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Stochastic Characterization of Post-Earthquake, Community-Scale Recovery

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Abstract: Post-earthquake recovery models can be used as decision-support tools for pre-event planning. Two types of stochastic process simulation models are presented and used to re-enact the recovery following the 2014 South Napa earthquake, focusing primarily on the reconstruction of damaged buildings. The objective of the study is to validate the simulation methodology and formulate a generalized model that can be used to generate recovery predictions for future earthquakes.

1 Introduction

The relative infrequency and spatiotemporal scale of major earthquake events make longitudinal collection of quantitative recovery data difficult. In light of this, simulation modeling is one critical research advancement necessary for understanding and quantifying the complex processes driving post-earthquake recovery and the myriad of influences on outcome trajectories over time. The pace of recovery depends on the extent of building and lifeline damage, the availability of utilities, government assistance, and how quickly communities can repair or replace damaged infrastructure. As such, the time-dependent effects of hazard events on the built environment is increasingly becoming prominent in discussions on how to improve post-earthquake recovery through policy and planning interventions.

Several simulation techniques have been employed in modeling post-earthquake recovery (reconstruction and restoration) including resource constraint models [1-5], statistical curve fitting [6-11], agent-based modeling [12-20], discrete event simulation [21-31], stochastic process simulation [32-37] and network modeling [38-40]. Most studies have focused on modeling the restoration and/or reconstruction of specific built infrastructure systems such as lifelines [1,2,7,8,10] and buildings [6,9,36,37]. Other studies incorporate both the social and built infrastructure systems within specific economic sectors such as households and businesses [11-20]. However, due to a lack of available data, there have been very few opportunities to validate and/or calibrate these models.

This paper describes the use of building damage, permitting and repair data from the 2014 South Napa Earthquake, to evaluate a stochastic process simulation post-earthquake recovery model. Damage data was obtained for 1470 buildings and permitting and repair-time data was obtained for a subset (456) of those buildings. A "blind" simulation is shown to adequately capture the shape of the recovery trajectory despite overpredicting the overall pace of the recovery. Using the mean time-to-permit and repair time from the acquired dataset significantly improves the accuracy of the recovery simulation. A generalized simulation model is formulated by establishing statistical relationships between key time parameters and endogenous and exogenous factors that have been shown to influence the pace of recovery.

2 Stochastic Process Recovery Simulation Models

Stochastic process simulation is a modeling technique that is used to represent different types of discrete and continuous phenomena that randomly evolve in space and/or time. The recovery of social (households, businesses, communities) and built (buildings and lifelines) infrastructure systems following an earthquake can be described using discrete states that, with a great degree of uncertainty, change with space and time making stochastic process simulation models useful for representing different post-disaster recovery processes. In this study, two types of discrete-state stochastic simulation models are used to quantify recovery trajectories for damaged buildings: discrete-time, state-based models and time-based models [41]. Discrete-time state-based models, such as Markov chains, characterize the probability that the building transitions to a higher recovery state within a discrete time interval conditioned on a set of explanatory variables such as the extent of damage to the building, neighborhood demographics or, in the case of residential buildings, household income. Time-based models on the other hand, characterize a probability density function of the time it takes to transition to a higher recovery state (also referred to as state duration) given the same explanatory variables. The formulation of both models starts with defining the discrete states that capture the recovery trajectory. The recovery states can be selected based on the entity that is being represented and the information that is available to characterize these states within the simulation environment. In previous studies, recovery states for buildings have been characterized based on damage [13], loss, functionality[36] and recovery activities [37].

Figure 1 shows a conceptual recovery path that describes the repair/reconstruction of a damaged building using the states described earlier, which are based on the issuance of construction and completion permits. The continuous stochastic recovery function is also shown in Figure 1. The basic assumption is that there is a probabilistic relationship between the various exogenous and endogenous factors described earlier and the time spent in each state. Additionally, the sequence of state transitions for a given recovery path is pre-determined and based on the order in which the activities that comprise the recovery path will occur. The variables used to construct the discrete state probabilistic models include the cumulative continuous recovery level, $Q(t)$, the vector of observed explanatory variables, $\overline{X}$, and the discrete state of the building, $Y(t)$, at time t, measured from the time of the earthquake. The time spent within state i is denoted by T_i. The time spent in the *PreCon, Con* and *Com* states is denoted by T_{PreCon}, T_{Con} and T_{Com} respectively. Since the recovery is modeled as a stochastic process, T_i is a random variable. After establishing the discrete states associated with a 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_i, the probability of transitioning out of state i to the subsequent state $i+1$ at some future time $t_i+\Delta$ is the probability of $i+1$ occurring at time $t_i+\Delta$ conditioned on state i being observed at time t_i. This conditional probability, $P(t_i < T < t_i + \Delta \mid T > t_i)$, is described using the following equation.

