel} = n_i(DS4) * occ_i + n_i(DS5) * occ_i \quad (11)$$

The number of relocated persons is provided as a fragility function conditioned on the initial cost.

$$P[n_{rel} \leq n | ic = ic_m] \quad (12)$$

where ic is the initial cost, and ic_m is the initial cost of the specific community mitigation plan *m*. The computation of the cost for relocation was adopted from the HAZUS methodology, and incorporated into the objective economic loss.

$$c_{rel,i} = fa_i \cdot \left[(1 - per_i) \cdot \sum_{ds=4}^{5}\left(p_{ds,i} \cdot dc_i\right) + per_i \cdot \sum_{ds=4}^{5}\left(p_{ds,i} \cdot (dc_i + rent_i + rt_{ds,i})\right)\right] \quad (13)$$

where, $c_{rel,i}$ is the relocation cost for archetype *i* based on occupancy class; fa_i is the floor area of archetype *i*; $p_{ds,i}$ is the probability of archetype *i* being in damage state *ds*; dc_i is the disruption costs for archetype *i* based on occupancy class in units of dollars per square foot ($/sf); $rt_{ds,i}$ is the recovery time for archetype *i* in damage state *ds*;

per_i is the percent owner occupied for archetype i; $rent_i$ is the rental cost for archetype i based on occupancy class in units of \$/sf/day. The values for dc_i, per_i, and $rent_i$ were obtained from HAZUS. The values for $rt_{ds,i}$ were the mean values for repair time, $RepT_{ds,i}$. To determine the economic loss due to relocation, EL_{RL}, the relocation cost for archetype i was multiplied by the total number of archetypes i in the community, and summed for all archetypes.

$$EL_{RL} = \sum_{i=1}^{n_{arch}} c_{rel,i} \cdot n_i \tag{14}$$

2.2.4. Repair Time

The repair times were modeled identically to the repair costs in Sec. 2.2.2, replacing mean subassembly repair costs with subassembly repair times obtained from the same source. The specific computation of repair time will not be provided here due to its repetitiveness.

2.3. Objectives

As detailed in Sec. 2, four objectives were considered in this study. Their individual computations are provided in the following subsections.

2.3.1. Initial Cost

The initial cost, RO_1, was computed as the sum of the cost for all new retrofits for that specific generation in the algorithm relative to the initial population.

$$RO_1 = ic_{ret} \tag{15}$$

The new retrofit costs, ic_{ret}, were computed using a unit cost per square foot for the respective archetype and respective retrofit, $c_{ret,i}$, multiplied by the total floor area of the archetype, fa_i. New retrofits were determined by subtracting the total number of buildings retrofitted in the current generation, $n_{gen,i}$, from the initial generation, $n_{o,i}$.

$$ic_{ret} = \sum_{i=1}^{n_{arch}} c_{ret,i} \cdot fa_i \cdot (n_{gen,i} - n_{o,i}) \tag{16}$$

2.3.2. Economic Loss

The economic loss, RO_2, was computed as the sum of direct and indirect costs. These costs included: repair costs, EL_{RC}, relocation costs, EL_{RL}, and morbidity costs (e.g., injury costs, PTSD treatment costs, PTSD downtime costs, and the value of lost life), EL_M, where the computation of each of these variables was provided in previous sections.

$$RO_2 = EL_{RC} + EL_{RL} + EL_M \tag{17}$$

2.3.3. Number of Morbidities

The number of morbidities, RO_3, was computed by multiplying the morbidity rates by the population size of the community,

$$RO_3 = \sum_{ds=1}^{n_{ds}} \left[\left(\sum_{is=1}^{n_{is}} MR_{is,ds} + MR_{pr,ds} \right) \cdot \sum_{i=1}^{n_{arch}} \left(n_{i,ds} \cdot occ_i \right) \right] \tag{18}$$

where $n_{i,ds}$ is the number of archetypes i in damage state ds, and occ_i is the occupancy for each archetype i. The morbidities included all injury severity levels, and PTSD diagnoses.

