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TOWARDS THE SEISMIC RESILIENCE OF RESIDENTIAL COMMUNITIES: A CONCEPTUAL FRAMEWORK AND CASE STUDY

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Abstract

A conceptual framework and case study for quantifying the seismic resilience of residential communities is presented, which incorporates and the explicit simulation of post-earthquake recovery. A probabilistic assessment of physical damage is used to link the immediate post-earthquake condition of damaged buildings to the decisions and actions that are needed to bring about recovery. The building level limit states, which include damage triggering inspection, loss of functionality, unsafe to occupy, demolition and collapse, are characterized using fragility curves that link ground shaking intensity to the probability of exceedance. A methodology is presented for mapping the fragility parameters for damage states used in loss modeling (slight, moderate, extensive complete) to the recovery-based damage states considered in this study. Two alternative approaches to accounting for the uncertainty in the decision-outcomes of households affected by the disaster is presented. The first approach uses a purely theoretical model in which the household decision is assumed to be based on achieving the maximum utility. In the second approach, a statistical model is formulated based on the results of surveys in which participants are asked to choose from alternative courses of action based on a lived or simulated earthquake scenario. The post-earthquake recovery of occupiable housing is simulated using two alternative discrete-state probabilistic models. A preliminary case study was used to demonstrate the link between building fragilities and the immediate post-earthquake reduction and recovery of occupiable housing. The link between the duration of key activities and various stages of the recovery is highlighted.

Keywords: seismic resilience, residential communities, recovery, decision modeling,, performance-based earthquake engineering

1. Introduction

Housing makes up the greatest portion of the building stock in any community and is a key sector in the nation's financial infrastructure as well as the social development of cities [1]. Recent events like Hurricane Katrina and Super Storm Sandy have highlighted the vulnerability of residential communities to disasters. Housing is linked to every aspect of post-disaster recovery, since schools, businesses, neighborhood districts and cultural establishments all rely on residents remaining in the affected region [2]. The ability to model the trajectory of permanent housing recovery is central to quantifying and mitigating the long-term consequences that disasters have on the lives of affected populations.

Two key bodies of research are identified as providing the groundwork for current efforts to quantify seismic resilience and simulation models of post-earthquake recovery. The Multidisciplinary Center for Earthquake Engineering Research (MCEER) developed a conceptual model which describes four properties (robustness, redundancy, resourcefulness, and rapidity) and four dimensions (technical, organizational, social, and economic) of resilience. A multidimensional space of performance measures including the probability of failure, the consequences of failure and time to recovery [3] was used to quantify seismic resilience. The MCEER framework has since been extended by several of the original authors [4-6]. Miles and Chang [7-10] formulated a simulation model of post-disaster recovery in which socioeconomic agents (households and businesses) and their environments are explicitly represented. Recovery is assessed at the household, neighborhood and community scales while incorporating the key role of lifeline systems. The functions used to represent recovery trajectories are implemented as Markov chains that capture the time spent in various states of damage, defined based on some fraction of the building value. The model was operationalized into a computer simulation platform (ResilUS) and used to conduct case studies for the Northridge and Kobe earthquakes.

The City of Los Angeles County is one of several large urban centers in the United States and its residential communities are among the most diverse in the world, comprising many different languages, cultures and ethnicities. Due to its close proximity to several active faults, the city has a high likelihood of experiencing a large earthquake that could result in significant damage to the supporting infrastructure. In the wake of such an event, the availability of safe livable housing will play a major role in the recovery process, since schools, businesses, neighborhood districts and cultural establishments all rely on residents having healthy living conditions and remaining in the city to support the restoration activities. As such, understanding the time-dependent effects of seismic events on housing is necessary for enhancing resilience through interventions such as pre- and post-disaster mitigation plans.

2. Probabilistic Assessment of Physical Damage

2.1 Overview

A rigorous evaluation of seismic resilience requires probabilistic methods for assessing limit states that influence post-earthquake functionality, which can be incorporated in modeling the recovery of the building stock. The methodology incorporates a set of building performance limit states that specifically inform community seismic resilience [11]. These limit states have been adapted from the building performance categories defined by SPUR. They include (i) damage triggering inspection, (ii) loss of functionality, (iii) building unsafe to occupy, (iv) irreparable damage and (v) collapse. The event tree shown in Figure 1 illustrates a logical method for assessing the possible consequences of building damage and the implications to post-earthquake recovery. Fragility functions are used to probabilistically link the ground shaking intensity at a particular building site to the probability of exceeding a particular limit state.

