Integrating Household Decisions in Quantifying the Seismic Resilience of Communities Subjected to a Sequence of Earthquakes

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ABSTRACT

A distributed simulation model is presented that integrates post-earthquake household decisions into quantifying the seismic resilience of communities subjected to a sequence of earthquakes. A Simple Multi-Attribute Rating Technique (SMART) is used to model post-earthquake household decision making at the building level while the earthquake sequence is modeled using time-dependent analysis during recovery from the first shock. Incremental dynamic analysis is used to develop fragility curves for first shock-damaged structures which are distinguished from the conventional fragility curves of undamaged structures. A case study of a prototype community that comprises households with different socio-economic characteristics in accordance with a typical small U.S. community is used to show the influence that household decisions have on the overall seismic resilience of the community. The results suggest that seismic events with a larger first shock have a more severe impact on the seismic resilience of communities than events with a smaller first shock regardless of the magnitude of the subsequent shock.

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INTRODUCTION

Severe earthquakes are rare events whose occurrence can lead to catastrophic social and economic losses. The extent of these losses plays a key role in the post-disaster decision of households to stay or abandon their residence within the community. The decision to leave can profoundly influence the recovery trajectory of the overall community since population loss can lead to a reduction in the allocated federal and state disaster funds (Xiao and Van Zandt 2012). The resulting cycle, whereby population loss leads to a reduction in the influx of disaster relief funds, slows down recovery and promotes further population loss. This cycle can severely hamper the long-term recovery of a community. The process, which is dynamic in nature, is not well understood at present and provides general motivation for this research.

The few available studies of post-event household decisions after various types of natural disasters (Brokopp et al. 2015, Nejat et al. 2016, Hikichi et al. 2017, Cong et al. 2018, and Burton et al. 2018) typically focus on three dimensions: 1) the types of decisions made by the households (repair, demolish and rebuild, abandon, etc.); 2) the factors affecting household decision (repair cost, household income, insurance coverage, etc.); and 3) the rules used to predict the decisions made by households. Chandrasekhar and Finn (2015) performed a field study after hurricane Sandy by distributing 100 surveys to homes within the Rockaways Peninsula of New York City. Three types of decisions made by households were reported: stay, undecided, or relocate. Based on the response of households to the survey, three factors were noted to affect the decisions made by households: social interaction (i.e., interaction with different civic groups and organizations), ability to find a job after the hurricane, and ability to find support from organizations to repair their damaged houses. Polese et al. (2018) studied the decisions made by different owners of severely damaged RC buildings after the L’Aquila earthquake in Italy. The study focused on the decision to repair or demolish/rebuild as a function of repair and retrofit costs, construction age, number of stories above ground, floor area, and total area covered. Markhvida and Baker (2018) proposed a framework that combines performance-based engineering with the decisions made by building owners based on real estate investment analysis. Burton et al. (2019) developed a housing recovery model that accounts for the decisions made by the households in the community after seismic events.

None of the above studies accounted for the time-dependent nature of the problem, i.e., that household decision may vary during the recovery stage, nor did they consider the effect of earthquake sequences. Studies that considered the effect of earthquake sequences have focused only on individual building behavior and not community response, e.g., Li et al. 2014, Ryu et al. 2011, Abdelnaby 2017, Silwal and Ozbulut 2018, and Abdollahzadeh et al. 2019. Yet, earthquake sequences can have a profound effect on community resilience as evinced by the 2010-11 Canterbury earthquakes (Potter et al. 2015 and Wilson 2013) and the 2011 Tohoku seismic events (Nojima 2012). To address the identified drawbacks in this little studied area, a distributed computing platform is used to dynamically model the response of communities subjected to earthquake sequences. The platform connects simulators, each of which addresses a particular aspect of the seismic resilience of communities (social, engineering and economic), while stepping through time. Deviating from most of the previous studies, this work incorporates household decisions at the building level rather than in an aggregate manner.

The simulation model used in this paper employs different structural, social and economic parameters in predicting household decisions based on detailed models of each building, i.e. actual downtime and repair costs evaluated at the component level as discussed in Sediek et al. (2019a,b). These decisions are then considered in the recovery behavior of the community. Incremental dynamic analysis (IDA) (Vamvatsikos and Cornell 2002) is used to develop fragility curves for different archetypes of buildings to accurately account for the reduction in strength of the building set due to the effect of the first shock. The ability of the simulation model to step through time allows community response to be modeled during the different stages of the disaster, i.e., during the first shock, recovery from the first shock, during the second shock, and recovery from the second shock taking into account the actual state of the community at the time of each event. The proposed simulation model is demonstrated through a case study in which a small virtual community named "*Pseudo City*" is developed and then subjected to earthquake sequences to investigate its resilience.

SIMULATION MODEL OVERVIEW

Figure 1 shows the simulation model implemented in this study which extends the work in Sediek et al. (2019a,b) and Sediek et al. (2020a,b). The simulation model is designed to be modular where each aspect of the community is represented by a "simulator", which is considered as a separate unit in the model. The simulators are connected together through a distributed computing scheme. The simulation model explicitly models the different stages of the disaster (i.e., first shock and second shock) and the recovery of the community.