2.3.4. Time to Recovery

The quality of life and mental health of the population is important in order for a community to have a successful economy. One way to measure the impact on the quality of life of the population is through the estimated recovery time. To compute the community's time to recovery, RO_4, the maximum was taken over the recovery time for each morbidity category, RT_M, and the total repair time, RT_{Rep}.

$$RO_4 = max \begin{cases} max(RT_M) \\ RT_{Rep} \end{cases} \tag{19}$$

2.4. Genetic Algorithm Fitness Function

As previously mentioned, a genetic algorithm (GA) was used to optimize the community-level retrofit. GAs are advantageous in this case due to their robustness and multiple-solution output. That is, rather than providing a single solution, GAs provide a "population" of solutions in every generation which allows for the formation of the pareto-optimal set of solutions if desired. A simple genetic algorithm was employed here using a single point crossover operator, a single point mutation operator, and tournament selection. Tournament selection is based on the fitness of each individual in the population (here an individual is represented by the woodframe building stock of a community). The fitness was computed by using only the mean values for each of the variables derived in the previous sections to provide strict numbers for each objective. The objectives were normalized by the minimum population value of each respective objective in order to keep each on the same order of magnitude. Once normalized, the objectives, ro_i, were weighted, w_i, and summed together.

$$fitness = w_1 \cdot ro_1 + w_2 \cdot ro_2 + w_3 \cdot ro_3 + w_4 \cdot ro_4 \quad (20)$$

The weights allow input of the decision maker preferences and can be changed to provide more diverse solutions. The lower the fitness value, the more fit the individual, and the more likely for it to be duplicated in future generations, this is the premise of a genetic algorithm.

3. COMMUNITY-LEVEL CASE STUDY

This case study uses only a single floor plan designed by two seismic provisions providing two archetypes to comprise the decision space. This is a simplified version of the options available to a community for demonstration purposes of this paper. The floor plan is a three-story soft-story woodframe apartment building with tuck-under parking. The building was designed using the 1959 SEAOC Blue Book [SEAOC (1959)] seismic recommendations and the ASCE Standard 7-05 [ASCE (2005)] equivalent lateral force procedure. The use of only two archetypes simplifies the decision space considerably, but still illustrates the framework.

3.1. Inputs

The community under consideration was Los Angeles County, California. Table 3 provides the community input data for the case study obtained from 2010 Census data [U.S. Census Bureau (2012)]. The seismic hazard was set as the maximum considered earthquake (MCE) for Los Angeles, California (Sa = 2.5g). The weights shown in Eq. (21) were set to unity and were not changed during the analysis. The population size was set to 5,000 buildings.

Table 3: Community-Level Case Study Input Data.

Variable	*Data for Los Angeles County, CA*
Age (0-9 y.o.)	*13.1%*
Age (10-18 y.o.)	*14.6%*
Age (19-29 y.o.)	*15.4%*
Age (30-45 y.o.)	*21.9%*
Age (46-59 y.o.)	*24.2%*
Age (60+ y.o.)	*10.9%*
Ethnicity (minority)	*72.2%*
Ethnicity (non-Hispanic white)	*27.8%*
Partnered Household	*32.3%*
Single Household	*72.2%*
Family Household (children)	*37.2%*
Gender (male)	*49.3%*
Gender (female)	*50.7%*
Salary (average)	*$81,729*
SES (low)	*27.6%*
SES (moderate)	*43.4%*
SES (high)	*29.0%*

3.2. Results

The results presented here were developed using the following genetic algorithm parameter values: probability of crossover = 0.85, probability of mutation = 0.1, 30 individuals (i.e. communities of buildings) in the population, and 80 total generations. This provided 2,400 data points (i.e. total retrofitted communities in the analysis). As an output, the minimum, maximum, and mean population fitness values for each generation were plotted. Although not shown here, the GA was stopped before it could converge to a single solution. Presenting the converging solution was not felt to be relevant to the framework since the pareto-optimal set requires diverse solutions, and a number of diverse solutions were produced during the 80 generations. The optimal solution must be based on the decision maker or community preferences of the objectives which were not incorporated in this case study, but could be incorporated through the objective weights shown in Eq. (21).

The GA produced community fragility functions for the latter three objectives conditioned on the first objective.

