Community-Level Framework for Seismic Resilience. II: Multiobjective Optimization and Illustrative Examples

Elaina J. Sutley, A.M.ASCE[1]; John W. van de Lindt, M.ASCE[2]; and Lori Peek[3]

Abstract: This two-part study focuses on the development and application of a coupled socioeconomic and engineering framework for community-level seismic resiliency. Part I provided the coupled framework, including quantifying the effect that six socioeconomic and demographic variables—age, ethnicity/race, gender, family structure, socioeconomic status, and the age and density of the built environment—have on four resilience metrics. This companion paper, Part II, presents and exemplifies the multiobjective optimization component of the framework which is shown to identify the optimal set of seismic retrofit plans for a community's woodframe building stock. In the analysis, the largest difference in total financial loss occurred at a design basis earthquake (DBE) seismic intensity. The work highlights the importance of including social, economic, and engineering factors in estimating losses; not including social factors in loss estimations resulted in millions of dollars difference in projected economic loss, and a 182% underestimation in the number of morbidities for a DBE event. The underestimations are exacerbated for a highly vulnerable population with an outdated or structurally deficient building stock. For Los Angeles County, the total financial loss for the unretrofitted case was higher at multiple levels of seismic intensity than for the retrofitted case, although there was no associated initial cost in the former case. When considering the reduced number of morbidities and lower total financial loss associated with the retrofitted solution, it is clear that the initial cost of retrofitting is justified. **DOI:** 10.1061/(ASCE)NH.1527-6996.0000230.

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Introduction

The present work addresses community disaster resilience by designing a series of optimal seismic retrofit plans for the woodframe building stock based on a community-level loss-estimation model that considers socioeconomic and demographic (SED) variables and building performance. The optimal community retrofit plans are based on four resilience metrics, employed as objectives in the optimization, namely the initial cost, potential economic loss, the number of potential morbidities [i.e., injuries, fatalities, and posttraumatic stress disorder (PTSD) diagnoses], and the time to recovery. Ultimately, this work will allow decision makers, in concert with engineers and other scientific experts, to develop comparisons between multiple resilience levels with the associated risk-based performance criteria. See Part I (Sutley et al. 2016), the companion paper, for the framework development and the analytical modeling of six SED variables—age, ethnicity/race, family structure, gender, socioeconomic status, and the age and density of the built environment—which was based on their influence on the three morbidity rates. Part I concluded with an in-depth look at the six variables through a sensitivity study using population data for five communities (three California communities and two virtual communities). These communities were selected and analyzed based on the differences in their population makeup. Part II follows with a summary of the multiobjective optimization used for identifying the optimal, or optimal set of, seismic retrofit plans for a community's woodframe building stock. A calibration procedure is presented and tested against the reported losses from the 1994 Northridge earthquake. Lastly, several illustrative examples using Los Angeles County, California, as the focal community are presented. The results from the Los Angeles County analyses highlight the importance of including social, economic, demographic, and engineering factors in estimating losses, planning, and recovery efforts.

At this time, the framework is a fully developed application ready to be applied. In its current form, analytical inputs and decision-maker preferences can be incorporated, or adjusted, by any person familiar with optimization algorithms and the *MATLAB* coding language. Results from the optimization are interpreted from fragility curves. A probability of nonexceedance may be selected and used for extraction of strict values for each objective and several complementary damage values, which map back to individual community-level seismic retrofit plans. These strict values may be tabulated or plotted and provided to the decision maker. If decision-maker preferences were not originally employed, the set of optimal seismic retrofit plans would be identified from the analysis. In this case, the set of objective values and complementary damage values could be provided to the decision maker. Then the decision maker could use their preferences to compare between the objective values and select the best seismic retrofit plan for their community. All coding for the genetic algorithm and coupled framework was written in *MATLAB* by the first author, and the built-in genetic algorithm toolbox in *MATLAB* was not used.

[1]Assistant Professor, Dept. of Civil, Architectural, and Environmental Engineering, Univ. of Kansas, Lawrence, KS 66045-7608 (corresponding author). E-mail: enjsutley@ku.edu

[2]George T. Abell Distinguished Professor in Infrastructure, Dept. of Civil and Environmental Engineering, Colorado State Univ., Fort Collins, CO 80523-1372.

[3]Professor and Director, Dept. of Sociology and Natural Hazards Center, Univ. of Colorado-Boulder, Boulder, CO 80309.

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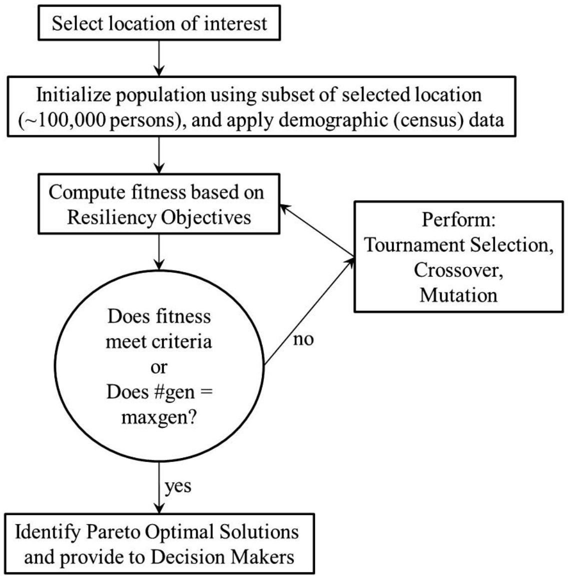

Fig. 1. Generalized genetic algorithm procedure

Multiobjective Optimization

As defined and established in Part I (Sutley et al. 2016), the SED category factors are essential to the loss estimations computed within the framework. They are what allow the framework, and solution, to be community-specific, rather than general for all communities in the United States. The morbidity rates computed by building damage and adjusted based on the SED category factors are used to estimate three objectives: economic loss, the number of morbidities, and the time to recovery. The multiobjective optimization uses these objectives, and additionally, the initial cost of the seismic retrofit plan, to identify the optimal seismic retrofit plan for the community given a specific earthquake scenario event.

To perform the optimization within the coupled socioeconomic and engineering framework, a multiobjective genetic algorithm (GA) was employed. Genetic algorithms are especially beneficial in solving multiobjective optimization problems due to the population of solutions generated with every iteration (Goldberg 1989). In this work, the GA will produce the Pareto-optimal set of solutions for the decision maker(s) by extracting diverse solutions generated with each iteration. The optimal solutions are identified by the fitness function, which minimizes the objectives and follows any constraints. The general procedure for the GA employed here is shown in Fig. 1. The population is initialized using building statistics for each archetype based on census data for the community, and the population initial fitness is computed. The population goes through the selection, crossover, and mutation operators and the population fitness is recalculated. If the number of generations (iterations) is less than the maximum set number of generations, a new generation is spawned repeating the crossover, mutation and selection operators until the solution converges or meets the specified maximum number of generations.