The proposed model is divided into seven different stages (see appended numbers in the simulator boxes in Figure 1). In stage 0, the *city simulator* broadcasts the attributes of the studied community. During stage 1, *the ground motion*, *structural analysis*, *building damage*, *component damage*, *casualties*, and *debris* simulators step through time (time step in sub-seconds) to simulate real-time seismic damage and losses associated with the first shock. At stage 2, the *repair cost*, *downtime*, and *unsafe placard* simulators run for one time step to evaluate the final seismic losses resulting from the first shock. During stage 3, the *available resources*, *physical recovery*, *downtime*, *household decision*, *healthcare system*, *social recovery*, and *total recovery* simulators step through time (time step in days) to simulate the real-time recovery of the community from the first shock until the second shock is triggered by the *ground motion simulator*. During stages 4 and 5, the same procedures are repeated from stages 1 and 2, respectively, for the second shock while considering the state of the community and its buildings at the point when the second shock occurs. The final stage, stage 6, is where the recovery of the community is simulated and the seismic resilience of the community to the earthquake sequence is evaluated. More details about the implementation of each simulator can be found in Sediek et al. (2020a) and the MATLAB simulators developed/used in this study can be found in Sediek et al. (2021)

DISTRIBUTED COMPUTING ENVIRONMENT

Unlike the previous studies in Sediek et al. (2019a) and Sediek et al. (2020a), distributed computing in the simulation model in this study is enabled by the *Simple Run-Time Infrastructure* (SRTI 2019) developed at the University of Michigan under Project ICoR (Interdependencies in Community Resilience (ICoR 2019)). SRTI (2019) is designed to handle the data traffic between simulators. It ensures that data published by a simulator is directed to the simulator that needs to subscribe to it. This manner of passing data makes the proposed simulation model scalable and expandable. Adding/modifying any simulator in the model is a straightforward task where a user can add/modify any simulator without affecting the other simulators in the system as long as the outputs and inputs remain the same.

The simulators can run on the same machine or on different machines to allow for the reuse of existing simulation models and distribution of execution cost of complex models to multiple nodes/processors (Lin et al. 2020, 2021). Figure 2 shows the distributed computing architecture of the proposed simulation model using the SRTI server. The *Time Manager simulator* shown in Figure 2 controls time stepping and the order of execution of the simulators within each time step. The developed *Time Manager* and other simulators in this study can be found in Sediek et al. (2021).

MODELING POST-EARTHQUAKE DECISIONS OF HOUSEHOLDS

The *household decision simulator* models the decision making process of a household; it (1) defines the possible decisions that can be made by the household in the wake of the earthquake, (2) defines and quantify the attributes that affect the household decision, and (3) formulates appropriate decision rule to predict household behavior. For the sake of simplicity, the simulator is limited to decisions made by those residing in single-family homes (one family per building). Decisions made by commercial building owners and residence of multifamily homes are outside the scope of this study but could conceivably be included using a similar methodology to that adopted here.

Each household in the community is assumed to make one of three possible decisions after an earthquake. The first decision is “repair” which means that the household will do all the repairs required to restore the house to full functionality as specified in FEMA P-58 (FEMA 2012). The second alternative is “demolish” which means that the household will demolish and rebuild the house according to current seismic provisions (code A as specified in Sediek et al. (2020a)). The last decision is “abandon” which means that the household will leave the community without doing the first two options. In that case, the house is removed from the repair list in the *physical recovery simulator* and the functionality of that building is set to zero during the recovery stages (i.e., stage 3 and 6). Also, the population of the community is reduced by the number of persons in that house, i.e., population loss.

The decision made by households are evaluated each time step during the recovery stage (stages 3 and 6 shown in Figure 1) as the conditions change. Households that made a “repair” decision at a given time step will have three options in the next time step (repair, demolish or abandon). On the other hand, households that made a “demolish” decision will only have two options (demolish or abandon). It is assumed that households that made an “abandon” decision cannot return to either “repair” or “demolish” decisions and their houses are therefore removed from the repair list in the *physical recovery simulator*. Clearly, it is conceivable that households could reverse this decision, thus prompting a return of their homes back to the repair list in the *physical recovery simulator*. However, these cases are considered beyond the scope of the proposed simulation model. Treating the household decision as a time-dependent variable allows for modeling the variation of household decisions during the recovery from the first shock as well as the damage caused by the second shock.

Decisions are based on the set of structural, economic and social attributes listed in Table 1 and are related to the socioeconomic characteristics of the household and the extent of damage the building suffered during the earthquake. Structural attributes include the construction age of the house and expected downtime, which is computed during the recovery stage by the *downtime simulator* as discussed in Sediek et al. (2020a). Although structural repairability is not included as an attribute in Table 1, it is automatically considered in FEMA P-58 (FEMA 2012), which is adopted in the current study. In other words, if the structure is irreparable then it will be automatically replaced in FEMA P-58 and the household will then have one of two options “demolish” or “abandon. Repair will not be an option in this case. Economic attributes include the repair cost evaluated by the *repair cost simulator*, insurance coverage, household income, post-earthquake employment status, and disaster relief support received from organizations such as FEMA. Social attributes include social interaction of the household with the surrounding community, length of residence in the community, full-time residency, immigration status, racial and ethnic minority status, and affected students in the household evaluated based on the functionality of the surrounding schools in the community subscribed from the *physical recovery simulator*.