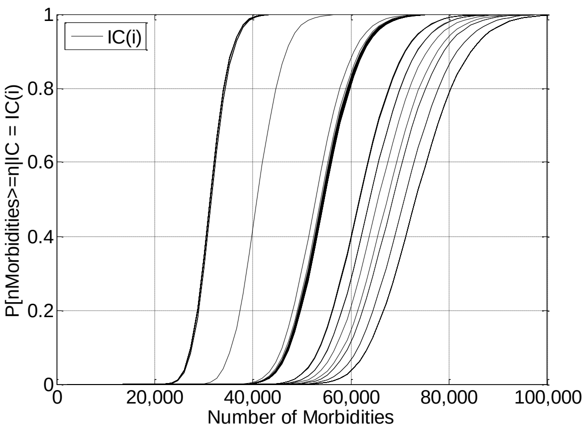

Figure 1 provides the probability of nonexceedance for the number of morbidities conditioned on initial cost.

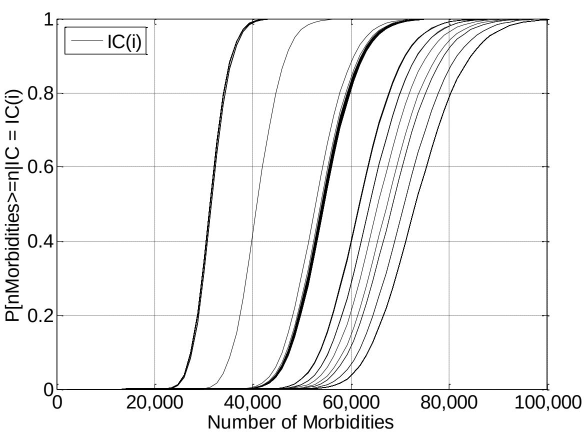

Figure 1 has 2400 fragility curves plotted on it, one from each community in each generation. Many of the solutions are identical. If more archetypes are used, there will be more variety allowed in the solutions, and a much more diverse solution base will be generated. The 50th percentile values were extracted from

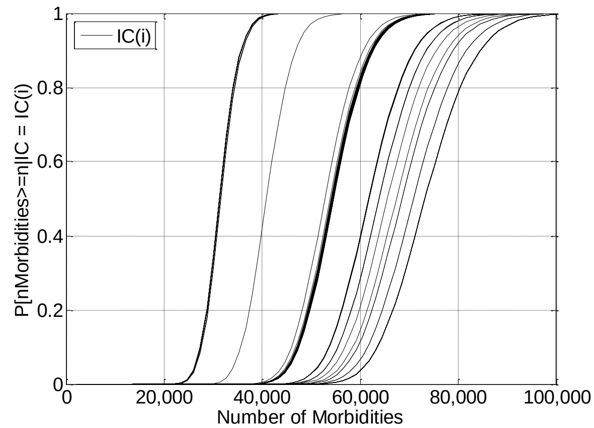

Figure 1 and plotted against the initial cost, shown in

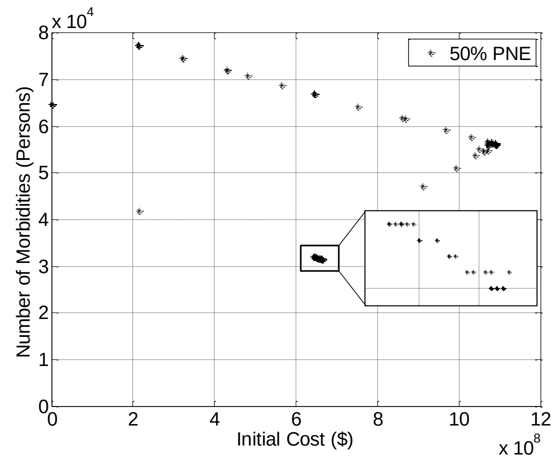

Figure 2.