The objectives modeled, as presented in Sutley et al. (2016), for measuring community-level seismic resilience include initial cost, economic loss, number of morbidities, and time to recovery. The first objective, initial cost, introduces conflict between the latter three objectives assisting the GA in producing more diverse solutions. That is, a seismic retrofit plan that has minimal initial cost intuitively will have a higher economic loss, higher number of morbidities, and a longer recovery time since the buildings, or retrofits, will be cheaper. In this study, the GA was designed to develop the Pareto-optimal set of solutions for the decision maker(s) by producing and extracting diverse solutions throughout the analysis. The Pareto-optimal set is defined as the set of solutions which represent the optimal trade-offs between the objectives. A Pareto-optimal solution may be optimal for one or more objectives, but is not optimal for all objectives. Table 1 provides the genetic algorithm terminology and how each term was specifically modeled or defined for the current study.

In this study, the community being analyzed was modeled by its woodframe building stock and represented as a numeric string. The string is a single seismic retrofit plan for the woodframe building stock, where the woodframe building stock was modeled as a collection of archetypes. The value of each characteristic in the string represents the quantity of each different archetype, present in the community. Within a community, there are multiple types of woodframe structures designed by various codes or provisions. Therefore, to improve the accuracy, a representative range of archetypes is needed, such as multiple single-family dwellings, multiple multifamily dwellings, and multiple low-rise commercial buildings, were designed at various periods in time to model the variety in the woodframe building stock of a community.

Fitness Formulation

In genetic algorithms, the fitness function allows for the optimal solution(s), to be identified. Recall, the objectives and other damage measures are interpreted from fragility functions. In this study, the fitness was computed by using the 50th percentile values for each of the objectives to provide a strict number for comparison. The 50th percentile values were chosen as an example; the user, however, could select any percentile value of interest. The 50th percentile values of the objectives, o_i, were normalized by the minimum population value of each respective objective. Once

Table 1. Comparison of Terminology

Genetic algorithm	Current study
String; individual; the string is n concatenated characteristics	The community being studied, modeled by the woodframe building stock consisting of n archetypes; this is a seismic retrofit plan for the woodframe building stock; a single solution
Population; a collection of "individuals"	Multiple collections of the woodframe building stock differing by the number of each archetype present in the study-community
Feature; characteristic	A single building archetype
Feature value; characteristic value	The number of that building archetype present in the study-community
Crossover	Executed using double-point crossover
Selection; survival of the fittest	Executed using tournament selection
Mutation	Executed using single-point mutation on randomly selected gene
Fitness	Normalized objective values (initial cost, economic loss, number of morbidities, recovery time)
Iteration	Another succession following the selection-crossover-mutation operators

normalized, the objectives were weighted, w_i, and summed together. The fitness function may be expressed as

$$\text{fitness} = w_1 \cdot o_1 + w_2 \cdot o_2 + w_3 \cdot o_3 + w_4 \cdot o_4 \quad (1)$$

where o_1 = normalized initial cost; o_2 = normalized economic loss; o_3 = normalized number of morbidities; and o_4 = normalized time to recovery. If decision-maker preferences were to be incorporated in the GA, this would occur through the weights, otherwise these weights would equate to unity. The lower the fitness value, the better the seismic retrofit plan, and the more likely for it to be duplicated in future iterations; this is the premise of a GA.

Selection, Crossover, and Mutation

There are three major substeps in any genetic algorithm: selection, crossover, and mutation. The selection process uses the computed fitness to determine which seismic retrofit plans will move on to the next iteration. The tournament selection procedure is commonly used in optimization problems and was employed here.

A crossover routine randomly exchanges archetype quantities between randomly selected seismic retrofit plans. A double point crossover was employed here due to the characteristic makeup of the seismic retrofit plans. The two crossover sites were set at the same locations for each seismic retrofit plan entering into the crossover operator, and separated the outdated archetype designs from the new and state-of-the-art archetype designs and retrofits. This way, the GA was able improve the community resilience by increasing the number of retrofitted buildings through decreasing the number of structurally deficient buildings.

The mutation operator changes one or more archetype quantities within a selected seismic retrofit solution. In this study, a single-point mutation site was used, and randomly selected as any of the structurally deficient archetypes.

Constraints and Penalty Functions

There were multiple constraints and penalty functions imposed in the GA used here. A constraint requires a solution to follow it. A solution may not meet the penalty function, and if it does not, then its fitness is altered in a negative way. The constraints imposed in this genetic algorithm were all based on controlling the number of each archetype, the total number of each floor plan over all designs, and the total number of all archetypes in a single solution.

Penalty functions may be incorporated into a genetic algorithm as a way to impose checks on the solutions so as to encourage the solution in a more optimal direction. There were three penalty functions imposed in the genetic algorithm. Two of the three penalty functions were imposed based on the budget input by the user (decision maker), and the third penalty function was for further controlling the total number of archetypes in the community. The values used for the budget and within the penalty functions are all hypothetical at this point, but could be set by the decision maker in a real world application. In each case, if the check was not met by the solution, the corresponding fitness was penalized by being multiplied by a factor of two. The first penalty function was for directing the initial cost of the optimal solution to be less than the budget set by the user. The first penalty function for limiting the initial cost may be expressed as

$$\begin{aligned} &\text{IF} \quad O_{1,j} > \text{budget} \\ &\text{THEN} \quad \text{fitness}_j = 2 \cdot \text{fitness}_j \end{aligned} \quad (2)$$

where O_1 = initial cost of the jth individual in the current generation.

The second penalty function was for directing the total economic loss of the optimal solution to be less than 10 times the budget, for example, to be set by the user. The second penalty function for limiting the total economic loss may be expressed as

$$\begin{aligned} &\text{IF} \quad O_{2,j} > 10 \cdot \text{budget} \\ &\text{THEN} \quad \text{fitness}_j = 2 \times \text{fitness}_j \end{aligned} \quad (3)$$

where O_2 = economic loss of the jth individual in the current generation.

The last penalty function was imposed for controlling the total number of archetypes in the community to equal 1,00,000. The third penalty function may be expressed as

$$\begin{aligned} &\text{IF} \quad \sum_{\text{arch}=1}^{37} n_{\text{arch},j} \neq 100{,}000 \\ &\text{THEN} \quad \text{fitness}_j = 2 \times \text{fitness}_j \end{aligned} \quad (4)$$

The constraints were imposed following the crossover and mutation operators, and the penalty functions were imposed prior to the selection operator. The factor of two was s chosen after several trial runs identified it to as effective at controlling the solutions to follow the penalty functions.

Illustrative Examples in Los Angeles County, California

In this section, the optimization algorithm and community resilience framework are applied to several illustrative examples over a subset of Los Angeles County. Prior to the illustrative examples, the framework was calibrated to the reported morbidity rates from the United States Geological Survey (USGS) Shakeout Scenario (Jones et al. 2008).

Framework Calibration

The USGS Shakeout Scenario looked at a much larger geographic area consisting of approximately 1 million people. In the present work, the framework is applied to a subset of 100,000 buildings, equating to approximately 1 million people. The morbidity rates predicted in the Shakeout Scenario for a very large earthquake were approximately matched at a spectral acceleration of 2.5g, corresponding to a maximum considered earthquake (MCE) seismic hazard, which would be caused by a ground shaking intensity approximately equal to the worst section of what was examined in the Shakeout Scenario. At 2.5g spectral acceleration, the framework was applied using the Los Angeles County population with the SED category factors set to unity, since the Shakeout Scenario did not have such factors incorporated within it, and therefore neither did the Shakeout Scenario's predicted losses.