As shown in Table 1, the attributes affecting the decisions made by households can be classified into two types: binary or continuous. Binary attributes have only two possible values while continuous attributes can have any value within a specific range. For instance, the post-earthquake employment status of the household is a binary attribute where the possible values are employed or unemployed. However, household income is a continuous attribute that can take any value between the minimum and maximum household income in the community. A unified scale is necessary to add the effects of different types of attributes on the decisions made by households. To do so, continuous attributes, except downtime and repair cost, are first normalized using the following equation:

$$Z_i = \frac{Y_i - Y_{i,min}}{Y_{i,max} - Y_{i,min}} \tag{1}$$

where, Z_i is the normalized attribute i, Y_i is the value of attribute *i* before normalization, and $Y_{i,min}$ and $Y_{i,max}$ are the minimum and maximum values of attribute *i*, respectively. The downtime and repair cost of the house are normalized with respect to the replacement time and cost of the house, respectively. For binary attributes, two values are used (1 for yes and -1 for no). For example, insurance coverage is 1 if the building is insured and -1 if uninsured. The second step is to map the normalized continuous attributes to corresponding binary values. To do so, the following formula is used:

$$X_i = \begin{cases} 1 & Z_i \geq 0.5 \\ -1 & Z_i < 0.5 \end{cases} \tag{2}$$

where, X_i is the mapped binary value of attribute *i* and Z_i is the normalized attribute *i* evaluated from Eq.(1).

The attractiveness of a decision is evaluated using the Simple Multi-Attribute Rating Technique (SMART) (Edwards 1971) which is widely used due to its efficiency and simplicity in modeling human decisions. The SMART technique is based on a linear additive model where the overall value of a specific decision k is evaluated using the total sum of the performance score of each attribute multiplied by the weight of that attribute. The SMART technique is modified to consider both the combination of different types of attributes (i.e. continuous and binary attributes) and the different effect of each attribute on different decisions (i.e. one attribute may possess a positive effect on a decision while it possesses a negative effect on another decision). For instance, high repair cost (i.e. $X_3 = 1$) has a positive effect on "demolish" and "abandon" decisions, while it has a negative effect on the "repair" decision. The first challenge is addressed by mapping all of the attributes to an equivalent binary value (X_i) which is used as the performance score of each attribute. The second challenge is addressed by the sign of the weights in the weight's matrix shown in Table 1. The key idea of the SMART technique is that the higher the total score of a specific decision, the higher expectation of the household to make that decision, and vice versa. The total score associated with each type of decision can be represented mathematically as follows:

$$U_k(t) = \sum_{i=1}^{12} w_{ik} * X_i(t) \qquad \forall\, K \epsilon \{1,2,3\} \tag{3}$$

where $U_k(t)$ is the total score for decision k at time step t, k is an index for the available decisions (1 for repair, 2 for demolish and 3 for abandon), $X_i(t)$ is the binary value of attribute i evaluated from Eq.(2) at time step t, and w_{ik} is the weight that represents the effect of attribute i on decision k.

The uncertainty in the influence of the considered attributes on different decisions is considered by assuming $w_{ik}'s$ to be random variables having lognormal distributions with median of 1 and dispersion of 0.4. However, due to the scalability and adaptability of the proposed model, these values can be refined as more data becomes available from real communities (i.e. surveys from real households). After evaluating $U_k(t)$ for each decision k at time step t, the household will choose the decision with maximum $U_k(t)$. Table 2 shows the attributes of three different hypothetical example households in the same community (hypothetical community for illustration purposes), Table 3 shows the weights matrix for the example households, and Table 4 shows the evaluation of their post-earthquake decision to showcase the realism of the proposed model and its potential to simulate the behavior of households in the wake of earthquakes.

MODELING THE SECOND SHOCK

The effect of the second shock on the studied community is considered in the simulation model by running the same simulators from stage 1 shown in Figure 1 (i.e., *ground motion*, *building damage*, etc.) with updated building capacities (i.e., fragilities) to reflect damage to a building from the first shock. To this end, incremental dynamic analysis (IDA: Vamvatsikos and Cornell 2002) is used to develop fragility curves for the first shock-damaged structures in the community which are distinguished in the presented study from the fragility curves associate with the undamaged structures.