$$P\left(t_i < T < t_i + \Delta \mid T > t_i\right) = \frac{P\left(t_i < T < t_i + \Delta\right)}{P\left(T > t_i\right)} = \frac{F\left(t_i + \Delta\right) - F\left(t_i\right)}{1 - F\left(t_i\right)} \tag{1}$$

where $F\left(t_i\right) = 1 - e^{-\lambda_i t_i}$ is the CDF of the exponential distribution. The mean rate of transitioning from the current state is $\lambda_i = \frac{1}{\mu_i}$, where the mean time to complete the activities involved in that state, μ_i, can be obtained from empirical data from past earthquakes. Substituting the exponential CDF into Equation 1 produces the following functional form for the transition probability which is used in the state-based model:

$$P\left(t_i < T < t_i + \Delta \mid T > t_i\right) = 1 - \frac{e^{-\lambda_i\left(t_i + \Delta\right)}}{e^{-\lambda_i t_i}} \tag{2}$$

For the time-based model, the uncertainty in the duration of each recovery state is (e.g. time to acquire construction permit, repair time) is considered by randomly sampling the duration T_i. Monte Carlo simulation is used for both the time- and state-based models to generate multiple realizations of the recovery path. For the state-based model, a single realization of a recovery path is generated by randomly sampling the state at incremental points in time using the transition probabilities from equation (2). For the time-based model, a single realization of a recovery path is constructed by randomly sampling the duration of each recovery state using their associated exponential distribution parameters. The extension of the discrete-state (time- and state-based) probabilistic models to include the explanatory variables can be achieved by developing a statistical model in which $\overline{X}$ is the vector of independent variables and μ_i (or λ_i) is the dependent variable.

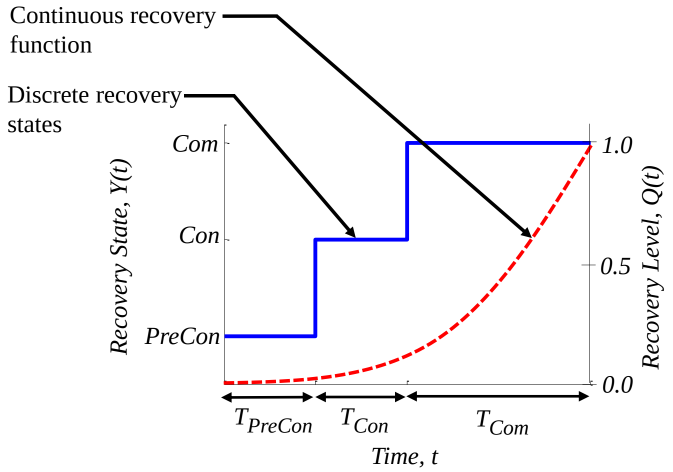


Figure 1. Conceptual representation of stochastic process modeling of building-level recovery using discrete states derived from on the issuance of construction and completion permits

3 Re-enacting the Recovery Following the 2014 South Napa Earthquake

3.1 Description of Study Region and Key Data

A building damage dataset for the city of Napa was obtained from the Earthquake Engineering Research Institute (EERI) clearinghouse website (http://eqclearinghouse.org/map/2014-08-24-

south-napa/). 1470 damaged buildings are included in the dataset, which contains several types of building-specific information that are relevant to this study including location (address, latitude and longitude), occupancy type, post-earthquake inspection date, ATC-20 [42] placard (yellow and red) and a brief description of the damage caused by the earthquake. The permit issue and completion date for repair-work related to the Napa earthquake was acquired for 456 of the buildings (31.0%) included in the damage dataset described earlier. This information was obtained from the online permitting and project review website (http://etrakit.cityof-napa.org/etrakit2/) for the city of Napa. Using these two pieces of information, the time-to-permit is taken as the number of days from the date that the earthquake occurred to the permit issue date and the repair time is estimated as the number of days from permit-issue to the completion date. Figure 2 shows histograms of the time-to-permit and repair times. The shape of the histograms suggest that a lognormal or exponential function would be appropriate for modeling the probability distribution of these two time parameters.