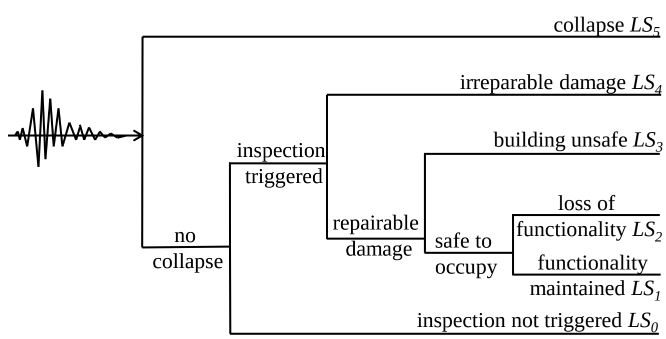


Fig. 1 – Event tree for assessing limit states relevant to recovery decision-making

2.2 Description of Recovery-Based Limit States

The five discrete limit states shown in Fig. 1 are explicitly linked to post-earthquake recovery-related activities. Each limit state is associated with a unique combination of actions to restore building function. *LS0* represents the case where damage is *below the threshold that would trigger inspection*. In *LS1*, inspection is triggered, however, the primary functionality of the building is not disrupted. This is the minimum damage threshold that would *require post-earthquake inspection and/or evaluation*. *LS2* refers to the condition where the building is structurally safe, occupiable and accessible but unable to carry out its primary function. *LS3* infers that the building is either *inaccessible or not safe to occupy* following an earthquake. The loss of structural safety will likely be due to a substantial loss in the load carrying capacity of the gravity or lateral system that poses a life safety threat in the event of an aftershock. It is also possible but less likely for non-structural damage to compromise the safety or prevent access to the building. This is usually in the form of some type of falling hazard (e.g. brick façade or infill panels); however, these types of dangers can be mitigated in a short period of time. *LS3* is of particular importance to residential buildings as it is directly related to the shelter-in-place performance goal emphasized in SPUR's resilient city initiative. *LS4* pertains to cases where the building is damaged to such an extent that *repair becomes technically or cost prohibitive, necessitating demolition and replacement*. The three main earthquake-related situations that can lead to demolition include (1) large permanent deformations and story drifts that make repairs unfeasible, (2) direct economic losses that exceed the limit set by insurance providers triggering full-value pay-out leading to complete replacement and (3) damage to key structural components that could significantly impede the repair process. *LS5* is associated with *complete or partial collapse*, which is generally associated with either excessive lateral deformations (sidesway collapse) or the local or global loss of vertical load carrying capacity.

2.3 Mapping from Loss-Based to Recovery-Based Fragility Function Parameters

Risk modeling platforms such as HAZUS [12] use limit state fragility functions that relate earthquake ground shaking intensity to building damage. These "loss-based" limit states are used to link ground motion intensity to direct economic losses (loss curves) that result from having to repair or replace damaged buildings. The limit states, which include slight, moderate, extensive and complete damage, are classified based on construction type and are described in terms of the type and extent of physical damage to the building. For wood frame single- and multi-family residential buildings, s*light* damage refers to the presence of small cracks in non-structural elements and slippage in bolted connections. For *moderate* damage, there are small cracks across shear walls, large cracks at doors, windows and masonry veneer, topping of tall masonry chimneys, minor slack in diagonal rod bracing and small cracks and split in bolted connections. *Extensive* damage includes large cracks across shear wall plywood joints, large slack at diagonal and broken braces, permanent lateral movement at floors and roof, topping of most brick chimneys, small cracks in foundations, split and/or slippage of sill plates and partial collapse at garage with soft-story configurations. *Complete* damage includes the presence of large permanent lateral displacement, collapse, imminent collapse, some structures slip off foundations, large foundation cracks and broken brace rod or failed framing connections.

This section describes a methodology that can be used to map the fragility function parameters for the loss-based limit states used in *HAZUS* to those of the recovery-based limit states described in Section 2.2. We start by estimating the conditional probability of being in a particular recovery-based limit state given the occurrence of a loss-based damage state. $P(RBDS = rbds_i \mid LBDS = lbds_j)$ is the probability that the recovery-based damage state $rbds_i$ occurs given that the loss-based damage state $lbds_j$ has been observed. Estimates of these conditional probabilities are provided in Table 1. The current values are based on engineering judgement. They were obtained by examining the physical description of damage provided for the loss-based limit states and inferring the likelihood that this type of damage would trigger each of the six (*LS0* through *LS5*) recovery-based limit states. Future work will focus on refining these estimates based on the results from nonlinear response history analyses of typical woodframe buildings using the *OpenSees* modeling platform. The results from the structural response simulation will be used to establish analytical fragility functions for both types of limit states. This process will enable the development of a more explicit relationship between the fragility parameters for the two types of limit states. The conditional probabilities estimates can be further refined using heuristic data obtained from expert opinion.

