A Stochastic Approach to Model Household Re-occupancy in A Community Following A Natural Hazard

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ABSTRACT: The re-occupancy of displaced households in a community following a hazard event is a complex social process driven collectively by the functionality states of community building portfolios and supporting lifelines. This study presents a novel approach for household re-occupancy (HRO) modeling using discrete state, Discrete Time Markov Chain (DTMC). Our hypothesis is that the re-occupancy state of a displaced household at a post-event time is collectively determined by the joint functionality status (JFS) (of its related school(s), workplace(s) and pre-event dwelling unit) and by the resourcefulness of the household largely determined by its income level. Accordingly, we construct a one-step transition probability matrix of the DTMC modeling the household's JFS as a function of the functionality states of its school(s), workplace(s) and pre-event dwelling unit; additionally, based on available social science studies, we further define a set of time-dependent conditional re-occupancy probability functions (CRPFs) that give the probability of a household re-occupying its pre-event dwelling units at any time conditional on the change in household's JFS and its income level. Finally, the time-variant household-level re-occupancy probability is derived by solving the DTMC with partially absorbing boundary conditions described by the CRPFs. The community-level HRO is then obtained through aggregating the household-level re-occupancy state across the community over the recovery time horizon. The model will be further calibrated by data collected in ongoing field studies with an ultimate goal of supporting further researches on community resilience planning.

1. INTRODUCTION

In recent years, disaster research has recognized the needs to go beyond physical damage to capture the social and economic impact of a community caused by natural or man-made disaster events. For example, the on-going efforts in the NIST-funded Center for Risk-based Community Resilience Planning are targeted at the development of measurement science and technology to integrate science-based models of community socio-economic systems and supporting interdependent infrastructure. While loss estimation models and recovery prediction models are expanding, overcoming the significant gap between the engineering and the social science approaches is always a challenge. An understudied topic, among many others, is the occupancy recovery of dislocated households. Modeling the post-disaster household re-occupancy process would be valuable to key decision makers to identify the most vulnerable zones, which can further inform decisions regarding financial resource allocation to people in most need of assistance.

The re-occupancy of dislocated households in a community following a hazard event is a complex social process driven collectively by the functionality status of community building portfolios and supporting lifelines. Despite empirical studies of past events have documented numbers of variables that affect the course and outcome of this process, post-disaster household re-occupancy (HRO) is seldom investigated and quantitatively analyzed. The difficulties mainly come from integrating existing engineering and social science models. On one hand, structural engineers have made great progress in developing models that predict the probability of a building that is likely (or numbers of buildings within the community that are likely) to be damaged or become unfunctional due to a natural hazard event [e.g., HAZUS-MH (FEMA/NIBS, 2003), MAEViz (Steelman et al., 2007); Vitoontus & Ellingwood, 2013; Bonstrom & Corotis, 2014; Lin & Wang, 2016; Zhang et al., 2018]; as well as models predicting the functionality recovery process of buildings after the hazard event (Burton et al., 2015; Lin & Wang, 2017a,b). On the other hand, social scientists have long been engaged in finding socioeconomic factors that serve as significant predictors of household dislocation and population recovery from field study of historical events (Bolin & Stanford, 1991; Peacock & Girard, 1997; Whitehead et al., 2000; Whitehead, 2005). Moreover, the household re-occupancy process is further complicated due to its stochastic nature, both temporally and spatially, which presents additional challenges to model the HRO in a quantitative manner.

In this study, a novel stochastic approach is developed to model HRO in a community following a natural hazard event. Our hypothesis is that the re-occupancy state of a displaced household at a post-event time is collectively determined by the joint functionality status (JFS) (of its related school(s), workplace(s) and pre-event dwelling unit) and by the resourcefulness of the household largely determined by its income level. Accordingly, we simulate the HRO through constructing a discrete-state, discrete time Markov Chain (DTMC) subjected to partially absorbing boundary conditions. The next section discusses the overall simulation framework and mathematical formulation, which is followed by conclusions summarized in Section 3.