Building Models

Three different building materials are considered: steel, RC, and wood buildings to simulate the distribution of building archetypes at the community level. Steel buildings are assumed to be the same as the special moment frame prototype buildings designed in NIST (2010) with four different heights: 2, 4, 8, and 20 stories. The buildings have three-bay steel SMFs on each of their exterior sides, which are assumed to resist all the seismic demands on the building. The interior frames are gravity frames that do not contribute to the seismic resistance of the building. The frames were designed with W24 columns and reduced beam sections (RBS) using ASTM A992 steel. The behavior of the steel archetype buildings is represented by 2D concentrated plasticity *OpenSees* (McKenna et al. 2000) models of the perimeter SMFs. In 2D concentrated plasticity models, the beams and columns of SMFs are modeled using elastic beam-column elements and connected by zeroLength elements which serve as rotational springs to represent the structure's nonlinear behavior. The springs follow a bilinear hysteretic response based on the Modified Ibarra Krawinkler Deterioration Model (Ibarra et al. 2005) to simulate the strength and stiffness deterioration properties due to cyclic loading. A leaning column with gravity loads is linked to the frame by truss elements to simulate P-Delta effects. The parameters of the Modified Ibarra Krawinkler Deterioration Model are quantified using the experimental database of Lignos and Krawinkler (2012).

RC buildings are assumed to be the same as the space special moment frame prototype buildings designed in Haselton and Deierlein (2007) and FEMA P695 (2009) with four different heights: 4, 8, 12, and 20 stories. They consist of four RC special moment resisting frames in each direction, which are assumed to resist all the seismic demands on the building. The bay width of the typical RC special moment resisting frame varies from 6.1 m (20 ft) for the 8 and 12 story buildings to 9.1 m (30 ft) for the 4 story building. For all building heights, the first story height is 4.57 m (15 ft) and the typical upper story height is 3.96 m (13 ft). The building is designed for a general high seismic site in California (Design category D, soil class D, S_{ms} = 1.5g, and S_{m1} = 0.9g). The longitudinal rebar diameters commonly used in the beams and columns are 25 mm (#8) and 28 mm (#9) with yield strength of 400 MPa (60 ksi). The design dead and live loads are 8 kN/m^2 (175 psf) and 2.4 kN/m^2 (50 psf), respectively. Further design details can be found in Haselton (2006). The same abovementioned modeling approach is used to simulate the behavior of the RC archetype buildings except that the parameters of the modified Ibarra-Medina-Krawinkler deterioration model (Ibarra et al. 2005) are quantified using the equations proposed by Haselton and Deierlein (2007) based on calibration to previous flexural column tests.

The seismic demands of the wood-framed buildings are assumed to be resisted by wood shear walls. The behavior of the wood archetype buildings is represented by 3D *OpenSees* (McKenna et al. 2000) models of a conventional 2 ft × 6 ft (609.6 mm × 1828.8 mm) shear wall with overall dimensions of 8 ft × 8 ft (2438.4 mm × 2438.4 mm). The wood shear wall consists of an Oriented Strand Board (OSB) attached to horizontal and vertical framing members through equally spaced nails that provide the lateral strength to the wood shear walls. The wood framing members are modeled using elastic beam columns while the OSB is modeled using shell elements (ShellMTC4 in *OpenSees*). The nails that connect the OSB to the framing members are modeled using zero length elements. The cyclic behavior of the sheathing-to-framing connectors (i.e. the nails) is modeled using the *SAWS* material model developed by the CUREE-Caltech Wood frame Project (Folz and Filliatrault 2001) and implemented in *OpenSees* (McKenna et al. 2000). The nonlinear nailing parameters are calibrated to physical data by Kong (2015). More details about the modeling approach of wood shear walls can be found in Kong (2015).

Ground Motions

A suite of 22 far field ground motions (FEMA 2009) is used for both the first shock and second shock records to model the variability in both the mainshock and aftershock. The magnitude for each of the ground motions was between M6.5 and M7.6. Spectral scaling at a period of 0.21 s with 5% elastic damping was used. There are many methodologies for modeling of ground motion sequences (e.g., Ryu et al. 2011, Hu et al. 2018, Khansefid and Bakhshi 2019, and Nithin et al. 2020). In this work, the second shock records are selected randomly from the 22 ground motions to represent the variability between the first shock and the second shock records as per Nazari1et al. (2013) and Ryu et al. (2011). The earthquake sequences are applied to the *OpenSees* models by applying the first shock record, then waiting 20 seconds (i.e., applying a zero magnitude ground motion acceleration for twenty seconds of the time history) and then applying the second shock record. The spectral acceleration at the fundamental period of each building archetype with a damping ratio of 5% (*Sa* (T_1, *5%*)) is used as the ground motion intensity measure for the first shock and second shock.

Fragility of Intact Buildings

Incremental dynamic analysis (IDA) is performed using a total of 44 ground motion records (two components for each earthquake). Due to space limitations, the resulting IDA curves of one representative building archetype (steel 8-story SMF) are shown in Figure 3(a). Four damage states are defined in the developed fragility curves based on the HAZUS methodology (FEMA 2003): slight, moderate, extensive, and complete. The description of each damage state for each building archetype can be found in FEMA (2003). The engineering demand parameter (*edp*) used to define each damage state is the average inter-story drift ratio which is defined in FEMA (2003) as the roof displacement divided by the building height. The peak *edp* for each damage state for each design code (i.e., code A, B, and C defined in Sediek et al. (2020a)) is defined also in FEMA (2003) and shown for the representative building archetype (with code A) in Figure 3(a). The resulting fragility curves for the intact steel 8-story SMF archetype are shown in Figure 3(b).