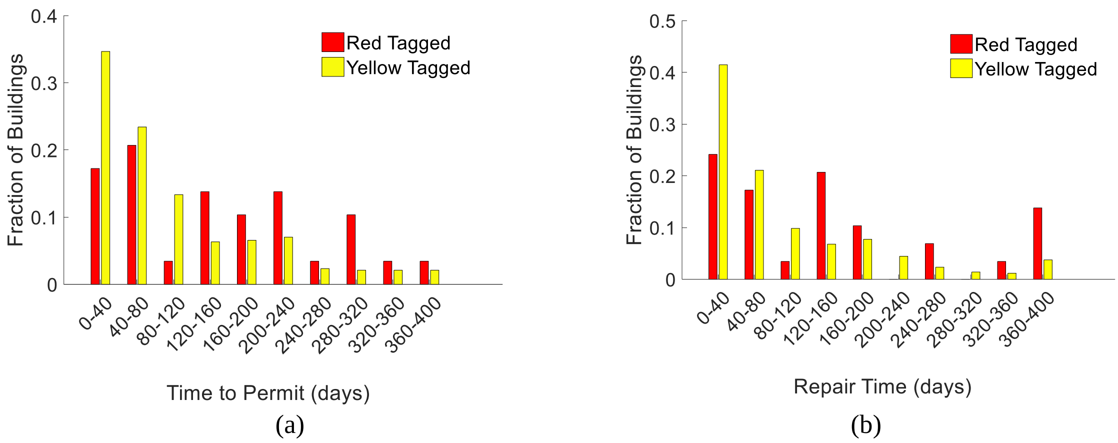


Figure 2. Histogram of (a) time-to-permit and (b) estimated repair times for buildings in permit-issue-completion dataset

A key objective in this study is to evaluate the efficacy of the stochastic process simulation model in estimating the recovery trajectory of the buildings damaged during the earthquake. This will be done by comparing the simulated and observed recovery trajectories, the latter of which is generated using the permit-issue-completion dataset. To establish the observed recovery trajectory, three building-level recovery states are defined. At any given time t (days) following the earthquake, a building is described as being in the *pre-construction (Pre-Con)* state if the building permit has not yet been issued. Between the permit-issue and completion date, a building is in the *construction (Con)* state. After the completion permit is issued, the building is in the *completion (Com)* state. We recognize that the issuance of a completion permit may not correspond to the restoration of full functionality or occupancy in the building. However, given the lack of data related to the functionality and occupancy of individual buildings, in this study, the issuance of the completion permit (*Com*) is used as the penultimate recovery state. To facilitate generating the recovery curve, the *Pre-Con*, *Con* and *Com* states are assigned numerical values of 0, .5 and 1 respectively.

Figure 3 shows the observed recovery trajectory for the 456 buildings in the permit-issue-completion dataset. For this subset of buildings, the general trend is that the reconstruction is somewhat stagnant during the first 20 days following the earthquake. Following this period, the rate of reconstruction rises sharply until around 250 days from the time of the earthquake, after which the slope of the recovery curve gradually declines towards the tail end.

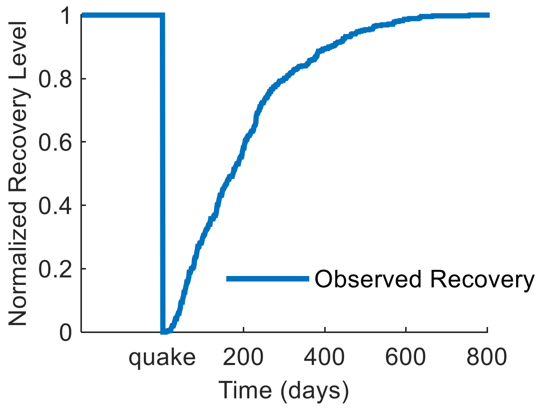


Figure 3. Observed recovery trajectory for all 456 buildings in the permit-issue-completion dataset