Once a satisfactory level of calibration was achieved for the morbidity rates, the framework was reapplied to a different scenario earthquake, namely the 1994 Northridge earthquake. The estimated morbidities were determined using the SED category factors computed using similar data in Table 2, with Eqs. (11) and (12) in Sutley et al. (2016) for Los Angeles County to compare the loss estimates with the reported losses from the 1994 Northridge earthquake. The 1994 Northridge earthquake was the last major earthquake in terms of economic loss to have occurred in the United States and thus selected for the calibration check. The Los Angeles County SED category factors were used when comparing to the reported losses from the 1994 Northridge event because these were real losses measured from the Los Angeles community. These losses thus could be more accurately matched by the framework

Table 2. Community Input Data

Variable	2010 Los Angeles County Input Values
Total population size	9,818,605
Mean annual income	$81,729
Mean household size	2.98
Percentage of households with children	37.2
Age	
Child (0–9 years old)	13.1%
Adolescent (10–19 years old)	14.6%
Young adult (20–29 years old)	15.4%
Middle-aged adult (30–45 years old)	21.9%
Older adult (46–64 years old)	24.2%
Elder (65+ years old)	10.9%
Ethnicity/race	
White, non-Hispanic	27.8%
Non-White, non-Hispanic	72.2%
Family structure	
Single	32.3%
Partnered	67.7%
Person <18 years old in household	37.2%
Gender	
Female	50.7%
Male	49.3%
Socioeconomic status	
Low	27.6%
Moderate	43.4%
Upper	29.0%

by using the 1990 census data to compute SED category factors for adjusting the morbidity rates. The data in Table 2 is from the 2010 U.S. Census (2010), and was used in the community-level optimizations to provide insight into the present day situation in Los Angeles County. The 1990 census data are not presented here for conciseness.

Most woodframe residential structures have fundamental periods near 0.2 s. A range of peak ground acceleration (PGA) values (less than $0.3g$ and up to greater than $0.6g$) were recorded from the 1994 Northridge ground motion. The PGA for this study was taken as $0.5g$ resulting in an average spectral acceleration of $1.1g$ for buildings with a fundamental period of 0.2 s. Shierle (2003) conducted an extensive retrospective investigation on the damage to woodframe structures caused by the 1994 Northridge earthquake as part of the Consortium of Universities for Research in Earthquake Engineering (CUREE)-Caltech Woodframe Project. The project reported various loss estimations, including the subassembly repair costs and repair times that are used in the present study (Reitherman and Cobeen 2003). CUREE *Publication No. W-09* reported that around half of the $40 billion in property loss caused by the quake was due to damage to woodframe buildings. Therefore, the economic loss from the framework should be approximately, but less than, $20 billion.

Applying the framework to the Los Angeles County population at $1.1g$ spectral acceleration at the same occupancy rates that were expected to have been experienced during the Northridge earthquake (peak occupancy for residential structures due to time of day), the 50th percentile value for the economic loss was approximately $16 billion, which was deemed close enough to the Northridge earthquake estimate to prove the framework's accuracy in predicting economic loss. Additionally, the CUREE publication reported 48,000 housing units were uninhabitable, therefore the total number of archetypes being classified as temporarily uninhabitable or collapsed (i.e., Damage States 4 and 5, respectively) were summed and calibrated to equal approximately 48,000.

The calibrations discussed above were achieved by multiplying the resulting distributions for the estimated losses by factors to achieve the reported values. The expression used for computing the number of morbidities was provided in the companion paper. Rearranging that expression and incorporating the calibration factors, the expression for computing the number of morbidities becomes

$$O_3 = F_{inj} \cdot \sum_{ds=1}^{n_{ds}} \left[\left(\sum_{is=1}^{4} MR_{is,ds} \right) \cdot \sum_{i=1}^{n_{\mathrm{arch}}} (n_{i,ds} \cdot occ_i) \right] + F_{\mathrm{fat}} \cdot \sum_{ds=1}^{n_{ds}} \left[MR_{is5,ds} \cdot \sum_{i=1}^{n_{\mathrm{arch}}} (n_{i,ds} \cdot occ_i) \right] + F_{\mathrm{PTSD}} \cdot \sum_{ds=1}^{n_{ds}} \left[MR_{pr,ds} \cdot \sum_{i=1}^{n_{\mathrm{arch}}} (n_{i,ds} \cdot occ_i) \right] \quad (5)$$

where F_{inj}, F_{fat}, and F_{PTSD} = calibration factors for the injury, fatality, and PTSD diagnoses counts, respectively. The calibration factors were determined to be 0.5 in all cases, indicating that the originally predicted morbidity counts were twice as high as the calibration studies which could have been caused by the limitation of applying a constant seismic intensity to all buildings in the analysis, rather than spatially distributing the seismic intensity. $MR_{is,ds}$, $MR_{is5,ds}$, and $MR_{pr,ds}$ = morbidity rates for injury severity level is, fatality rate $is5$, and PTSD diagnosis rate pr in damage state ds, respectively; $n_{i,ds}$ = number of archetypes i in damage state ds; and occ_i = occupancy of archetype i.

Building Archetypes

Building performance is measured by an engineering demand parameter (interstory drift), which maps to five damage states, as discussed in Sutley et al. (2016). The five damage states were also mapped to the morbidity rates, and thus provided the connection for the SED and engineering systems. To model the variety in an assumed existing residential building stock, and for obtaining the building performance in the illustrative examples presented in this study, 37 woodframe building archetypes were modeled (Table 3). These 37 archetypes consisted of 7 diverse floor plans: two one-story single-family dwellings (SFD) (one with and one without an attached garage), two two-story SFD (one small and one large), one two-story multifamily dwelling (MFD), and two soft-story buildings (one three-story MFD and one four-story office building).

These seven floor plans were designed to five different seismic provisions: the 1959 Structural Engineering Association of California (SEAOC) Blue Book, 1978 National Earthquake Hazard Reduction Program (NEHRP), American Society of Civil Engineers (ASCE) 7-2005 Equivalent Lateral Force Procedure, two performance-based seismic retrofits (PBSR) using the simplified direct displacement design procedure (SDDD) to two limit states [i.e., immediate occupancy (IO) and life safety (LS)], and additionally, the two soft-story buildings were retrofitted following the Federal Emergency Management Agency (FEMA 2012) P-807 procedure. This set of 37 archetypes was selected in an effort to accurately model the existing building stock in the Los Angeles County, California area, which would include older and newer designed buildings, where older was taken as pre-1994 Northridge earthquake construction, and newer was taken as post-1994 Northridge earthquake construction in this study.