Fragility of First Shock-Damaged Buildings

Three different IDAs are performed for each first shock-damaged building based on the post-first shock damage state (i.e., slight, moderate, or extensive). The post-first shock damage state is associated with the peak first shock response which is assumed to be uncertain for each damage state (Ryu et al. 2011). The peak first shock response is assumed to have a lognormal distribution with a median equal to the median threshold for each damage state based on the limits defined in FEMA (2003) and a dispersion of 0.4 (Ryu et al. 2011). The first shock record is scaled so that the peak first shock response is equal to the target response. The IDA is then performed using sequences of first shock-second shock records where the second shock is scaled up to collapse. Due to residual deformation resulting from the first shock, the direction of the second shock plays an important role in the response of the buildings. Thus, the second shock responses are computed by applying both positive and negative scaling factors to the second shock records and considering the larger response. These procedures are then repeated for each building archetype (total of 9), design code (3 for each archetype) and post-first shock damage state (3 for each archetype) resulting in a total set of 108 fragility curves (intact and damaged). The parameters of the fragility curves of the 9 considered building archetypes with the latest and most stringent design code (code A) are listed in Table 6.

Damage and loss estimation

The *building damage simulator* evaluates the new damage states of the buildings during the second shock using the ground intensity measure at each building subscribed from the *ground motion simulator* (i.e. S_a (T_1, *5%*)). The new capacities of the buildings (limits of different damage states) are evaluated using the developed fragility curves based on the flowchart shown in Figure 4. It is assumed that partially repaired buildings at the time of the second shock are at the same first shock damage state (i.e., damaged fragilities are used). The *component damage simulator* subscribes to the building damage states and the structural responses from the *building damage* and *structural analysis* simulators, respectively, where the new damage states of all the components are evaluated using the log-normal fitted responses (engineering demand parameters) from the IDAs described earlier based on the post-first shock damage state of the building.

The damage states of buildings and their components during and after the second shock stage depend on the damage states resulting from the first shock and the repair status of the buildings at the time of the second shock (obtained from stage 3 shown in Figure 1), which demonstrates the necessity of using time-dependent analysis. The *casualties simulator* subscribes to the building and component damage states in the community from the *building damage* and *component damage simulators*, respectively, to evaluate the casualties resulting from the second shock in buildings that are in the re-occupancy functionality state (RO) (obtained from the *physical recovery simulator* at the end of stage 3 (see Figure 1)). Casualties in temporary shelters after the first shock are not considered in the scope of this study. The debris, repair cost and unsafe placard status of the buildings are evaluated based on the new damage states of the buildings and their components after the second shock (i.e., after stage 4 shown in Figure 1). The downtime of the building after a second shock, DT_{AS}, is calculated using the flowchart in Figure 6 and:

$$DT_{AS} = T_{AS} + T_{imp}^{AS} + T_{rep}^{AS} \tag{4}$$

where DT_{AS} is the downtime of the building after the second shock defined from the beginning of stage 3 (see Figure 1), T_{AS} is the time of the second shock defined from the beginning of stage 3, T_{imp}^{AS} is the delay time due to the impeding factors after the second shock defined from the beginning of stage 6 (see Figure 1), T_{rep}^{AS} the time required to repair all the components in the building after the second shock, and DT_{MS} is the downtime of the building after the first shock defined from the beginning of stage 3 (see Figure 1).

Based on the new seismic losses evaluated in stages 4 and 5 (see Figure 1), the *physical recovery simulator* evaluates the new functionality of the buildings. Then, all the simulators in stage 6 continue evaluating the recovery paths of the community considering both the first shock and second shock.

CASE STUDY: SEISMIC RESILIENCE OF PSEUDO CITY

Building Portfolio

A simplified protype community named “*Pseudo City*” is developed and modeled in order to demonstrate the capabilities of the simulation model. Figure 6 shows the spatial distribution of the buildings in *Pseudo City*. It consists of nine blocks or zones with a total of 1094 buildings and a population of approximately 8,000. Each zone represents households with different socioeconomic characteristics. The buildings have different occupancies, structural systems, heights and design codes leading to a total of 29 different archetypes that are listed in Table 7 and designated according to the naming scheme described in Sediek et al. (2020a). The buildings are designated as ABC-D-E, where “A” is the material, “B” is the structural system, “C” is the design code, “D” is the number of stories and “E” is the occupancy of the building. For example, “CFA-12-1” is a concrete moment frame, new code (after 1994) 12-story commercial building. The naming scheme used by the *city simulator* is listed in Table 8. Most of the buildings are wooden residential buildings designed according to old codes which are typical of U.S. communities (Sediek et al. 2020a). The distribution of construction age and building type in *Pseudo City* (i.e., numbers listed in Table 7) is taken as the same as in Shelby county (NCSA 2018). More information about the distribution of the buildings in *Pseudo City* can be found in Sediek et al. (2021).