3.2 Evaluating the Time-based Stochastic Simulation Model

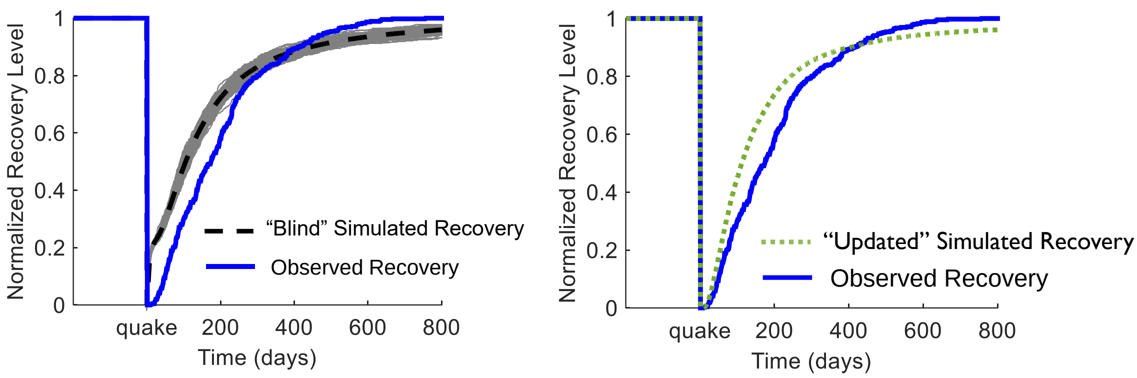
The model is evaluated by performing a blind prediction of the reconstruction trajectory of the buildings in the permit-issue-completion dataset. The goal here is to evaluate the model used to simulate recovery trajectory (not the damage simulation model). As such, the observed spatial distribution of damage is used for the blind prediction.

The formulation of the time-based stochastic process simulation model starts with defining the discrete states that are used to describe the recovery path. Tables 15.10 of HAZUS [43] provides estimates of the overall recovery times for different building types conditioned on the damage state. The recovery times for the building types considered in this study (primarily single-family light residential woodframe buildings) are 5 days, 120 days, 360 days and 720 days for slight, moderate, extensive and complete damage respectively. Since the HAZUS recovery times are aggregated, only two states are considered in the blind prediction model: (a) the building is damaged and (b) the building is fully recovered, which are assigned recovery levels of 0 and 1 respectively.

For the time-based model, the recovery time is modeled using an exponential probability distribution function with mean values and standard deviation corresponding to the recovery times provided in HAZUS. A single realization of the recovery trajectory for the time-based model is obtained by sampling the recovery time for each building from the exponential probability distribution and constructing a recovery curve for the building portfolio. The uncertainty in the recovery trajectory is incorporated by generating 200 realizations of the recovery curve, which is shown in Figure 4a along with the observed recovery trajectory. The number of realizations is chosen such that the maximum coefficient of variation in the mean recovery curve is less than or equal to 5%.

Figure 4a shows that the blind prediction model adequately captures the overall shape of the recovery curve including the steep slope in the early stages and the gradual reduction in the overall rate of recovery with time. However, we also observe that the blind prediction model significantly overpredicts the recovery level from the early stages up to the time when 80% of the buildings have recovered. For example, at 50 days and 100 days following the earthquake, the recovery level is overpredicted by factors of 2.6 and 1.5 respectively.

The fact that the overall shape of the recovery trajectory is reasonably captured suggests that the accuracy in the prediction model can be improved by using more refined estimates of the input time parameters. To test this hypothesis, a second prediction model is constructed using the mean time-to-permit and repair times from Figure 2 normalized by the square footage of the building and conditioned on the inspection tag (yellow and red). The normalized mean time-to-permit is 0.066 days/ft^2 and 0.097 days/ft^2 and the repair time is 0.063 days/ft^2 and 0.104 days/ft^2 for yellow- and red-tagged buildings respectively. In Figure 4b, the (mean) recovery trajectory labeled "Updated Recovery Simulation" is obtained when using these mean values and three recovery states (*Pre-Con, Con* and *Com*). It shows that the prediction model is vastly improved when the observed mean-value time parameter inputs are used. Considering the same time points used to evaluate the blind simulation model (50 days and 100 days following the earthquake), the "updated" model estimates the recovery level within 20% and 40% respectively of the observed values.