2. METHODOLOGY

This study is aimed at predicting stochastic re-occupancy process for pre-event household reoccupying their pre-event dwelling unit (as opposed to a dwelling unit occupied by a new household). Examining existing studies on population recovery, it is found that population demographics (e.g., family income) and the severity of damage to the built infrastructure are important predictors of whether evacuees returned to their houses (Groen & Polivka, 2010; Fussell et al., 2010). Moreover, a household's decision to return in most cases is strictly dependent on whether the dwelling unit is safe to occupy, the residents can go to work, and whether children can go to school (FEMA/NIBS, 2003; Peacock et al., 2008; Lin, 2009; Xiao & Van Zandt, 2012; Masoomi et al., 2017).

Accordingly, our hypothesis is that the re-occupancy state of a displaced household at a post-event time is collectively determined by the JFS of its dwelling unit, school(s), and workplace(s) and by its income level. At household-level, a unique household's post-event re-occupancy state is simulated by three analysis modules: (1) a discrete state DTMC that simulates the JFS of school(s), workplace(s), and pre-event dwelling unit associated with a unique household is developed; (2) a set of time-dependent conditional re-occupancy probability functions (CRPFs) are defined that give the probability of a household re-occupying its pre-event dwelling unit at any time conditional on the change in household's JFS and its income level; (3) the time-variant household-level re-occupancy probability is derived by solving the DTMC with partially absorbing boundary conditions described by the CRPFs. A flowchart of the stochastic model to predict household-level re-occupancy state is illustrated in Figure 1 with aforementioned three steps colored in yellow. Lastly, the community-level HRO recovery curve is obtained through aggregating the re-occupancy states of all households across the community over the recovery time horizon.

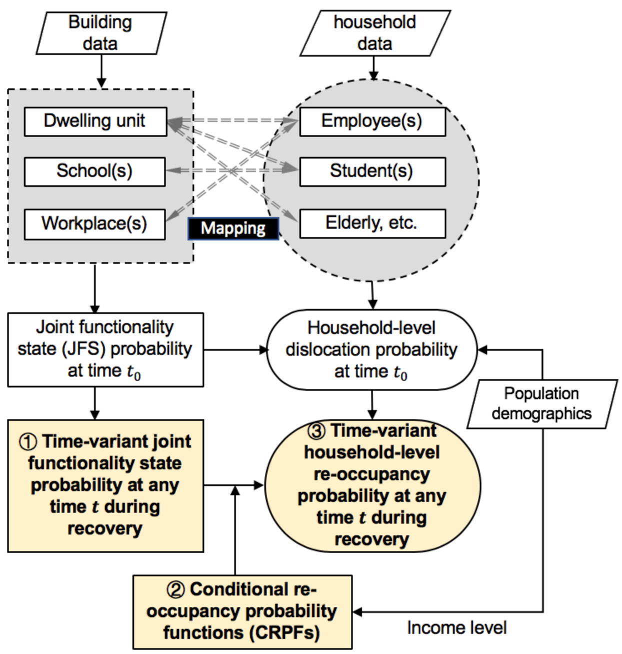

Figure 1: Flowchart of the stochastic model to predict household-level re-occupancy state

2.1 DTMC modeling JFS of dwelling unit, workplaces, and schools

A household consisting of children, employees and perhaps elderly, are geographically linked to a dwelling unit, a school (or schools), and workplaces. The post-disaster functionality states of these buildings, as stated above, serve as key driving factors of the HRO model. For instance, a household would not return to their house unless the severely damaged building is repaired, or the destroyed building is reconstructed; a household would probably choose to shelter in place before utility service at the building site is restored.

2.1.1 Functionality states of individual buildings

In the literature, a building's functionality is defined as the capability of that building to serve its intended purpose and can be categorized into five functionality states —*Restricted Entry* (*RE*), *Restricted Use* (*RU*), *Re-Occupancy* (*RO*), *Baseline Functionality* (*BF*) and *Full Functionality* (*FF*) (Lin & Wang, 2017a). Based on this definition, in the present study the dwelling unit (i.e., residential building)'s functionality status is classified into three groups: (1) G1: *RE* and *RU*, in which case buildings are not safe to be occupied; (2) G2: *RO*, in which case buildings can be occupied but lack utility supply; (3) G3:*BF* and *FF*, in which case buildings both are re-occupiable and have utility supply. Compared with dwelling units, schools and workplaces have less influences on HRO, thus their functionality status is defined binary for simplicity: *Functional* (denoted as *F*, buildings are re-occupiable and have utility supply) or *Non-Functional* otherwise (denoted as *NF*).