In Table 1, each row provides the probability of being in each of the recovery-based limit states given the occurrence of the loss-based limit state in the first column of that row. For example, it can be observed that for a building that is in the loss-based limit state corresponding to moderate damage, the probability of being in recovery-based limit states *LS0*, *LS1*, *LS2* and *LS3*, is 0.2, 0.4, 0.3 and 0.1 respectively with a zero probability of being in the remaining limit states (*LS4* and *LS5*). Given that the recovery-based limit states are mutually exclusive and collectively exhaustive, each row must sum to one.

Table 1 – Conditional probabilities used to map fragility parameters for loss-based to recovery-based limit states

Loss-Based Damage States	$P(RBDS = rbds_i \mid LBDS = lbds_j)$					
	LS0 Inspection not Triggered	*LS1* Inspection	*LS2* Loss of Functionality	*LS3* Unsafe to Occupy	*LS4* Damaged Beyond Repair	*LS5* Collapse
None	1.0	0.0	0.0	0.0	0.0	0.0
Slight	0.6	0.4	0.0	0.0	0.0	0.0
Moderate	0.2	0.4	0.3	0.1	0.0	0.0
Extensive	0.0	0.0	0.2	0.4	0.3	0.1
Complete	0.0	0.0	0.0	0.0	0.2	0.8

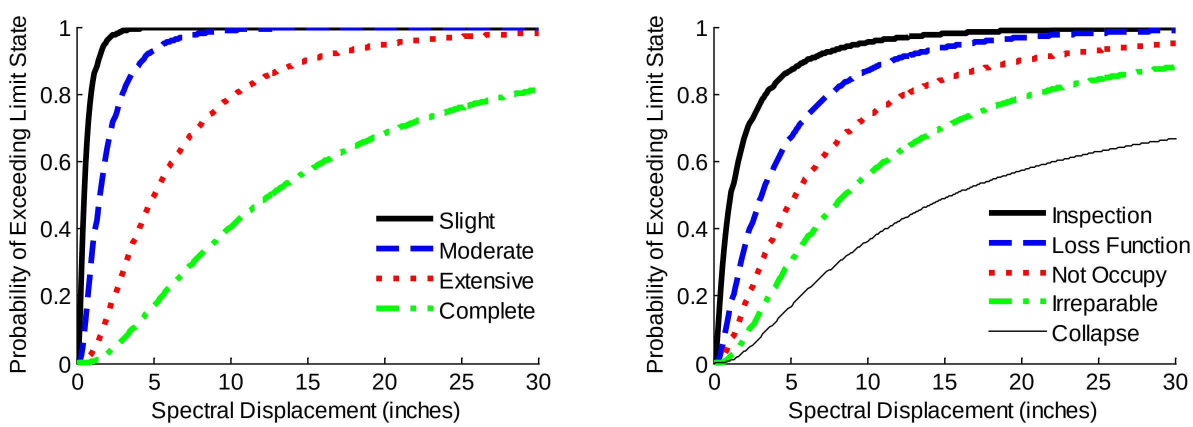
Given the loss-based fragility function parameters provided in *HAZUS* and the conditional probability estimates in Table 1, the probability of occurrence of a particular recovery-based limit state can be obtained using the total probability theorem:

$$P(RBDS = rbds_i \mid S_d) = \sum_{j=1}^{n_{lbds}} P\left(PRBDS = rbds_i \mid LBDS = lrbds_j\right) \cdot P\left(LBDS = lrbds_j \mid S_d\right) \tag{1}$$

Where $P\left(PRBDS = rbds_i \mid LBDS = lrbds_j\right)$ is taken from Table 1 and $P\left(LBDS = lrbds_j \mid S_d\right)$ is the probability of being in loss-based limit state i conditioned on the spectral displacement demand, which can be obtained from the fragility functions of the loss-based limit states. Given the probability of being in recovery-based limit state i, the probability of exceeding that limit state is taken as the sum of the probabilities of occurrence of all limit states equal to and greater than i.

$$P(RBDS > rbds_i \mid S_d) = \sum_{i}^{n_{rbds}} P\left(RBDS = rbds_i \mid S_d\right) \tag{2}$$

Equation (2) can then be used to compute the median spectral displacement, $\bar{S}_{d,rbds_i}$ and dispersion β_{rbds_i} for the recovery-based limit state fragilities. Figures 2, 3, 4 and 5 provide a comparison of the recovery- and loss-based fragility functions.