There were several constants for the case studies presented here. These included the initial building inventory, provided in Table 3. The framework assumes that all buildings within the community are at an equal distance from the epicenter of the earthquake,

Table 3. Description of Building Stock

Seismic provision	Floor plan	Number of stories	Area m^2 (ft^2)	Archetype	Percentage of 100,000 in initial population
1959 Blue Book	1	1	111.5 (1,200)	1	9.59
	2	2	261.9 (2,820)	2	9.59
	3	2	674.5 (7,260)	3	6.90
	4	3	983.5 (10,586)	4	10.43
	5	1	131 (1,410)	5	9.59
	6	2	137.1 (1,476)	6	9.59
	7	4	1,912.3 (20,584)	7	20.22
1978 NEHRP	1	1	111.5 (1,200)	8	2.26
	2	2	261.9 (2,820)	9	2.26
	3	2	674.5 (7,260)	10	1.63
	4	3	983.5 (10,586)	11	2.46
	5	1	131 (1,410)	12	2.26
	6	2	137.1 (1,476)	13	2.26
	7	4	1,912.3 (20,584)	14	4.77
ASCE7-05	1	1	111.5 (1,200)	15	0.26
	2	2	261.9 (2,820)	16	0.26
	3	2	674.5 (7,260)	17	0.19
	4	3	983.5 (10,586)	18	0.21
	5	1	131 (1,410)	19	0.26
	6	2	137.1 (1,476)	20	0.26
	7	4	1,912.3 (20,584)	21	0.41
SDDD-IO	1	1	111.5 (1,200)	22	0.26
	2	2	261.9 (2,820)	23	0.26
	3	2	674.5 (7,260)	24	0.19
	4	3	983.5 (10,586)	25	0.21
	5	1	131 (1,410)	26	0.26
	6	2	137.1 (1,476)	27	0.26
	7	4	1,912.3 (20,584)	28	0.41
SDDD-LS	1	1	111.5 (1,200)	29	0.26
	2	2	261.9 (2,820)	30	0.26
	3	2	674.5 (7,260)	31	0.19
	4	3	983.5 (10,586)	32	0.21
	5	1	131 (1,410)	33	0.26
	6	2	137.1 (1,476)	34	0.26
	7	4	1,912.3 (20,584)	35	0.41
FEMA P-807	4	3	983.5 (10,586)	36	0.21
	7	4	1,912.3 (20,584)	37	0.41

therefore a subset of the population size was used, rather than the entire population for Los Angeles County as mentioned earlier. The subset population size was set as 100,000 buildings. The distribution of the 100,000 buildings shown in Table 3 was modeled after the building inventory of Los Angeles County based on 2010 U.S. Census data. The order of buildings listed in Table 3 is the order in which the archetypes appeared in the GA's string. For the buildings likely designed to a modern code, it was not evident from the census data which seismic provision was used in the design. Therefore, the quantity of modern buildings was evenly distributed over the last 23 archetypes in the string for each respective floor plan. Subsequently the initial percentages for the subcategories of the built environment were constant for all case studies. The genetic algorithm and optimization inputs were held constant for all examples. The probability of crossover was set to 0.85, the probability of mutation was set to 0.10, the number of seismic retrofit plans (individuals) in the population per generation was set to 50, and the maximum number of generations was set to 100, selected based on a preliminary sensitivity study not presented here, and limitations in the computational capacity. A collapse limit of 10% interstory drift was employed on all archetypes. Peak interstory drift values for each archetype were obtained from nonlinear time history analyses conducted prior to the case study. The peak interstory drift values used here were extracted at 50% probability of nonexceedance. The objective weights in Eq. (1) were set to unity in all cases so that the decision maker(s) could employ preferences at the end.

Community-Level Optimization of Los Angeles County at a MCE Seismic Hazard Using Coupled Framework

The community-level optimization was conducted using the coupled-framework at a MCE seismic hazard. The resulting 50th percentile values for the four objectives are plotted in the following figures. Each plotted point on the individual figures map back to a community-level seismic retrofit plan. The circles highlight the Pareto-optimal solutions in each figure. Recall, the Pareto-optimal surface represents the optimal trade-off with respect to the two objectives being compared, and therefore is not identical in the different figures. Fig. 2 provides the relationship between the estimated economic loss and the associated initial cost of the solutions. There is a large cluster of solutions which demonstrated a trend indicating that the higher the initial cost, the lower the economic loss. Three solutions formed the Pareto-optimal surface for these two objectives, although not completely visible from the figure.

Fig. 3 illustrates the relationship between the estimated number of morbidities and the associated initial cost of the solutions. In this case, the same three solutions were identified on the Pareto-optimal surface to provide the optimal trade-offs between the number of morbidities and the initial cost. Similarly to Fig. 2, a trend revealed

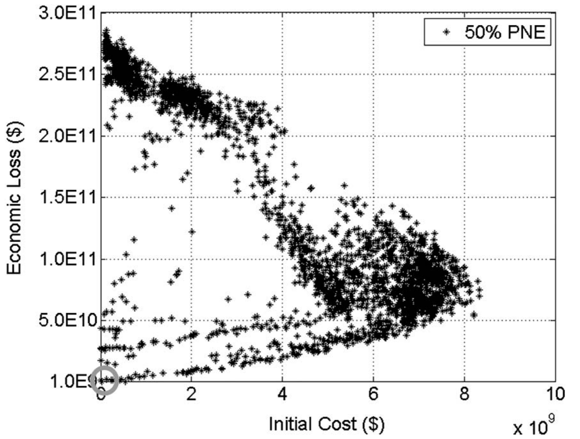

Fig. 2. 50th percentile values for economic loss versus Initial cost for Los Angeles County at MCE with Pareto-optimal surface labeled

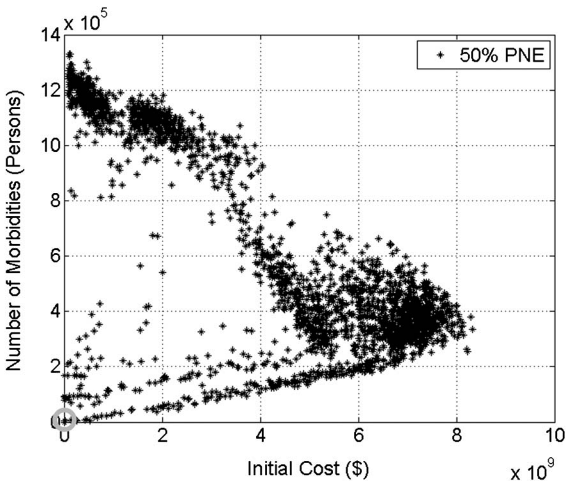

Fig. 3. 50th percentile values for number of morbidities versus initial cost for Los Angeles County at MCE with Pareto-optimal surface labeled

that the higher the initial cost, the fewer estimated number of morbidities.

Fig. 4 provides the relationship between the estimated recovery time and the associated initial cost of the solutions, where only a single optimal solution was identified. The results in Fig. 4 demonstrated that the higher the initial cost, the shorter the time to recovery.

The relationship between the estimated economic loss and the recovery time of the solutions is shown in Fig. 5, with two optimal solutions identified. Fig. 6 shows the relationship between the estimated number of morbidities and the recovery time of the solutions, with the same two optimal solutions identified as in Fig. 5. Similarly in Figs. 5 and 6, trends showed that the shorter the recovery time, the lower the economic loss and the fewer morbidities.

Fig. 7 illustrates the relationship between the estimated number of morbidities and the associated economic loss of the solutions. In this case, one solution was identified to form the Pareto-optimal surface. Here it was shown that there was a direct correlation between the number of morbidities and economic loss, and as one increased or decreased, so did the other objective.