Mathematically, the functionality states of dwelling units, schools, and workplaces can be simulated using discrete state, DTMC process. Taking dwelling unit (D) unit as an example. Let us consider a DTMC, $\{S^D(k), k \in \boldsymbol{T}\}$, modeling time-variant functionality state of a dwelling unit. Given discrete time steps $\boldsymbol{T} = \{1,2,\dots,k,\dots\}$, the $\lambda_1^D(k)$ is defined as the one-step transition probability of residential buildings upgrading from functionality state G1 to G2 at k-th time step; $\lambda_2^D(k)$ is defined as the one-step transition probability of residential buildings upgrading from G2 to G3 at k-th time step. Accordingly, the one-step transition probability matrix of $S^D(k)$ is described by

$$\boldsymbol{P}^D(k) = \begin{pmatrix} 1-\lambda_1^D(k) & \lambda_1^D(k) & 0 \\ 0 & 1-\lambda_2^D(k) & \lambda_2^D(k) \\ 0 & 0 & 1 \end{pmatrix} \quad (1)$$

Similarly, for constructing DTMC of schools and workplaces, $\lambda^S(k)$ and $\lambda^W(k)$ are defined as the time-variant one-step transition probabilities of school (*S*) and workplace (*W*) upgrading from *NF* state to *F* state at *k*-th time step, respectively. These one-step transition probabilities can be either obtained from empirical study through field survey or calculated from analytical approach using building-level restoration functions (Lin & Wang, 2017a).

2.1.2 JFS of dwelling unit, schools, and workplaces

With the above functionality state categorizations, we further construct 12 JFSs (ranging from J1 to J12) of dwelling unit, workplace(s), and school(s) associated with a specific household, as shown in Table 1. In the table, the schools (workplaces) are considered *F* only if all schools (workplaces) linking to that household are functional. Note that this assumption can be relaxed by introducing more JFSs to include different combinations of multiple schools and workplaces.

Table 1: Definition of JFSs of school(s), workplace(s), and dwelling unit

JFS	School(s)	Workplace(s)	Dwelling unit
J_1	*NF*	*NF*	*RE, RU*
J_2	*F or NA*	*NF*	*RE, RU*
J_3	*NF*	*F or NA*	*RE, RU*
J_4	*F or NA*	*F or NA*	*RE, RU*
J_5	*NF*	*NF*	*RO*
J_6	*F or NA*	*NF*	*RO*
J_7	*NF*	*F or NA*	*RO*
J_8	*F or NA*	*F or NA*	*RO*
J_9	*NF*	*NF*	*BF, FF*
J_{10}	*F or NA*	*NF*	*BF, FF*
J_{11}	*NF*	*F or NA*	*BF, FF*
J_{12}	*F or NA*	*F or NA*	*BF, FF*

*NA— not available

A household's JFS, as a function of the functionality states of its school(s), workplace(s) and pre-event dwelling unit, is simulated using a discrete state, DTMC. This DTMC is denoted as $\{JFS(k), k \in \boldsymbol{T}\}$, with its time-variant probability vector, $\boldsymbol{X}(k), k = 0,1,2,\ldots$, taking the following form,

$$\begin{aligned}\boldsymbol{X}(k) &= [x_1(k), \ldots, x_{12}(k)] \\ &= \boldsymbol{X}(0) * \boldsymbol{P}^X(1) * \ldots * \boldsymbol{P}^X(k)\end{aligned} \tag{2}$$

in which $\boldsymbol{X}(0)$ is the initial JFS probability vector after occurrence of the hazard event; $\boldsymbol{P}^X(k)$ is the one-step transition probability matrix with its element defined as

$$\begin{aligned}p^X_{m,n}(k) &= \\ &P[JFS(k) = J_n | JFS(k-1) = J_m]\end{aligned} \tag{3}$$

in which $m = 1,2, \ldots, 12; n = 1,2, \ldots 12$.