(a) (b)

Fig. 2 – Fragility curves for (a) loss-based and (b) recovery based limit states for light wood frame buildings with high-code seismic design (building type description based on *HAZUS*)

3. Modeling Household Decisions in Post-Disaster Environment

Household decisions play a major role in post-disaster recovery of residential communities. The decision of residents (and businesses) regarding whether to remain in their community and rebuild or relocate affects housing recovery. Quantifying this effect requires models that capture the spatiotemporal characterization of post-disaster decisions and actions of affected households. Fig. 3 shows an event tree that is conceived as an extension of the one shown in Figure 1a to facilitate the assessment of possible post-disaster decision outcomes for owners and occupiers of residential buildings. It illustrates examples of possible post-event building owner actions given the extent of damage as measured by the building performance limit state that will be considered in this research. Each of these actions has strong implications to recovery at the household and neighborhood level. For example, the recovery actions and resulting trajectory for the case of a single family residence with an owner-occupier who chooses to repair and reoccupy their home following a disaster will be different from the case where the house is sold without conducting repairs. Likewise, a home that is abandoned in the wake of a disaster will have a different recovery trajectory than the previous two.

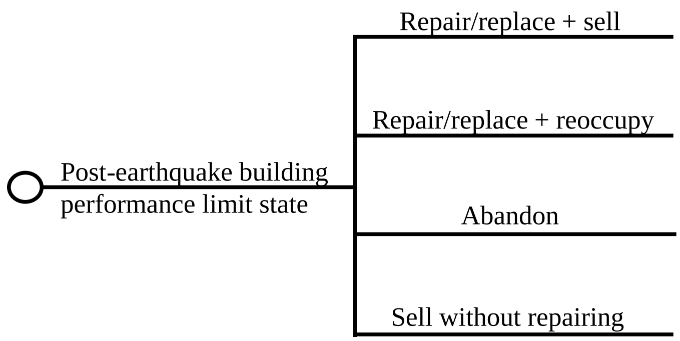


Fig. 3 – Event tree for post-earthquake actions of residential building owners

Faced with damage to property and the surrounding environment, homeowners must decide whether to stay and rebuild or relocate. This decision is driven by "signals" from neighboring homeowners as well as policy makers and community leaders [13]. Two alternative methods are being explored to model household decision-making in the post-earthquake recovery context. The first is a theoretical model in which we assume that a household will always make the decision that maximizes its utility. For example, the utility representing the net-present value of a property following an earthquake can be described using the following equation [13].

$$NPV(U(y),t) = \gamma' \left[z_y - ln\left(\frac{\nu_y c_y}{i_y} \right) \right] \tag{3}$$

where $NPV(U(y),t)$ is the utility function representing the net-present value of household y, ν_y and z_y are the property value before and after damage respectively, c_y are the repair costs, i_y represents financing obtained for repairs such as insurance reimbursements or federal funding and γ' is a discount factor. Utility-based models offer the advantage of not requiring data for calibration and not being limited to a specific demographic. However, there is always the question of whether or not the utility function provides a realistic representation of household behavior. An alternative to the utility-based model is the empirical approach in which statistical models are developed to establish the discrete probability distribution of the various decision outcomes. These models are constructed using data obtained from surveys of households affected by real earthquakes. Alternatively, a behavioural experiment can be carried out in which the participants are surveyed using a simulated earthquake scenario. Using the results of such a survey, a multinomial logistical regression model can be developed in which the decision outcomes (Fig. 3) are the categorical dependent variables and the drivers of those decisions are the independent variables. Examples of classes of explanatory variables include (1) the extent of building damage, (2) socioeconomic demographics, (3) tenure of residents (renters or homeowners), (4) the extent of neighborhood or city damage and disruption and (5) and local and federal recovery capacity (e.g., existence of pre-event recovery plan). An example of one such regression model is described in Equation 4 [13].

$$log\left(\frac{P(Y=j)}{P(Y=k)}\right)=\sum_i \beta_{i,j}x_i \quad (4)$$

where $log\left(\frac{P(Y=j)}{P(Y=k)}\right)$ is the log-odds of decision outcome j over outcome k, x_i is explanatory variable i and β_i is the regression coefficient for explanatory variable i.

4. Simulating Post-Earthquake Recovery of Housing

4.1 Discrete-State Probabilistic Models

A major challenge in developing post-disaster recovery models is that the functioning (or recovery) state of the entity being considered (in this case households) is often described on a discrete scale, such as “building is occupied with some loss in functionality”. Furthermore, post-disaster recovery is a stochastic process that varies widely with several factors, many of which are not captured by available data. As such, probabilistic discrete state models are appropriate for simulating recovery of different social units (households, businesses, neighborhoods, communities etc.). Two types of discrete-state probabilistic models are used to quantify recovery trajectories at the household level: discrete-time, state-based models and time-based models [14]. Discrete-time state-based models, such as Markov chains, characterize the probability that the household transitions to a higher (or lower) functioning state at a given discrete time, given a set of explanatory variables such as the extent of damage to the building, neighborhood demographics or household income. Time-based models on the other hand, characterize a probability density function of the time it takes to transition to a higher (or lower) functioning state (also referred to as state duration) given the same explanatory variables.