From Figs. 2–7, there were three unique solutions identified to form the Pareto-optimal set of solutions for all four objectives. In all

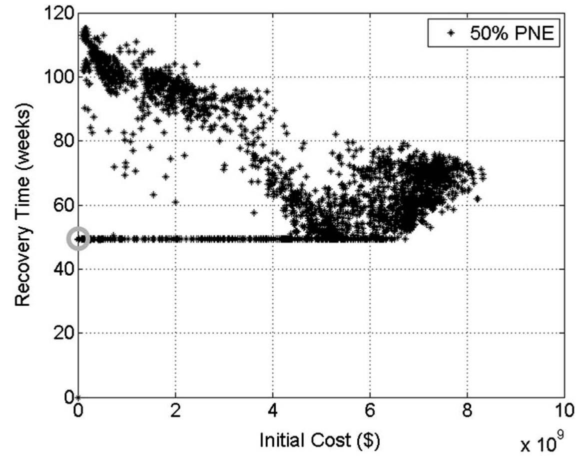

Fig. 4. 50th percentile values for recovery time versus initial cost for Los Angeles County at MCE with Pareto-optimal surface labeled

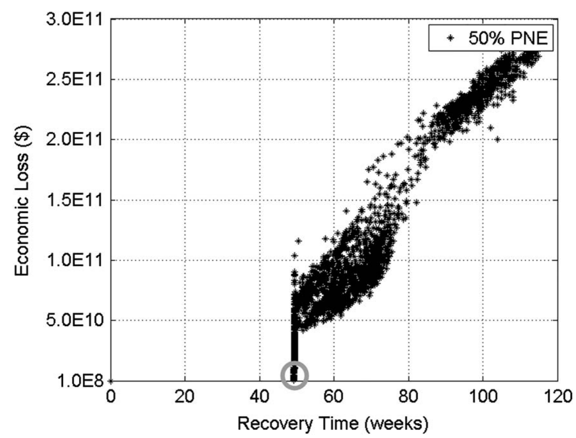

Fig. 5. 50th percentile values for economic loss versus recovery time for Los Angeles County at MCE with Pareto-optimal surface labeled

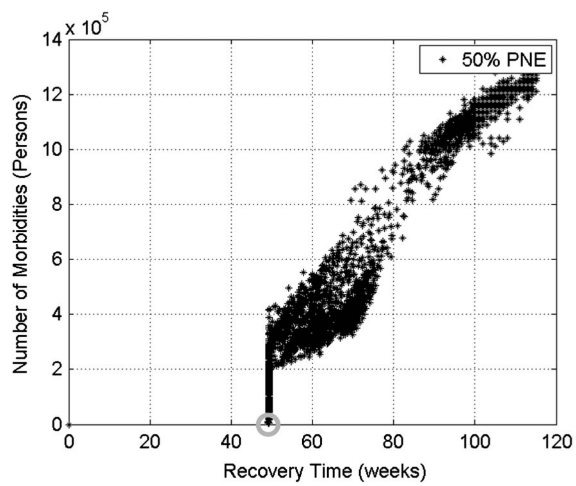

Fig. 6. 50th percentile values for number of morbidities versus recovery time for Los Angeles County at MCE with Pareto-optimal surface labeled

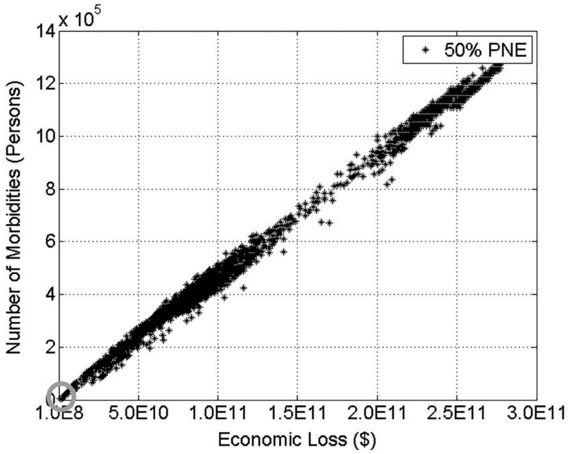

Fig. 7. 50th percentile values for number of morbidities versus economic loss for Los Angeles County at MCE with Pareto-optimal surface labeled

cases, the various objectives followed logical and hypothesized trends. In the figures that compared an objective versus the time to recovery, a vertical lower limit is shown at approximately 52 weeks, the recovery time set for PTSD in Sutley et al. (2016). This vertical lower limit suggests that at least one person in the exposed population would be diagnosed with PTSD, and therefore the recovery time could not be less than one year. Upon further inspection, the estimated repair time might be shorter than 52 weeks for some solutions. However, the detailed repair time results were not provided in addition to the recovery time results. It could also be the case that the recovery time could be less than 52 weeks. For example, a very small earthquake could have caused minimal building damage, but not PTSD diagnoses. In this case, the recovery time would have been less than 52 weeks. Additional examples demonstrating and providing these details were beyond the direct goals of demonstrating the framework, and thus not included.

A second analysis was conducted using the framework with the SED variables set to unity. Conducting the optimization twice, demonstrates the importance of including both sectors in loss estimations, planning, and recovery efforts. The results from both multiobjective optimizations were used to select five optimal solutions for further examination. In both optimizations, similar trends were developed when comparing the various objectives. Although only three solutions were identified to form the Pareto-optimal set of solutions in the multiobjective optimization example, a larger set could be provided to a decision maker and other nonoptimal solutions could be selected as well. It should be noted that using a population size of 50 seismic retrofit plans to compare, and a maximum number of 100 iterations will not generate every possible solution. These input parameters were felt to provide an extensive set of solutions for the illustrative examples.

Analyzing the Pareto-Optimal Surface Based on MCE Seismic Hazard

Following the multiobjective optimization, two solutions were extracted from each analysis (Los Angeles County values and unit values of SED variables) for further investigation. Using two solutions from each analysis, rather than the three identified optimal, was elected for brevity. In each case, one of the selected solutions provided the optimal trade-off for the number of morbidities and recovery time. The second selected solution provided the optimal trade-off for the initial cost and economic loss. The five solutions

Table 4. Initial Population and the Pareto-Optimal Set of Solutions Considering a MCE Seismic Hazard for Los Angeles County

Solution	A1	A2	A3	A4	A5	A6	A7
Alleles for 1959 Blue Book designs							
1	9,586	9,586	6,898	10,432	9,586	9,586	20,220
2	6,791	1	1	1	1	1	1
3	6,624	1	23	1	44	1	1
4	1	8790	1	1	8790	1	1
5	1	8242	1	1	8242	1	1
Alleles for the 1978 NEHRP designs							
1	2,261	2,261	1,627	2,460	2,261	2,261	4,768
2	1	1	1	1	1	1	1,974
3	1	1	1	1	1	1	1,806
4	1,464	1	830	1,664	1,464	1	3,972
5	1	1	823	1,116	917	1	3,425
Alleles for the 2005 ASCE-7 designs							
1	261	261	188	213	261	261	414
2	1,509	1,509	1,509	2,172	2,404	1,825	2,509
3	4,287	3,061	3,061	3,061	3,264	3,061	3,061
4	2,949	250	2,684	1,207	250	1,608	250
5	3,645	486	3,032	958	487	516	2,137
Alleles for the SDDD-IO retrofit designs							
1	261	261	188	213	261	261	414
2	5,559	6,687	4,899	6,120	6,041	4,999	3,292
3	5,054	6,360	4,595	4,758	4,302	3,220	3,061
4	4,220	4,507	2,672	4,662	4,384	5,100	5,682
5	4,220	4,507	2,739	4,914	4,446	4,654	6,797
Alleles for the SDDD-LS retrofit designs							
1	261	261	188	213	261	261	414
2	5,559	6,687	4,899	6,120	6,041	4,999	3,292
3	5,054	6,360	4,595	4,758	4,302	3,220	3,061
4	4,221	4,507	2,672	4,662	4,384	5,100	5,682
5	4,221	4,070	2,739	4,914	4,446	4,548	6,684
Alleles for the FEMA P-807 retrofit designs							
1	—	—	—	213	—	—	413
2	—	—	—	2,171	—	—	1,509
3	—	—	—	3,061	—	—	3,061
4	—	—	—	1,207	—	—	250
5	—	—	—	958	—	—	2,137

selected for further investigation are provided in Table 4. The fifth solution, and the first one listed in Table 4, was the initial population used in both of the above analyses. Recall that the two soft-story buildings A4 and A7 were additionally retrofitted following the FEMA P-807 (FEMA 2012) guidelines, and appear at the bottom of Table 4. These five solutions are used for conducting the remaining community-level case studies.