The total number of construction workers available in *Pseudo City* before the earthquake is taken as 300, which is approximately 3.5% of the community’s population representing the same percentage of construction workers in the U.S. population as per data from the Bureau of Labor Statistics (BLS 2019). Table 9 lists the distribution of different skilled laborers associated with repair of building infrastructure in *Pseudo City* based on the demand for each skill set evaluated using the REDi methodology (Almufti and wilford 2013). The proposed model deals with the availability of construction workers in a rigorous manner where the availability of construction workers with different skills is considered separately in the *Available Resources simulator*. Although the uncertainty of the availability of workers in the community is not explicitly modeled, they are implicitly considered in the "*available resources simulator*" shown in Figure 1. In this simulator, the number of available workers at each time step is related to the number of injuries in the community at this time step which is uncertain as described in Sediek et al. (2020). The repair of the buildings is prioritized as in Sediek et al. (2020a). Repair priority used in this research is as follows: hospitals, schools, residential houses, commercial buildings, retail and other occupancies.

Socioeconomic characteristics of households

Each zone of *Pseudo City* is defined by a median household income (high income *HI*, moderate income *MI*, and low income *LI*) and the social interaction of the households within the community (high social *HS*, moderate social *MS*, and low social *LS*). The density of the buildings in each zone is assumed to be proportional to the household income level as shown in Figure 6. The median annual household income in *Pseudo City* is around $60,000, which is close to the national median (US Census Bureau 2017(a)). According to Pressman (2015), the income of middle class households is between 67 percent and 200 percent of the national median. Thus, low income (*LI*) is defined as below $40,000, moderate income (*MI*) is defined between $40,000 and $120,000, and high income (*HI*) is defined as above $120,000. The distribution of household income in *Pseudo City* is taken the same as the 2017 distribution of household income in the U.S. (US Census Bureau 2017 (a)).

The social interaction of a household within the community is defined by the social network possessed by the household, neighborhood civic interaction, and engagement in community activities. It is quantified by an index that describes the degree of engagement of the household in the community. In real cities, this index can be measured through surveys. For *Pseudo City*, the social interaction index of the households in the community is randomized between the different zones to have low interaction (*LS*) below 33%, moderate interaction (*MS*) between 33% and 67%, and high interaction (*HS*) above 67%. Table 10 shows the distribution of building occupation, household income and social interaction in different zones of *Pseudo City*.

The damage caused by earthquakes is not typically covered by a standard homeowner insurance policy in the U.S. According to the Insurance Information Institute (I.I.I 2018), only 8% of homeowners who responded to a poll in May 2016 said they have earthquake insurance. In the Western US, this percentage can be as high as 14%. Based on these numbers, it is assumed that 10% of households in *Pseudo City* have earthquake insurance. It is also assumed that 90% of the households without insurance will receive government support after the earthquake. Modeling the interaction between the households and the government to receive disaster assistance after the earthquake is not within the scope of this study.

The length of residence of a household in *Pseudo City* is randomized with a lognormal distribution having a mean of 13 years, which is the average length of residence of households in U.S. communities (Emrath 2013). Around 25% of households in *Pseudo City* are considered racial minorities, which is the same percentage of racial minorities in the U.S. (US Census Bureau 2017 (b)). Only 41.4% of households in *Pseudo City* are assumed to have children in school (i.e. under 18 years old) matching the national average (NCES 2019). Based on national average data, 29% of these households have children in elementary or middle schools and 12.4% have children in high schools (NCES 2019). The students are assigned to the nearest school in *Pseudo City* based on the location of their home. More details about *Pseudo City* can be found in Sediek et al. (2021).

Seismic Hazard

Pseudo city is assumed to be located in the New Madrid seismic zone. The scenario earthquakes are assumed to have an epicenter at 35°18'N, 90°18'W shown in Figure 6 as per Adachi and Ellingwood (2009). Two ground motion records are used to represent feasible seismic activity at this location: RSN 1961 (designated as EQ1) and RSN 5223 (designated as EQ2) from NGA-East -- Central & Eastern North-America database in PEER (2019) recorded by the Lepanto Station. These ground motion records have been used by Lin and El-Tawil (2020) for the same seismic zone. The ground motion records are scaled at each building location to meet the PGA for a M_w 7.7 (for EQ1) and M_w 6.3 (for EQ2) earthquake scenario specified by USGS (2018) for this location. EQ1 is assumed to occur on a weekday at 11:00 AM while EQ2 is assumed to occur also on a weekday but at 8:00 PM. Figure 7 shows the scaled ground motion history for the two earthquakes at the location of one arbitrary building in *Pseudo City*.