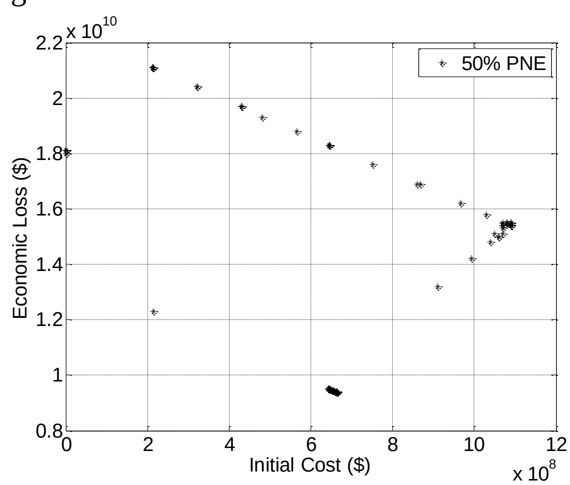

Figure 3 and

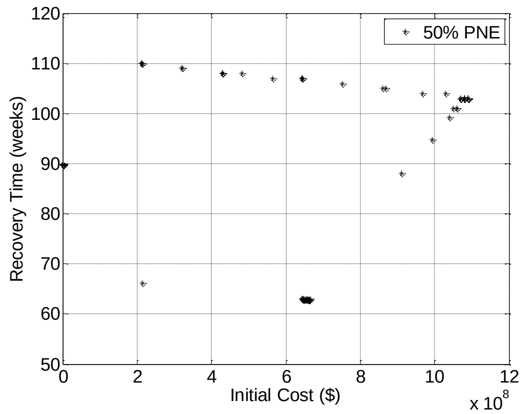

Figure 4 provide similar figures with 50th percentile values for the economic loss and time to recovery, respectively, versus the initial cost. One can see that there were very similar trends in the three objectives when compared to initial cost. Referring to Figures 3, 4, and 5, the pareto-optimal solutions would be the far left points and bottom points. These points represent the optimal tradeoffs between the respective objective and the initial cost. All other solutions are dominated by these points. The points in Figures 3, 4, and 5 may be mapped back to the associated community mitigation plan for presentation to the decision maker(s).

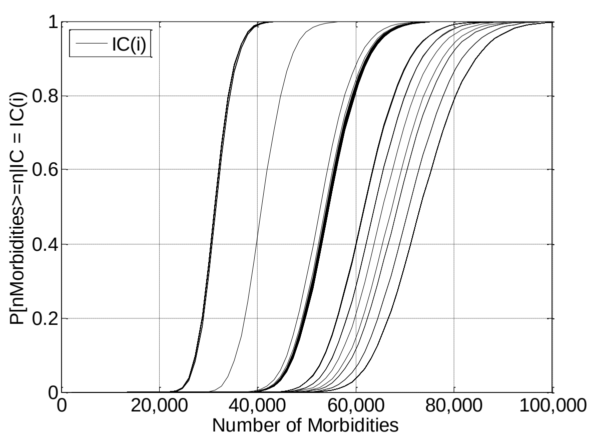

Figure 1: Nonexceedance Probability for the Number of Morbidities Conditioned on Initial Cost