The formulation of the either of the two models starts with defining the discrete states that capture the recovery trajectory. These discrete states can be characterized as activity states or functioning states. Activity states are established by first defining the key processes (or activities) that are involved in the path to recovery. For example, the key activities considered for household recovery include (1) building inspection (*Insp.*), (2) engineering and architectural assessments/designs and permitting (*Assmnt*), (3) mobilization for construction (*Mobil*), (4) demolition *(Demol)*, (5) repair and/or reconstruction (*Rep/Recon*). The recovery path for a particular building is defined by the activities/processes/stages involved in the recovery and the time spent in each stage. Note that the activities that comprise the recovery path for a given building depend on the limit state of that building immediately following the earthquake. For example, a building that is in limit state *LS1* (damage triggering inspection) and *LS2* (safe to occupy but with loss of functionality) will only require inspection and minor repairs. On the other hand, a building that is in limit state *LS3* (building unsafe to occupy) may require four of the five (not demolition) activities to achieve full recovery.

Functioning states are defined to capture the changing condition of the building with respect to its ability to facilitate its intended operation. The functioning states for modeling the recovery of shelter-in-place housing capacity include (1) the building is unsafe to occupy (*NOcc*), (2) the building is safe to occupy but unable to facilitate normal operations (*OccLoss*) and (3) the building is fully functional (*OccFull*). Note that these three states are specific to the shelter-in-place metric and would need to be re-defined for other measures of functionality. The key to defining the functioning states are that (1) they must be explicitly linked to the building level limit states described earlier and (2) each functioning state must be associated with a quantifiable measure of functionality. Note that the functioning states can also be described as an aggregation of the activity states. For example, the *NOcc* functional stage of a building that is in limit state *LS3* immediately following a seismic event will comprise of *Insp, Assmnt, Mobil* and *Rep/Recon* activity states.

Figure 4 illustrates the step functions that are used to describe household recovery using functional (Figure 4a) and recovery (Figure 4b) states. The functioning-state-based recovery path will be used in the formulation, however, the mathematical model can also be applied to the activity-based recovery paths. The basic assumption in the model is that there is a probabilistic relationship between the indicators of recovery and the underlying recovery process. Additionally, the sequence of state transitions for a given recovery path is assumed to be deterministic and based on the order in which the activities that comprise that path will occur. The variables used to construct the discrete state probabilistic models includes the cumulative continuous recovery level, Q_t , the vector of observed explanatory variables, $\overline{X}_t$, and the discrete state of the building, Y_t, at time t, measured from the time that the building entered the present state. The time spent within a particular state is denoted by $t = T$. Since the recovery is modeled as a stochastic process, T is a random variable.

After establishing the discrete functioning states associated with a particular recovery path, the discrete-time state-based model is constructed as a series of independent Poisson processes, each with their own mean rate of occurrence. Given the current time t, the probability of transitioning out of the state i to the subsequent state $i+1$ at some future time $t+\Delta$ is the probability of $i+1$ occurring at time $t+\Delta$ conditioned on state i being observed at time t. This conditional probability, $P(t<T<t+\Delta \mid T>t)$ is described using the following equation.

$$P(t<T<t+\Delta \mid T>t) = \frac{P(t<T<t+\Delta)}{P(T>t)} = \frac{F(t+\Delta)-F(t)}{1-F(t)} \tag{5}$$

where $F(t)=1-e^{-\lambda t}$ is the CDF of the exponential distribution. The mean rate transitioning from the current state, $\lambda = \frac{1}{\mu}$, where the mean time to complete the activities involved in that state, μ, can be obtained from empirical data from past earthquakes. Substituting the exponential CDF into Equation 5 produces the following functional form for the transition probability:

$$P(t<T<t+\Delta \mid T>t) = 1-\frac{e^{-\lambda(t+\Delta)}}{e^{-\lambda t}} \tag{6}$$

For the time-based model, the uncertainty in the duration of each functioning state is (e.g. T_{NOcc}, $T_{OccLoss}$, $T_{OccFull}$) is considered by randomly sampling the duration T. Monte Carlo simulation can be used for both the time- and state-based models to generate multiple realizations of the recovery path conditioned on the post-earthquake limit state The recovery path for a given post-earthquake limit state is then constructed by randomly sampling the duration of each functioning state using their associated distribution parameters. The extension of the discrete-state probabilistic models to include the explanatory variables can be achieved by developing a statistical model in which $\overline{X}_t$ is the vector of independent variables and μ (or λ) is the dependent variable.