Table 4 shows that the four optimal solutions attempted to retrofit all of the three-story and four-story buildings designed by the 1959 Blue Book (i.e., A4 and A7) demonstrating that these must have represented the most vulnerable structures with potential of causing harm to the population. The algorithm did not allow the counts to reduce to zero to prohibit numerical instabilities in the computations. The two optimal solutions obtained from the optimization using the coupled framework (Solutions 2 and 3) attempted to retrofit most of the outdated buildings, and overall retrofitted many more buildings than the optimal solutions obtained from the optimization which set the SED variables to unity.

Illustration of the Community-Level Framework

In this section, the five solutions provided in Table 4 were analyzed more closely. In all cases, these are real solutions which the search

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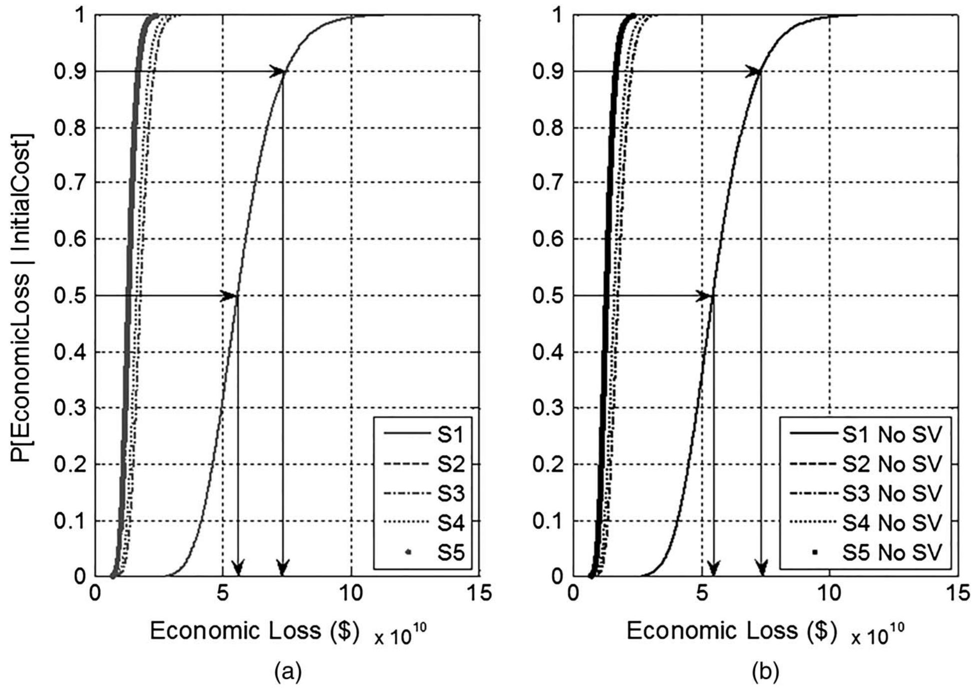

Fig. 8. Probability of nonexceedance for economic loss given a specific initial cost at (2/3) MCE: (a) Los Angeles County SED variables; (b) unit SED variables

algorithm found. The framework was applied at three seismic intensities. Rather than generating random solutions, the five selected solutions were input so that their associated losses could be obtained. (This method of execution is available to decision makers for when they have identified their optimal, or optimal set of, seismic retrofit plans, but would like to investigate the associated losses at multiple scenario events.) The three seismic intensities selected for study here are: 33, 66, and 100% of MCE (Sa $= 0.7$, 1.6, and $2.5g$, respectively) for Los Angeles County. As mentioned above, and discussed in Part I (Sutley et al. 2016), the seismic intensity was not modeled to vary spatially across the building archetypes. Although this is seen as a limitation to the study, it was not believed to compromise the main objectives.

Fig. 8 provides the resulting fragility curves at DBE (Sa $= 1.6g$) for economic loss conditioned on initial cost. The curves in Fig. 8(a) are the estimated loss distributions using the Los Angeles County SED variables, and those in Fig. 8(b) are with unit SED variables. The economic loss distribution was obtained through the computational development in Sutley et al. (2016).

The probabilistic distribution of recovery time was identical for the two cases. As shown, at the MCE intensity, the recovery time was controlled by building repair time which was not computationally modeled with the SED variables incorporated, and therefore gives identical recovery times due to morbidity, and was set at 52 weeks. Therefore, the recovery times were determined to be the same distributions for the two analyses independent of the SED variables' values. The 50th and 90th percentile values were extracted for all five solutions at the three seismic intensities. These values are tabulated for the economic loss fragility in Table 5, and for the number of morbidities fragility in Table 6. The arrows plotted within Fig. 8 demonstrate how the 50th and 90th percentile values were obtained. The abscissa value corresponding to the ordinate value of 0.5 and 0.9 is taken as the 50th and 90th percentile value for economic loss given initial cost for each respective solution. As seen in Fig. 8 and shown in Table 5, the estimated losses were less when the SED variables were set to unity for each respective solution. This held true for the five solutions at each of the three intensity measures for the economic loss and number of morbidities

Table 5. 50th and 90th Percentile Values for Economic Loss

	1/3 MCE		2/3 MCE		MCE	
Solution	50th	90th	50th	90th	50th	90th
S1	913×10^9	1.19×10^{10}	5.58×10^{10}	7.47×10^{10}	1.49×10^{11}	2.01×10^{11}
S1 (unit)	9.03×10^9	1.18×10^{10}	5.47×10^{10}	7.32×10^{10}	1.45×10^{11}	1.97×10^{11}
S2	4.59×10^9	5.92×10^9	1.38×10^{10}	1.78×10^{10}	5.51×10^{10}	7.31×10^{10}
S2 (unit)	4.56×10^9	5.88×10^9	1.35×10^{10}	1.76×10^{10}	5.4×10^{10}	7.17×10^{10}
S3	5.64×10^9	9.13×10^9	1.79×10^{10}	2.33×10^{10}	6.9×10^{10}	9.18×10^{10}
S3 (unit)	5.61×10^9	7.24×10^9	1.77×10^{10}	2.3×10^{10}	6.79×10^{10}	9.03×10^{10}
S4	4.46×10^9	5.73×10^9	1.64×10^{10}	2.13×10^{10}	6.02×10^{10}	7.98×10^{10}
S4 (unit)	4.43×10^9	5.69×10^9	1.62×10^{10}	2.1×10^{10}	5.91×10^{10}	7.85×10^{10}
S5	3.81×10^9	4.89×10^9	1.3×10^{10}	1.68×10^{10}	4.76×10^{10}	6.29×10^{10}
S5 (unit)	3.79×10^9	4.86×10^9	1.28×10^{10}	1.65×10^{10}	4.67×10^{10}	6.17×10^{10}