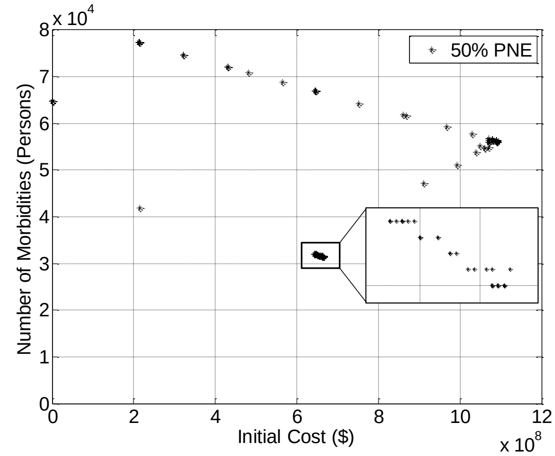

Figure 2: Number of Morbidities vs. Initial Cost

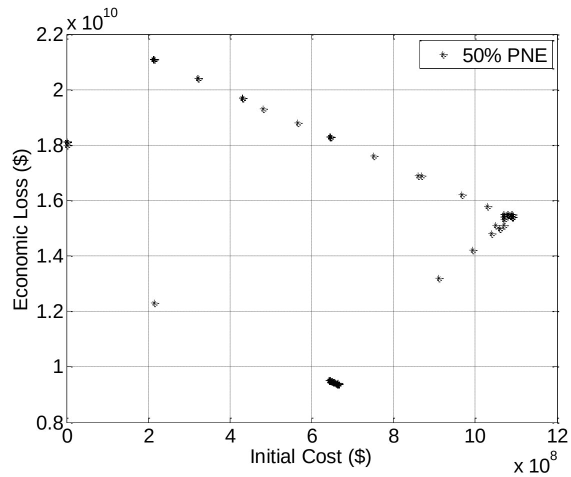

Figure 3: Economic Loss vs. Initial Cost

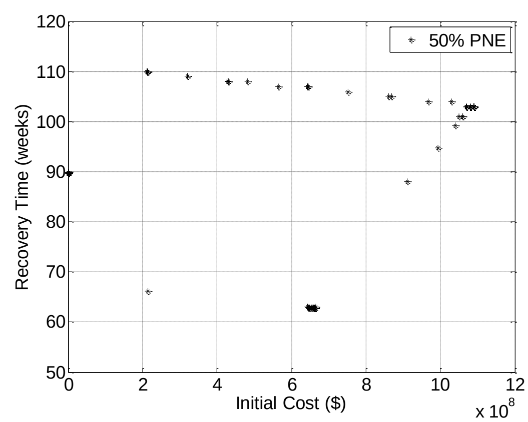

Figure 4: Recovery Time vs. Initial Cost

Looking at

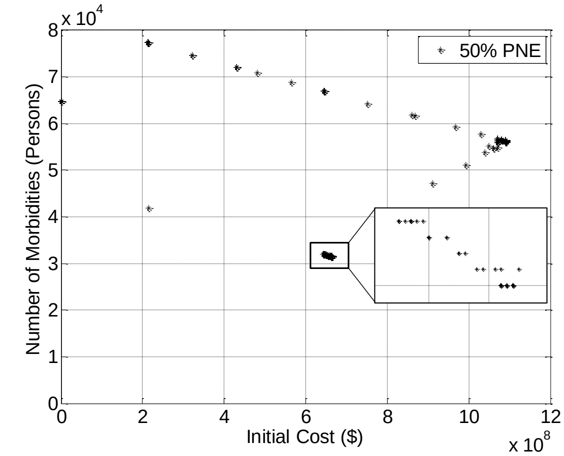

Figure 2, at $655 million initial cost and 31,700 morbidities, a single solution is encircled within the zoomed in section. This solution maps to

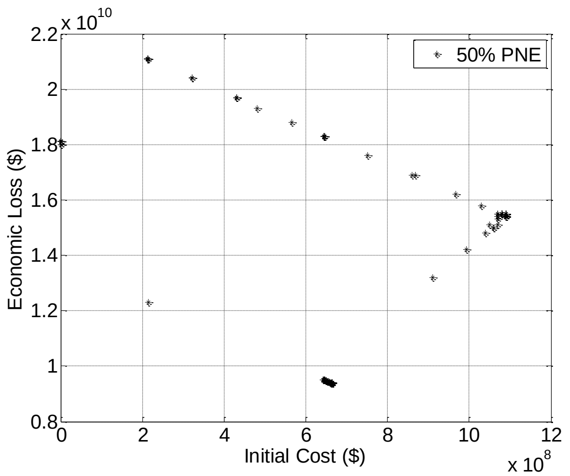

Figure 3 at $9.4 billion in economic losses, and maps to

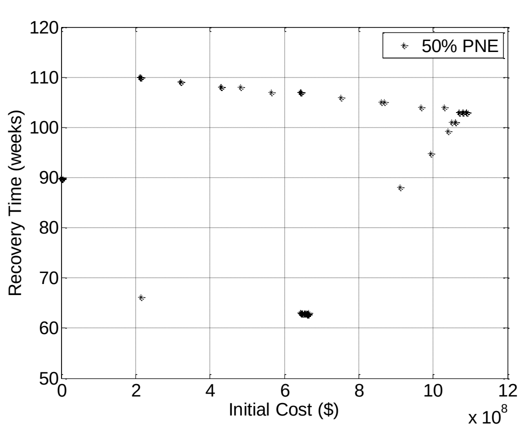

Figure 4 at 63 weeks recovery time. This solution corresponds to the mitigation plan of 2 of the 1959 SEAOC buildings and 4998 of the ASCE Standard 7-05 buildings in the community. Demonstrating that the lowest number of morbidities occured when nearly all of the outdated buildings were retrofitted. Decision makers can use results similar to