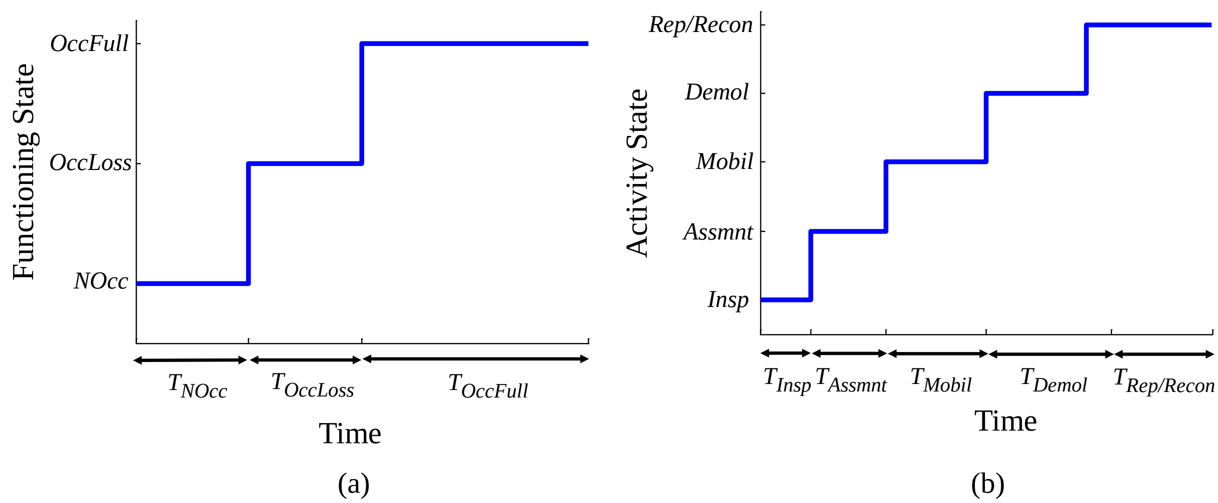


Fig. 4 – Description of building recovery paths based using (a) functioning and (b) activity states

4.2 Probabilistic Decision Path Model

A probabilistic decision path (PDP) model will be developed to account for the uncertainty in the possible household decision outcomes following a seismic event. The *PDP* model will incorporate elements of the decision analysis methods described in Section 3 and the discrete state probabilistic models outlined in Section 4. A set of probabilistically characterized decision paths will be defined at the individual building level based on (1) the possible decision outcomes of the building owner and occupiers and functioning states immediately following an event, (2) the activities needed to restore occupancy and functionality given the condition (limit-state) of the building immediately following the event and (3) the possible decision outcomes of the building owner and occupiers at various time intervals during recovery. The time spent (duration) in each functioning (or activity) state will be determined based on the processes needed to transition to a higher state as well as the decision outcomes at a given point in time. Figure 5 shows a conceptual illustration of the decision paths for a single building represented using the three functioning states described in Section 4.1 (*NOcc, OccLoss, OccFull*)