Neglecting the stochastic correlation among functionality states of dwelling unit, school, and workplace, as well as neglecting higher order probabilities (which is valid when the time step is small), $\boldsymbol{P}^X(k)$ is expressed as

$$\boldsymbol{P}^X(k) = \begin{pmatrix} \boldsymbol{A}_1(k) & \boldsymbol{B}_1(k) & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{A}_2(k) & \boldsymbol{B}_2(k) \\ \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{A}_3(k) \end{pmatrix} \tag{4}$$

in which $\boldsymbol{A_q}, q = 1,2,3$ are 4×4 upper triangular matrixes, with their elements tabulated in Table 2; $\boldsymbol{B_q} = \lambda^D_q(k) \cdot \boldsymbol{I}_{4\times4}$, $q = 1,2$, in which $\boldsymbol{I}_{4\times4}$ is the 4×4 identify matrix.

Table 2. Element of $\boldsymbol{A_q}, q = 1,2,3$ ($\lambda^D_3(k) \equiv 0$)

a_{ij}	Expression
a_{11}	$1 - \lambda^S(k) - \lambda^W(k) - \lambda^D_q(k)$
a_{12}	$\lambda^S(k)$
a_{13}	$\lambda^W(k)$
a_{14}	0
a_{22}	$1 - \lambda^W(k) - \lambda^D_q(k)$
a_{23}	0
a_{24}	$\lambda^W(k)$
a_{33}	$1 - \lambda^S(k) - \lambda^D_q(k)$
a_{34}	$\lambda^S(k)$
a_{44}	$1 - \lambda^D_q(k)$

2.2 Conditional re-occupancy probability functions (CRPFs)

With the pre-defined 12 JFSs associated with a household, the effect of restoring buildings' functionality on HRO is reflected in the CRPFs defined in this section. The CRPFs is defined as the probability of a household re-occupying its pre-event dwelling unit at any post-event time conditional on the status change in household's JFS and its income level.

Let a household's re-occupancy status be $\Theta(k)$, which is a two-state Markov chain (namely, occupancy, O and dislocation, $\bar{O}$). For a certain group of income level (IL), the CRPF, $\gamma_{m,n}^{IL}(k)$, is the re-occupancy probability of a displaced household at k-th time step given that the displaced household is upgrading from JFS J_m at previous time step $k-1$ to JFS J_n at current time step k, i.e. (the subscript IL of $\gamma_{m,n}^{IL}$ is not present in the following equations for simplicity purpose),

$$\gamma_{m,n}(k) = P[E^1(k)|E_{m,n}^2(k)] \tag{5a}$$

$$E^1(k) = [\Theta(k) = O|\ \Theta(k-1) = \bar{O}] \tag{5b}$$

$$E_{m,n}^2(k) = [JFS(k) = J_n\ |\ JFS(k-1) = J_m] \tag{5c}$$

in which $m = 1,2,\ldots,12; n = 1,2,\ldots 12$.

In this study, it is assumed that the household won't return as long as their dwelling unit is un-occupiable (functionality state RE and RU), therefore, $\gamma_{m,n} = 0$ for all $m \le 4, n \le 4$. Moreover, $\gamma_{m,n} = 0$ for all $n \le m$ since a household's JFS is always non-decreasing. The CRPF curves can be collected based on anecdotal evidence, expert opinion, and field work in multiple hazards over several decades (Peacock et al., 2008; Lin, 2009; Xiao & Van Zandt, 2012).

2.3 Stochastic household re-occupancy process

To derive the two-state Markov Chain $\{\Theta(k), k \in \boldsymbol{T}\}$, modeling a household's post-event re-occupancy state, we first examine the joint events $\Lambda_m(k) = [JFS(k) = J_m, \Theta = \bar{O}], m = 1,2\ldots,12$.