Table 6. 50th and 90th Percentile Values for the Number of Morbidities

Solution	1/3 MCE 50th	1/3 MCE 90th	2/3 MCE 50th	2/3 MCE 90th	MCE 50th	MCE 90th
S1	3,570	3,920	3.52×10^4	3.98×10^4	1.46×10^5	1.7×10^5
S1 (unit)	1,440	1,570	1.25×10^4	1.39×10^4	5.3×10^4	6.04×10^4
S2	1,370	1,500	4,740	5,190	4.6×10^4	5.24×10^4
S2 (unit)	684	741	1,920	2,080	1.61×10^4	1.8×10^4
S3	1,570	1,710	5,860	6,430	5.12×10^4	5.84×10^4
S3 (unit)	803	872	2,330	2,520	1.83×10^4	2.05×10^4
S4	1,470	1,710	5,690	6,230	5.25×10^4	5.99×10^4
S4 (unit)	737	800	2,370	2,570	1.9×10^4	2.14×10^4
S5	1,210	1,320	4,660	5,090	4.17×10^4	4.74×10^4
S5 (unit)	642	696	1,920	2,080	1.48×10^4	1.65×10^4

loss estimates. The initial population is S1; it had the highest estimated losses for all three seismic intensities independent of the SED variables' values.

To further demonstrate the significance of including the community-specific SED variables in loss estimation and mitigation planning, the 50th percentile values were extracted from the economic loss and number of morbidities fragilities presented above for Solutions S1 and S2 as an example. S1 was selected because it is the initial population, and S2 was selected to represent one of the optimal solutions. The 50th percentile values were not further investigated for the recovery time since these values matched for the two analyses. The 50th percentile values are plotted in Figs. 9 and 10. These figures show that when comparing the estimated losses between the community-specific Los Angeles County SED variables versus setting the SED variables to unity, the difference between values increases as the seismic intensity increases. This finding is also evident from the table inserted into each figure. The percent increase in S1 loss estimations was more significant than the percent increase in S2 loss estimations for both economic loss and the number of morbidities. That is to say, when computing loss estimations for a less resilient building stock, it is even more imperative to include community-specific SED variables—and considerations of the most socially vulnerable—into the loss estimations. Not including SED variables leads to large underestimations in losses, and this is exacerbated for a highly vulnerable population with an outdated or structurally deficient building stock.

In Fig. 10, the percent differences for the number of morbidities are large at all seismic intensities for both solutions. Recall that the

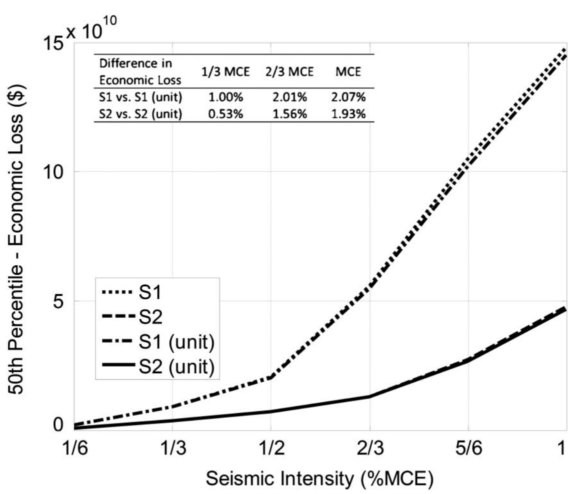

Fig. 9. 50th percentile economic loss versus seismic intensity

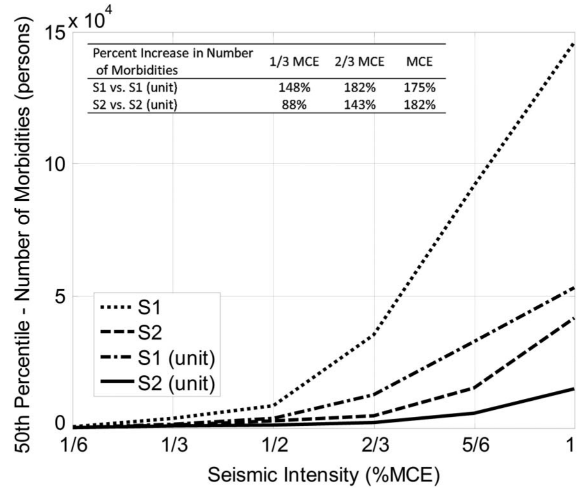

Fig. 10. 50th percentile number of morbidities versus seismic intensity

economic loss is a compilation of the repair costs, and the morbidities costs. Therefore, if the highest contributor to economic loss is repair costs (say for the initial population where the building stock is mostly old and structurally deficient), then one would expect to see a smaller difference in economic loss values when using community-specific versus unit SED variables. The number of morbidities, on the other hand, was completely based upon the morbidities; therefore independent of the building stock design level, one would expect to see major differences in the morbidity count when including the community-specific SED variables.

The percent differences between the economic losses determined when the SED variables are community-specific versus set to unity are provided in the table within Fig. 9, and may seem very small ranging from 0.53 to 2.07%, respectively. However, these small percentages equate to large monetary values (up to $4 billion at MCE). In fact, the small percent differences correspond to millions or even billions of dollars, depending on the earthquake intensity. Furthermore, if the 50th percentile values for economic loss are extracted from Fig. 8, and added to the initial cost for Solutions S1 and S2, then the total financial loss may be investigated. Table 7 provides these computations, along with the percent difference between the total financial losses for S1 and S2. In all cases, the initial population (S1) has a higher estimated total financial loss. This means that although there is no associated initial cost, the estimated economic loss, even for a small earthquake (i.e., 1/3 MCE), is greater than the total financial loss for the retrofitted case. Looking at the change in percent difference for each seismic intensity, the

Table 7. Comparison of Total Financial Loss for Three Case Studies

Solution[a]	Measure	Seismic intensity 1/3 MCE	Seismic intensity 2/3 MCE	Seismic intensity MCE
S1	Initial cost ($)	0	0	0
	Economic loss ($)	9.12×10^9	5.58×10^{10}	1.48×10^{11}
	Sum ($)	9.12×10^9	5.58×10^{10}	1.48×10^{11}
S2	Initial cost ($)	5.32×10^8	5.32×10^8	5.32×10^8
	Economic loss ($)	3.81×10^9	1.30×10^{10}	4.76×10^{10}
	Sum ($)	4.34×10^9	1.35×10^{10}	4.81×10^{10}
Difference in total financial loss (%)		52.4	75.7	67.5

[a]Solution was obtained by using the coupled framework with Los Angeles County SED variables.

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most significant difference occurs at $2/3$ MCE (i.e., DBE) with approximately 76% difference. This has significant implications because DBE is the seismic intensity that could very well be expected to occur in Los Angeles County or other areas along the San Andreas Fault. When considering the reduced number of morbidities associated with the retrofitted solutions, it is clear that retrofitting is a better solution, even if there is a higher associated initial cost.