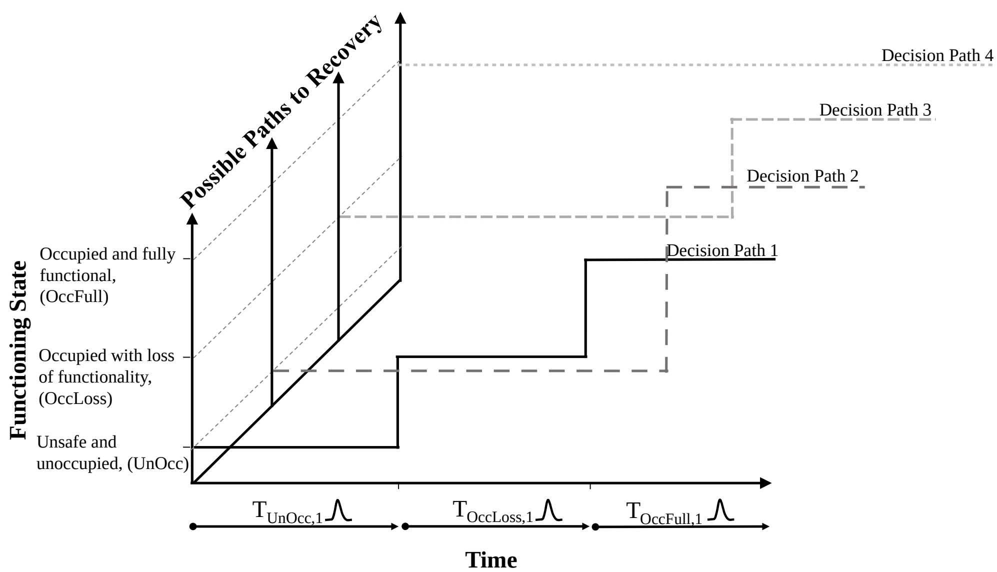


Fig. 5 – Partial conceptual representation of probabilistic decision-path model

5. Case Study for Koreatown, Los Angeles

There is an ongoing effort to further develop the proposed framework and apply it to several neighbourhoods throughout the city of Los Angeles. The preliminary results presented in this paper is for a single neighborhood. It provides insight into the sensitivity of the recovery trajectory to key assumptions and model parameters. Koreatown is located in central Los Angeles, and is the most densely populated district in Los Angeles County. There are approximately 120,000 residents housed in 1030 residential buildings in an area of 2.7 square miles. Ground shaking intensities associated with the Northridge earthquake were obtained by spatial interpolation [15]. The distribution of spectral accelerations in the neighborhood of interest is shown in Figure 6. The fragility parameters obtained using the approach presented in Section 2, coupled with the spatially interpolated spectral accelerations, are used to generate multiple realizations of building level damage within the target district. Given the spectral acceleration associated with the building, a discrete probability distribution is obtained for the six limit states (no damage, inspection, loss of functionality, closure, demolition and collapse). Monte Carlo simulation is used to generate 1000 realizations of damage for each building.

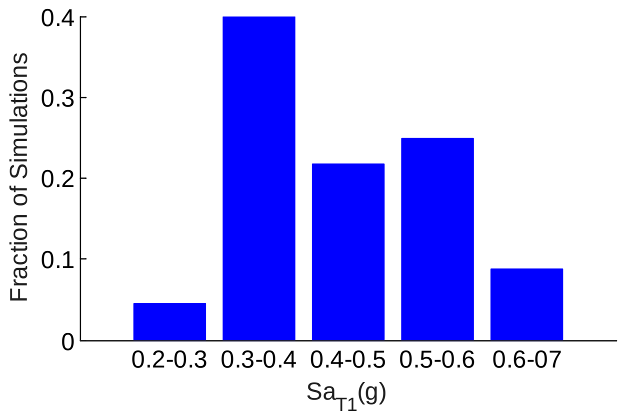


Fig. 5 – Distribution of spatially interpolated spectral accelerations for Northridge earthquake

The time-based model described in Section 4 was used to compute recovery trajectories for the damaged buildings using recovery paths based on functional states (Fig. 4a). Decision-making at the household level has not yet been considered. Fig. 6 shows the effect of building damage fragility on the expected recovery function. The damage fragility is varied by assuming different code types for the entire inventory with high- and pre-code being the least and most fragile of the buildings respectively. The plot shows that the building fragility affects both the initial loss of functionality as well as the overall recovery. For example, the initial loss of functionality for the high-code inventory is 55% compared to 65% for the pre-code inventory. Additionally, at 180 days (approximately 6 months) from the event, the high-code and pre-code inventories have recovered 95% and 80% of their functionality. Fig. 7 shows the effect of various time parameters on the probabilistic recovery trajectory for the target neighborhood. Fig. 7a shows that the time to inspection affects the slope of the recovery curve in the initial stages while the mobilization (Fig. 7b), assessment (Fig. 7c) and repair times (Fig. 7d) affect later stages. The mobilization time has the greatest effect on the middle to tail end of the recovery curve while the repair time has the smallest effect. It is worth noting that the repair and assessment times are damage-dependent (and therefore building-fragility dependent) while the inspection and mobilization times are assumed to be damage-independent.