(a) (b)

Figure 4. Comparing the (a) blind and (b) updated simulation results to the observed recovery trajectory for the 456 buildings in the permit-issue-completion dataset

3.3 Time-Based Stochastic Process Simulation Model for Predicting Future Post-Earthquake Recovery Trajectories

A Random Forest regression model is developed for the time-to-permit and repair time using the twelve predictors and all 456 buildings in the permit-issue-completion dataset. The statistical relationships between the time parameters and the various explanatory variables including physical building information and scial economic factors are used to formulate a generalized recovery model that can predict recovery trajectories for future earthquakes given the spatial distribution of building damage described by the HAZUS states. While the model will not be applicable to all scenarios, it can be used in cases where the affected region, earthquake and recovery typology are judged to be comparable to the 2014 South Napa consideration. In this study, the new model is used to generate a recovery trajectory for the 1470 buildings for which we have information on the damage state and predictors.

Figure 5 compares the simulated recovery trajectory for the dataset of 1470 buildings to the "statistical" simulated and observed trajectories for the 456 buildings in the time-to-permit dataset. It shows that the trajectory for the complete dataset closely follows that of the permit-issue-completion subset up to about 58 days following the earthquake, after which the former has a faster recovery. Without the permit-issue (where applicable) and completion date of the 1014 buildings not included in the permit-issue-completion dataset, a definitive explanation of this observation is not possible. However, we do know that many of those buildings were damaged below the threshold that would require a permit to perform the repairs. These buildings would generally have a faster recovery time than the buildings requiring permits. If the majority of the 1014 buildings are in this category, this could be a possible explanation for the steeper recovery trajectory (between 58 and 611 days after the earthquake) for the full dataset compared to the permit-issue-completion subset.

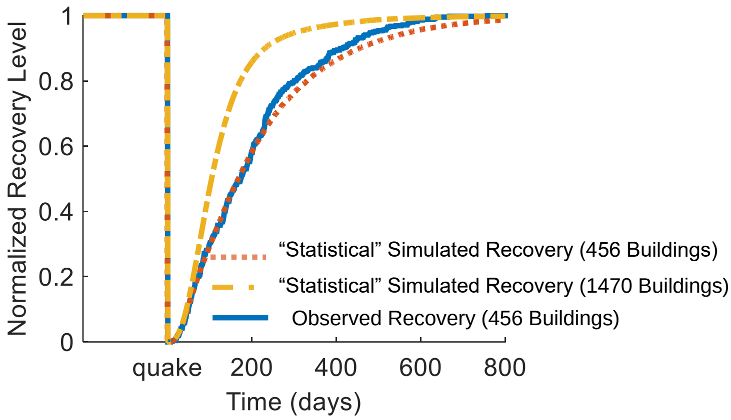


Figure 5. Comparing observed and statistical recovery simulation for the permit-issue-complete (456 buildings) data subset the complete (1470 buildings) dataset

4 Summary and Conclusions

Post-earthquake recovery simulation is useful for quantifying and enhancing the seismic resilience of communities. By exploring trends for multiple "what-if" recovery-scenarios, different types of resilience-building interventions can be evaluated including pre- (e.g. seismic retrofit of infrastructure) and post-event (e.g. incentivize residents to remain in affected community and rebuild) strategies. In this paper, stochastic process simulation models are used to re-enact the recovery of the damaged building stock following the 2014 South Napa earthquake. The study serves two purposes. First, the modeling technique is evaluated by comparing recovery predictions with empirical data on building repair and reconstruction following a real earthquake. Secondly, the empirical data is used to update the simulation model for application to future earthquakes, recognizing the inherent place- and event-specific nature of the model. The proposed recovery models can assist policy-makers, municipal governments, and planners in understanding and acting upon necessary solution alternatives for enhancing community resilience. The general approach is extendable to other disasters, such as hurricane and floods.

The effect of lifeline damage on the recovery trajectory for the portfolio of damaged buildings was not considered in this study. For the 2014 South Napa Earthquake, all major utilities and transportation systems was restored within a week. As such, lifeline damage and restoration did not have a major impact on the long-term recovery. However, for larger events with more widespread damage, lifeline restoration would be a major factor. Due to a lack of relevant information, building functionality was not considered in the recovery model. The "generalized" model was developed using data from a single event. As such, future applications of that model would need to be limited to scenarios where the target region, scale of damage and recovery typology are deemed similar to that of the 2014 South Napa earthquake.

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