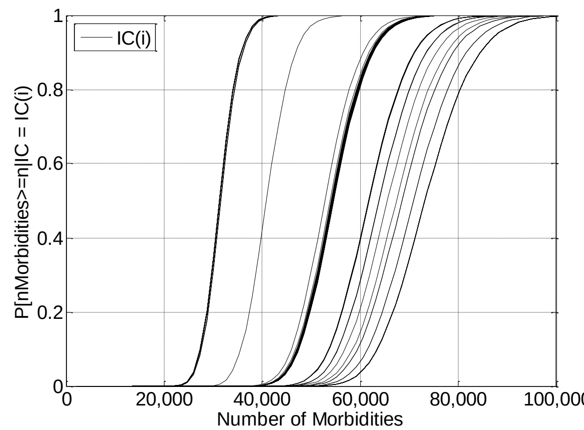

Figure 1, and apply a set confidence level to develop similar figures as those presented in

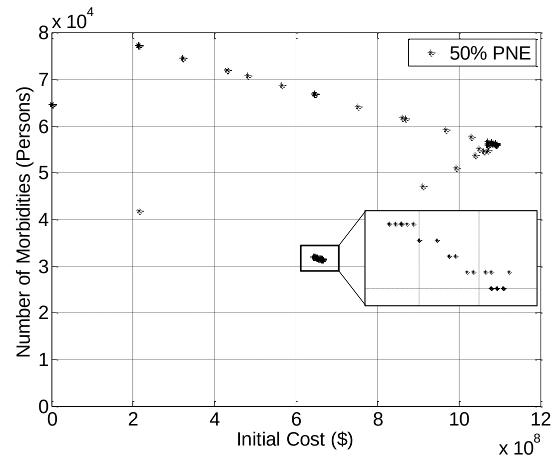

Figure 2 through

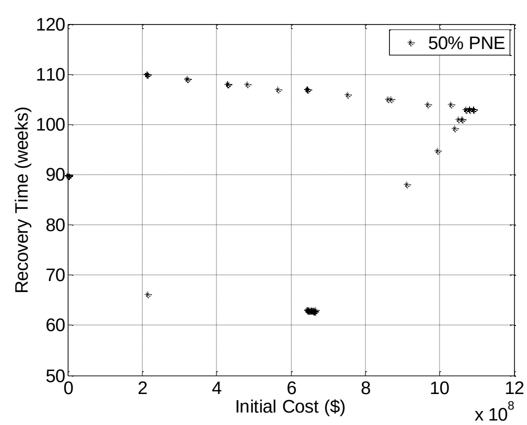

Figure 4 for identifying their optimal mitigation plan.

4. CONCLUSIONS

Deciding where money is best allocated such that it protects the population, preserves their quality of life, and maintains infrastructure involves a complex decision process. This is especially true considering the varied building stock and pronounced demographic diversity of some geographically adjacent communities. The framework presented herein aims to assist local government leaders and other stakeholders with respect to how best to allocate funds for mitigating the woodframe building stock of a community. To make those decisions and to move toward a more earthquake resilient community, it is thus critical to consider both the built and social environment.

Like any study, there were limitations to the approach described in this paper. There are more factors which influence individual- and community-level resiliency to earthquakes that were not considered here. The variables selected for this framework were chosen based on their presence in the literature and availability in publically accessible datasets. Additionally, the use of any number of archetypes is a simplification of a real-world scenario. In this study, all buildings in the community were assumed to be equal distance from the epicenter, and with no aging or repairs conducted. Despite these limitations, the presented framework provides decision makers with comparisons between mitigation plans, and allows the communities to examine multiple resilience levels with the associated risk-based performance criteria.

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