Effect of Post-Earthquake Household Decisions

To account for the many uncertainties in the proposed methodology (i.e., damage, loss, and household decision assessment), the proposed model uses a Monte Carlo procedure to perform seismic resilience assessment. The sampling is performed based on the distribution properties of each aspect specified in the FEMA P-58 methodology (FEMA 2012) related to the component damage, component repair cost and time, and casualties associated with the damage of each component as well as the distribution of household decision weights matrix described earlier. FEMA P-58 evaluates the damage state of each structural and nonstructural component in each building in the community at each time step during the earthquake (for the non-collapsed buildings) probabilistically based on the fragility curves specified in the FEMA P-58 database (FEMA 2012b). The damage states are then converted probabilistically into seismic losses (downtime, repair cost and casualties) using the consequence functions specified in the FEMA P-58 database (FEMA 2012b). All results presented are based on 500 realizations for each earthquake (i.e., EQ1 and EQ2). The number of realizations is selected based on a sensitivity study where the number of simulations is progressively increased until convergence occurs (after 500 simulations). Convergence is deemed to occur when changes in the range, mean and standard deviation of the recovery time (T_{RE}) and resilience index ($\%R$) do not exceed 10%. The results of the shown case study are fully documented in Sediek et al. (2021).

Figure 8 (a) and (b) show the evolution of the physical recovery of *Pseudo City* after EQ1 and EQ2, respectively for the conducted Monte Carlo simulations “recovery clouds” as well as the mean recovery trajectory. The term “recovery clouds” was previously used by Burton et al. (2019) and Sediek et al. (2020a) to show the full range of possible recovery trajectories taking into consideration the inherent uncertainties in the proposed methodology. As shown, EQ1 and EQ2 reduced the functionality of the *Pseudo City* to 42% and 81% on average, respectively.

Figure 8 (c) and (d) show the spatial distribution of post-earthquake household decisions in *Pseudo City* just after either EQ1 or EQ2 for one arbitrary Monte Carlo simulation. As shown, the percentage of households that decided to leave the community is significantly higher in zones with low to moderate household income for both earthquakes, which emphasizes the importance of considering the socioeconomic characteristics of the households in the community. Also, the percentage of households that decided to leave the community is significantly lower in zones with high social interaction for both earthquakes. After EQ1, only 2.5% of households decided to leave the community in zone 7 (*LI/HS*) while 14% of households decided to leave the community in zone 9 (*LI/LS*). Whereas, for EQ2, only 0.8% of households decided to leave the community in zone 7 (*LI/HS*) while 6.9% of households decided to leave the community in zone 9 (*LI/LS*). It should be noted that these results are for demonstration purposes and can be refined as more data is available.

To demonstrate the significance of considering households decisions in quantifying the seismic resilience of communities, Figure 9 compares the physical recovery trajectory of *Pseudo City* with and without considering the effect of household decisions on the functionality of the community for either earthquake (i.e., EQ1 and EQ2). The recovery of the community is affected in three ways: the final restored functionality ($\%Q_{max}$), the recovery time to maximum functionality (T_{RE}), and the physical resilience index defined as the normalized area under the physical recovery trajectory ($\%R_p$). *Pseudo City* recovered only 90% and 95% of its full functionality due to the abandoned houses for EQ1 and EQ2, respectively. These trends agree with the results from the recovery model proposed in Burton et al. (2019) and demonstrated on Koreatown, East Hollywood and Lomita neighborhoods in Los Angeles.

The recovery time (T_{RE}) decreased when considering the effect of household decisions from 160 weeks (~3.1 years) to 140 weeks (~2.7 years) and from 90 weeks (~1.7 years) to 75 weeks (~1.4 years) for EQ1 and EQ2, respectively. This decrease is attributed to the number of abandoned houses which are removed from the repair list in the *physical functionality simulator* thereby increasing the availability of resources for repair of other buildings (i.e., availability of construction workers in the community). Finally, the physical resilience index ($\%R_p$) decreased from 93% to 85% when considering the effect of household decisions for EQ1 which is about a 10% reduction (demonstrated by the shaded area in Figure 9 (a)) suggesting the importance of considering the interdependency between the decisions made by households after the earthquake and the functionality of communities. For EQ2, the reduction in the resilience index is only 4% (from 98% to 94%) suggesting that the effect of household decisions is only significant in the case of larger magnitude seismic events (i.e., EQ1).

Effect of Second Shock

Two seismic scenarios are implemented to quantify the effect of second shocks on the seismic resilience of communities. Scenario 1 includes EQ1 as a first shock and EQ2 as a second shock that strikes the community 5 months after the first shock (i.e., first shock is larger than the second shock). Whereas scenario 2 includes EQ2 as a first shock and EQ1 as an second shock that strikes the community 5 months after the first shock (i.e., second shock is larger than the first shock). Figure 10 (a) and (b) show the effect of scenario 1 and 2, respectively, on the building damage states in *Pseudo City*. The mean number of buildings in the complete damage state increased dramatically due to the effect of the second shock from 82 to 163 and from 4 to 98 in the case of scenario 1 and 2, respectively.