Breaking down the economic loss model further shows it is the sum of the repair costs, relocation costs, contents damage, cost due to injury, cost due to fatality, cost due to medical treatment of PTSD, and the downtime due to PTSD. All of these values are independent of the community's economic status except the last measure, downtime due to PTSD. The downtime due to PTSD was computed using the mean annual income of the community. Taking this one step further, the estimated number of work hours lost in one year due to employees exhibiting absenteeism and/or presenteeism while suffering from posttraumatic stress disorder may be determined for the current (i.e., initial) population. The 50th percentile value for this measure at DBE, using Eqs. (27) and (29) in Sutley et al. (2016), was computed as 7,200 h for Los Angeles County. Dividing the mean annual income by 260 work days per year at 8 h per day to determine an equivalent hourly rate, the total dollars lost due to downtime, but not medical costs, caused by persons having PTSD was computed as $74 million for Los Angeles County during the first year following the earthquake.

Discussion and Conclusions

This study introduced a multiobjective optimization problem that was solved via genetic algorithm using a coupled socioeconomic and engineering framework designed to improve community resilience by identifying optimal seismic retrofit plans for the woodframe building stock. The retrofit plans may be provided to decision makers to be used in determining where mitigation funds may most effectively be allocated by providing the associated risk with each retrofit plan. It was demonstrated that the retrofitted solutions had a lower total financial loss than the unretrofitted solutions, where total financial loss included the initial cost of retrofitting. When considering the reduced number of morbidities associated with the retrofitted solutions, retrofitting is clearly a better solution.

There are many assumptions and approximations embedded into the framework, which can lead to increasing uncertainty in the estimated losses. With this in mind, the framework was calibrated to meet several reported loss values for the 1994 Northridge earthquake, the most recent major earthquake disaster in the United States. Several illustrative examples were conducted as applications of the coupled socioeconomic and engineering framework for optimizing community seismic resilience. Through the illustrative examples, it was demonstrated that by not including socioeconomic and demographic indicators, and considerations of social vulnerability into the loss estimations, large underestimations in losses clearly result, and are exacerbated for a highly vulnerable population. It was shown that when computing loss estimations for a less resilient building stock, it is even more imperative to include community-specific SED variables into the loss estimations. In fact, difference in predicted economic loss differed by millions, and billions, of dollars depending on the earthquake intensity. This was consistent for all loss estimates, except recovery time for a very intense earthquake because (1) the repair times were not modeled using the SED variables; and (2) a limited number of examples were presented, which did not demonstrate the difference in recovery time due to morbidity. This clearly underscores the need for more robust fully coupled models of community resilience.

Through applying the framework to the Los Angeles County population, the work showed that extreme losses should be expected for the current woodframe building stock if a very large earthquake were to occur (and it is worth noting that Los Angeles is overdue for a very intense earthquake). For a maximum considered earthquake (e.g., 2,475 year return period, $\mathrm{Sa} = 2.5g$), economic loss estimations exceeded $148 billion. This amount was reduced to $47 billion for one of the retrofit plans investigated in the illustrative examples, equating to $101 billion saved by retrofitting. For an earthquake of this intensity, the number of morbidities was estimated at approximately 146,000 people under the current woodframe building stock. This count was reduced to 41,700 persons for one of the retrofit plans investigated, equating to over 104,000 people saved from being injured, killed or developing PTSD. The recovery time was reduced from 119 weeks to 78 weeks, nearly a year, by retrofitting. The aforementioned values were taken at a 50% probability of nonexceedance with the community-specific SED variables included in the analysis.

For a design-basis earthquake (i.e., 475 year return period, $\mathrm{Sa} = 1.6g$), the estimated economic loss and number of morbidities for the current building stock in Los Angeles County was $56 billion and 35,200 persons, respectively. When the optimal retrofit plan was implemented, these values were reduced to $13 billion and 4,660 persons, respectively. That means that $43 billion could be saved by retrofitting, and over 30,000 people could be saved from injury, fatality, or PTSD given a design-level earthquake. Moreover, the recovery time was reduced from 117 weeks to 52 weeks by retrofitting, over a year's worth of time saved.

The loss values in both cases are still high, although they were reduced by an order of magnitude for the MCE event, and reduced by a factor of 4 or more for the DBE event. A greater reduction could potentially be achieved if the input parameters to the genetic algorithm were increased allowing for more solutions to be explored. Economic loss reports following the 1994 Northridge earthquake ($\mathrm{Sa} = 1.1g$) reached $49 billion. In this study, the initial population for the focal community was estimated to incur $56 billion and $148 billion for a DBE event and MCE event, respectively. Due to the increases in ground motion intensity, the number of fatalities and the number of households required to relocate would subsequently be much higher and, severely increasing the total economic loss.

In the application presented above, the total financial loss (e.g., initial cost + economic loss) was higher for the unretrofitted case. When combining these financial savings with the reduced number of morbidities, it is clear that the higher initial cost associated with retrofitting the woodframe building stock greatly outweighs the risks and losses associated with not retrofitting. The largest difference in total financial loss was demonstrated to occur at a DBE seismic intensity. This finding should further encourage retrofit since a DBE event is very likely to occur in Los Angeles County.

An additional innovative feature of this work was the demonstrated importance of including the emotional health of the population for the community's economy and recovery. The 50th percentile values for the total number of work hours lost due to employees having PTSD was estimated as 7,200 h for Los Angeles County for a DBE seismic intensity. These hour estimates equated to $74 million in financial loss for the commercial industry based on the mean annual income. Considering these large estimated losses for a design bases earthquake, it is clear that including the mental health of the population is critical for recovery following disastrous events such as earthquakes, and it is important for future studies to take mental health measures such as PTSD morbidities into account.

In conclusion, this work has demonstrated the importance of coupling engineering and socioeconomic systems in community resilience research. Moreover, it has built on prior work that has shown the importance of retrofitting the existing building stock, while it has advanced knowledge by considering new variables such as morbidities with a specific emphasis on PTSD. Future investments should be made to ensure that this work is accessible to practitioners through the development of a graphical user interface.

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References

FEMA (Federal Emergency Management Agency). (2012). "Seismic performance assessment of buildings." *FEMA P-58-1*, Applied Technology Council (ATC), Redwood City, CA.

Goldberg, D. (1989). *Genetic algorithms in search optimization and machine learning*, Addison Wiley Longman, Reading, MA.

Jones, L. M., et al. (2008). "The shake out scenario." *USGS Open File Rep.-2008-1150, CGS Preliminary Rep. 25*, Sacramento, CA.

MATLAB [Computer software]. MathWorks, Natick, MA.

Reitherman, R., and Cobeen, K., (2003). "Design documentation of woodframe project index buildings." *CUREE Publication No. 29*, Federal Emergency Management Agency, Washington, DC.

Schierle, G. G., (2003). "Northridge earthquake field investigations: Statistical analysis of woodframe damage." *CUREE Publication No. W-09*, Federal Emergency Management Agency, Washington, DC.

Sutley, E. J., van de Lindt, J. W., and Peek, L. (2016). "Community-level framework for seismic resiliency. I: Coupling social vulnerability and engineering building systems." *Nat. Hazards Rev.,* 04016014.

U.S. Census Bureau. (2010). "State and county quickfact." ⟨http://quickfacts.census.gov⟩ (Apr. 25, 2014).