Define a stochastic process $\{\Lambda(k), k \in \boldsymbol{T}\}$, in which $\Lambda(k)$ is assumed to take one of the 12 joint events $\Lambda_1(k), \Lambda_2(k), \ldots, \Lambda_{12}(k)$. The time-variant state probability of $\Lambda(k)$ is

$$\begin{aligned}\boldsymbol{Y}(k) &= [y_1(k), \ldots, y_{12}(k)] \\ &= \boldsymbol{Y}(0) * \boldsymbol{P}^Y(1) * \ldots * \boldsymbol{P}^Y(k)\end{aligned} \tag{6}$$

in which $\boldsymbol{Y}(0) = [y_1(0), \ldots, y_{12}(0)]$ is the initial state probability vector of $\Lambda(k)$ determined by household dislocation model. The element of $\boldsymbol{P}^Y$ is

$$\begin{aligned}p_{m,n}^Y(k) &= [\Lambda_n(k)|\Lambda_m(k)] \\ &= P[\overline{E^1}(k)|E_{m,n}^2(k)] \cdot P[E_{m,n}^2(k)] \\ &= [1 - \gamma_{m,n}(k)] \cdot p_{m,n}^X(k)\end{aligned} \tag{7}$$

Eq. (7) is equivalent to solving the DTMC process modeling JFS of a household subjected to the following partially absorbing boundary conditions (as illustrated in Figure 2),

$$P[\overline{E^1}(k)|E_{m,n}^2(k)] = 1 - \gamma_{m,n}(k) \tag{8}$$

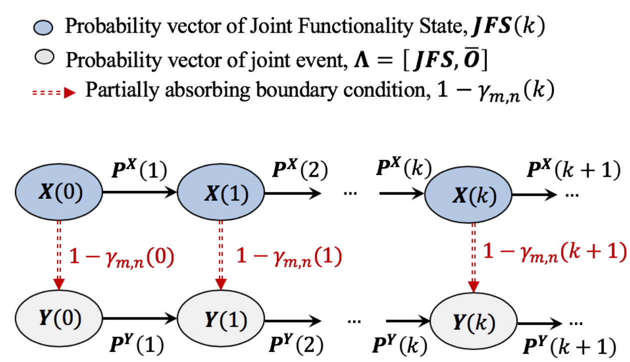

Figure 2: Illustration of applying partially absorbing boundary condition to DTMC modeling JFS of a household

Accordingly, the time-variant post-event HRO probability is obtained using the total probability theorem

$$\begin{aligned}[\Theta(k) = O] &= 1 - P[\Theta(k) = \bar{O}] \\ &= 1 - \sum_{m=1}^{12} y_m(k)\end{aligned} \tag{9}$$

Lastly, considering a community with N_H households, the community-level household re-occupancy curve (CHRO), defined as the expected percentage of households reoccupying their pre-event dwelling unit, is obtained by

$$CHRO(k) = \frac{1}{N_H}\sum_{l=1}^{N_H} P\left[\Theta^{(l)}(k) = O\right] \qquad (10)$$

in which $\Theta^{(l)}$ is the occupancy state of the *l-th* household in the community.

3 CONCLUSIONS

The re-occupancy of dislocated households in a community following a hazard event is a stochastic process largely determined by the functionality recovery of community building portfolios as well as households' socioeconomic characteristics. In this study a novel stochastic approach is proposed to model post-hazard HRO process, through integration of physical and social infrastructure systems within a community. The coupling of existing engineering models (building functionality recovery model) and social science models (population dislocation model) is fulfilled via imposing partially absorbing boundary conditions (described by the CRPFs in Section 2.2) to the discrete state, DTMC modeling JFSs of dwelling unit, schools, and workplaces associated with a household. Such a stochastic approach has enabled those key community socioeconomic characteristics to be included in the HRO model while to a great extent capturing the fundamental mechanisms of the post-hazard HRO process. The model will be further calibrated by data collected in ongoing field studies with an ultimate goal of supporting further researches on community resilience planning.

Overall, the approach presented herein is greatly distinguished from those conventional social science models, which have utilized regression analysis to quantify hazard-induced social losses using expected building damage as the major input variable along with other demographic characteristics. The HRO process is highly intricate and its stochastic nature can hardly be captured solely using conventional social science models. The merit of our approach lies in its capability to inherit consistent uncertainty treatment from existing engineering models, which can provide insight into interdisciplinary research on coupling engineering and social science models.