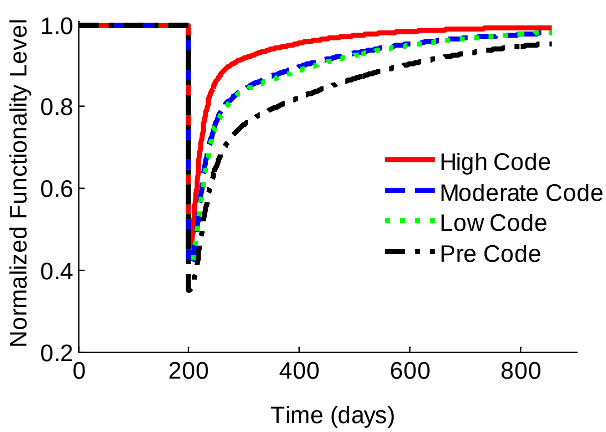


Fig. 6 Effect of building fragility on probabilistic recovery function

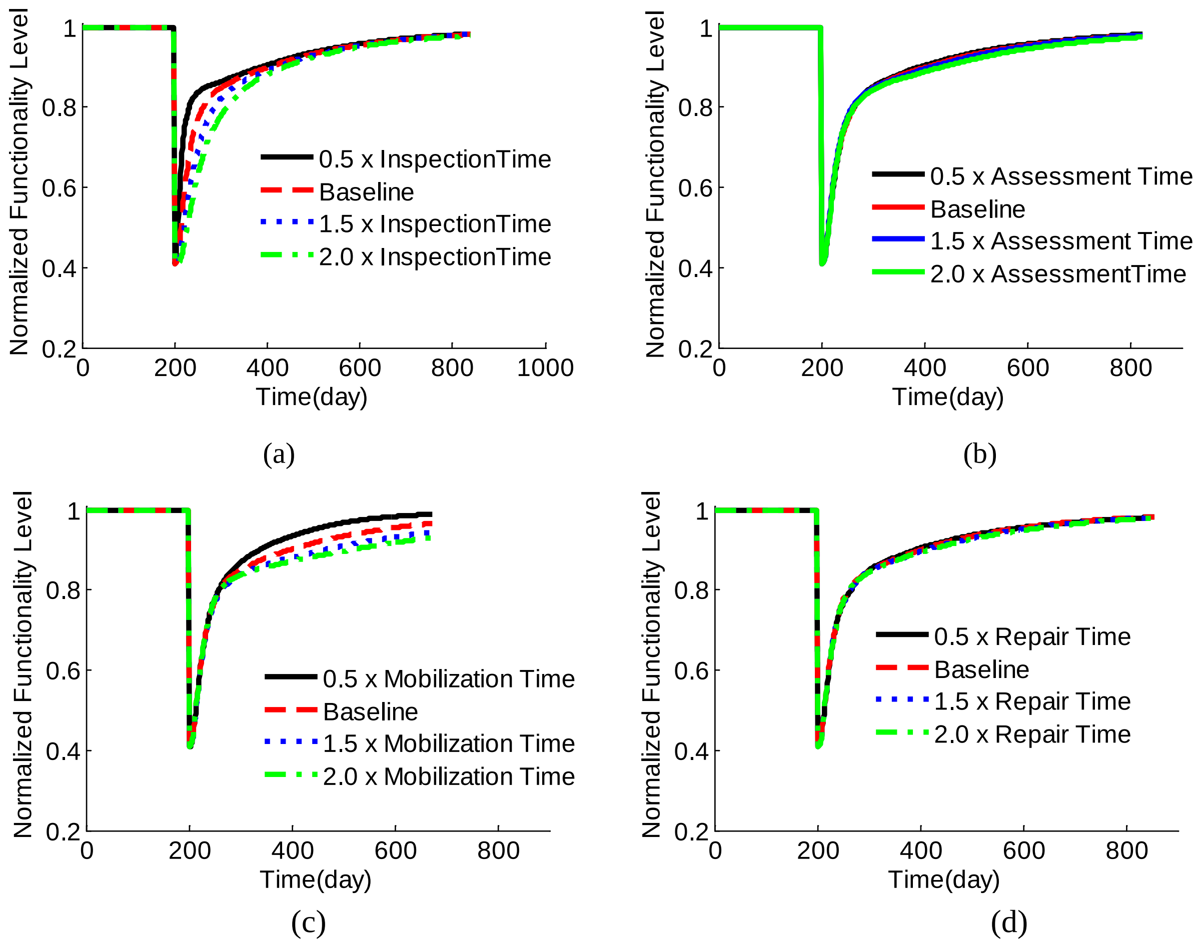


Fig. 7 Effect of various time parameters on recovery trajectory including (a) inspection time, (b) assessment time, (c) mobilization time and (d) repair time

6. Conclusions

One measure of the seismic resilience of a residential community is the ability to minimize the loss of livable housing immediately following a large event and recover in a timely manner. Minimizing the immediate impact and enhancing the pace of housing recovery will allow residents to put their energy and resources into rebuilding their neighborhoods and will reduce the likelihood of permanent outmigration of residents. This paper presents a conceptual framework for quantifying the immediate loss and time-dependent restoration of occupiable housing. The loss of occupiable housing is assessed by simulating damage to the residential buildings using limit states that are directly linked to post-earthquake recovery. These limit states are also used to inform the possible decision-outcomes of affected households. The uncertainty in these decisions can be captured using theoretical or empirical models. Theoretical models are based on maximizing the utility of the relevant stakeholders and empirical models are established based on the results of controlled surveys. A hybrid model can also be constructed in which utility functions are established from the results of behavioral experiments. Given the immediate post-earthquake state of a building and the probabilistic characterization of possible decision outcomes, a characteristic recovery path is established, which defines the discrete functioning states (or activities) needed to bring about recovery and the time spent in each state. To capture the uncertainty in the time spent in the various states, the recovery of functionality (or occupancy) is modeled as a stochastic process. The proposed framework is implemented in a preliminary case study using Koreatown as the target location. The results of the case study demonstrated the link between the fragility of the building inventory and the recovery trajectory. The sensitivity of various stages of the recovery to the time spent on specific activities is also investigated. Ongoing work is focused on constructing the decision models and performing a larger study for the several neighborhoods in the city of Los Angeles. The results of such a study is relevant to national efforts such as the Rockefeller Foundation's 100 Resilient Cities, which will bring attention to mounting issues related urban disaster resilience and provide information and tools to understand and act upon the necessary solution alternatives.

7. Acknowledgements

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