Scenario 1 (i.e. larger first shock than the second shock) has a more severe effect on the damage to buildings in *Pseudo City* (in terms of number of buildings in the complete damage state after the second shock). Also, for scenario 1, the influence of the second shock is more severe than the first shock even though the magnitude of the second shock is smaller, which agrees with the case of the 2010-2011 Canterbury sequences (Potter et al. 2015 and Wilson 2013). This result is attributed to the reduced capacity of the damaged buildings in *Pseudo City* after the first shock and the time of the second shock (i.e., repairs are not completed on the moderately and extensively damaged buildings prior to the second shock). Figure 10 (c) and (d) show the decisions made by the households of *Pseudo City* after both the second shock and the second shock for scenario 1 and 2, respectively. For both scenarios, the mean number of households deciding to leave the community or deciding to demolish and rebuild their houses increased after the second shock due to severe damage.

Figure 11 shows the recovery clouds of *Pseudo city* for the two implemented scenarios. As shown, scenario 1 has a more severe impact on the initial damage and overall recovery of

Pseudo city than scenario 2. This result is attributed to the fact that *Pseudo city* regained most of its functionality after the lower magnitude first shock in scenario 2 prior to the occurrence of the second shock (most of the buildings are intact). Whereas only 50% of the cities functionality is restored after the first shock in scenario 1 at the time of the second shock. Thus, the recovery time increased from 200 weeks (~ 3.8 years) in scenario 2 to 270 weeks (~ 5.1 years) in scenario 1. This increase in recovery time led to a decrease in the resilience index from 82% in scenario 2 to 73% in scenario 1. It can be concluded that the effect of the second shock is more dependent on the magnitude of the first shock than the magnitude of the second shock. Larger first shock scenarios result in more damage than smaller first shock scenarios regardless of the magnitude of the second shock. The effect of the second shock is also dependent on its time (i.e. percentage of buildings that regained their functionality prior to the occurrence of the second shock).

To demonstrate the significance of considering the fragility curves for the first shock-damaged building archetypes (developed earlier) in the second shock stage, the simulation model is modified to use the fragility curves for undamaged buildings during both the first shock and the second shock for the two previously described scenarios. Figure 12 shows the mean physical recovery trajectories for both scenarios. For scenario 1, the physical resilience index decreased from 82% when using the fragility curves for undamaged buildings to 73% when using the fragility curves that consider damage (12% reduction shown as the shaded area in Figure 12 (a)). For scenario 2, the physical resilience index decreased from 84% when using the undamaged building fragility curves to 82% when using the damaged building fragility curves (only 3% reduction shown as the shaded area in Figure 12 (b)). The presented results suggest that accurate fragility curves for the damaged buildings are important when evaluating community resistance for the case of a large first shock scenarios. For small first shock scenarios, the fragility curves for undamaged buildings can be used with little change in the physical recovery trajectory.

SIMULATION MODEL LIMITATIONS

Although the proposed simulation model combines the physical aspect of community resilience (related to the buildings) with the social aspect (related to the households in the community), there are other critical dimensions of community resilience that have not been accounted for in this study. For example, bridge and transportation network damage can affect traffic flow and, therefore, influence post-earthquake household decisions. Lifelines, such as power, gas and water systems, can also profoundly influence resilience, household decisions and the recovery trajectory of the community. Also, the interactions between the households in the community is not considered in the proposed simulation model. For example, if an individual household decided to abandon the community, this may affect surrounding households because there is now an abandoned property in the neighborhood. These aspects of community resilience and interactions can be accounted for in the future through the addition of relevant simulators.

SUMMARY AND CONCLUSIONS

This study presents a distributed computing simulation model that integrates post-earthquake household decisions into quantifying the seismic resilience of communities subject to an earthquake sequence. Post-earthquake household decision making is modeled using a Simple Multi-Attribute Rating Technique (SMART) based on a set of structural, economic and social attributes for each household in the community. Three possible decisions for each household are considered: repair the house, demolish and rebuild the house, or abandon the house. The second shock is modeled explicitly during the recovery stage from the first shock and incremental dynamic analysis (IDA) is used to develop fragility curves for the first shock-damaged buildings, which could still be under repair due to the first shock.

The proposed simulation model is demonstrated through a case study in which a small virtual community named "*Pseudo City*" is developed and modeled. *Pseudo City* is divided into nine zones with different socioeconomic characteristics of households. The studied community is subjected to two earthquakes with M_w 7.7 and M_w 6.3. The results show that households with low to moderate income are more likely to decide to abandon the community after an earthquake event. Also, considering the effect of the household decisions on the recovery of the community is more important in the case of large seismic events. After the M_w 7.7 event, considering the effect of the household decisions reduced the maximum restored functionality of the community by 10% on average and also reduced the resilience index by the same percentage. The simulation results suggest that a sequence with a larger first shock has a more severe impact on the seismic resilience of communities than a sequence with a smaller first shock regardless of the magnitude of the second shock. This is because the first shock damaged buildings are more prone to damage in the second shock, prolonging the recovery time.

DATA AVAILABILITY STATEMENT

Some or all data, models, or code generated or used during the study are available in a repository online in accordance with funder data retention policies. (https://doi.org/10.17603/ds2-zj63-ge63)

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