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5 REFERENCES

Bolin, R., & Stanford, L. (1991). Shelter, housing and recovery: a comparison of US disasters. *Disasters*, 15(1), 24-34.

Bonstrom, H., & Corotis, R.B. (2014). Building portfolio seismic loss assessment using the First-Order Reliability Method. *Structural Safety*, doi:10.1016/j.strusafe.2014.09.005.

Burton, H. V., Deierlein, G., Lallemant, D., & Lin, T. (2015). Framework for incorporating probabilistic building performance in the assessment of community seismic resilience. *Journal of Structural Engineering*, 142(8), C4015007.

FEMA/NIBS. (2003). Multi-hazard Loss Estimation Methodology Earthquake Model (HAZUS-MH MR4): Technical Manual. Washington, D.C.

Fussell, E., Sastry, N., & VanLandingham, M. (2010). Race, socioeconomic status, and return migration to New Orleans after Hurricane Katrina. *Population and environment*, 31(1-3), 20-42.

Groen, J. A., & Polivka, A. E. (2010). Going home after Hurricane Katrina: Determinants of return migration and changes in affected areas. *Demography*, 47(4), 821-844.

Lin, Y. (2009). Development of algorithms to estimate post-disaster population dislocation: A research-based approach. Ph.D. thesis, Texas A & M University.

Lin, P., & Wang, N. (2016). Building Portfolio Fragility Functions to Support Scalable Community Resilience

Assessment. *Sustainable and Resilient Infrastructure*, 1(3-4), 108-122.

Lin, P., & Wang, N. (2017a). Stochastic Post-Disaster Functionality Recovery of Community Building Portfolios II: Application. *Structural Safety*, 69, 106-117.

Lin, P., & Wang, N. (2017b). Stochastic Post-Disaster Functionality Recovery of Community Building Portfolios I: Modeling. *Structural Safety*, 69, 96-105.

Masoomi, H., van de Lindt, J. W., & Peek, L. (2018). Quantifying socioeconomic impact of a Tornado by estimating population outmigration as a resilience metric at the community level. *J. Struct. Eng*, 144(5), 04018034.

Peacock, W. G., B. H. Morrow, & H. Gladwin. (1997). *Hurricane Andrew: Ethnicity, Gender, and the Sociology of Disasters*. London: Routledge.

Peacock, W., Lin, Y., Lu, J., & Zhang, Y. (2008). Household dislocation algorithm 2: an OLS through the origin approach. Hazard Reduction and Recovery Center. Texas A&M University. HRRC Reports: 08-04R.

Steelman, Joshua, Junho Song, & Jerome F. Hajjar. (2007). Integrated Data Flow and Risk Aggregation for Consequence-Based Risk Management of Seismic Regional Loss. University of Illinois.

Vitoontus, S. & Ellingwood. B.R. (2013). Role of Correlation in Seismic Demand and Building Damage in Estimating Losses under Scenario Earthquakes. *Proc. Int. Conf. on Struct. Safety and Reliability (ICOSSAR 2013)*, New York, NY, Taylor & Francis, A.A. Balkema, The Netherlands.

Whitehead, J. (2005). Environmental risk and averting behavior: Predictive validity of jointly estimated revealed and stated behavior data. *Environmental and Resource Economics*, 32(3), 301-316.

Whitehead, J., Edwards, B., Van Willigen, M., Maiolo, J., Wilson, K., & Smith, K. T. (2000). Heading for higher ground: Factors affecting real and hypothetical hurricane evacuation behavior. *Environmental Hazards*, 2, 133-142.

Xiao, Y., & Van Zandt, S. (2012). Building community resiliency: Spatial links between household and business post-disaster return. *Urban Studies*, 49(11), 2523-2542.

Zhang, W., Lin, P., Wang, N., Nicholson, C., & Xue, X. (2018). Probabilistic Prediction of Post-Disaster Functionality Loss of Community Building Portfolios Considering Utility Disruptions. *Journal of Structural Engineering*, 144(4), 04018015.