Minimum Performance Targets for the Built Environment based on Community-Resilience Objectives

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ABSTRACT: Disrupted critical infrastructure systems following disasters can result in population outmigration which may subsequently negatively impact a community's indirect socioeconomic losses over time. In this study, a community was modeled with its interconnected physical-socio-economic attributes and population outmigration was used as a basic proxy community resilience metric. The probability of outmigration for each household was assessed based on the probability that the school-age students, household residents, and employees in the household are affected over a prescribed time period from the occurrence of the hazard to the full restoration of the community. Finally, the potential population outmigration for the community was assessed by aggregating the probability for all the households in the community. Additionally, a prediction model for the number of injuries and fatalities was implemented in the analysis to be served as a community-level life-safety metric. Ultimately, these metrics were combined and utilized to propose a framework for disaggregation of a set of community-level objectives into a set of performance targets for the components of the built environment. Such a model is desirable for policymakers and community leaders in order to make long-term decisions for their community.

1. INTRODUCTION

Studying the resilience of critical infrastructure systems has justifiably received the attention of researchers, community leaders, and policymakers after paying attention to the socioeconomic consequences of recent disasters such as the 2001 World Trade Center Attack, the 2003 North America Blackout, the Japan Earthquake and Tsunami of 2011, and Hurricane Maria in 2017. A resilient community has been defined as one that has planned for potential hazards in order to be able to resist, absorb, and adjust to changing conditions as well as to return to a level of normalcy within a reasonable time following a disaster (Alexander, 2013; Bruneau et al., 2003; Platt et al., 2016; PPD-21, 2013). Koliou et al. (2018) reviewed past community resilience studies with a focus on the effects of natural hazards on the built environment as well as social and economic sectors within a community. They also discussed the critical gaps to be addressed in order to enhance community-level resilience assessment methodologies. An example of these critical paucities in the literature is considering the dependencies and cross-dependencies across community components and networks to study a community-level resilience methodology that links the physical, social, and economic sectors within the community.

Lin et al. (2016) proposed a disaggregation framework that determines design performance targets for individual buildings by satisfying a community-level goal. The community-level metric defined in their study is the percentage of the buildings that are unsafe to occupy after a specified scenario. Reinhorn and Cimellaro (2014) and Cimellaro et al. (2015) proposed a resilience-based design framework which considers all the structures and networks within a community to define a resilience metric and use it further to find performance targets for individual structures. This framework provides information beyond those offered by current standards for decision makers and engineers. Zhang et al. (2018) developed a methodology for designing networks subjected to disruptive events, which minimizes the cost while satisfies system resilience goals as well. Salem et al. (2017) designed a blast-resilient methodology for buildings. Their methodology considers the direct loss to the building as well as downtime, but it neglects the importance of interactions between building and other components and networks within the community.

In this study, a framework is presented that elaborates on modeling the built environment of communities for resilience study and how to use some predefined community-level metrics (including resilience metrics) for designing individual structures in the built environment. The proposed methodology can be implemented for optimal recovery planning (Nozhati et al., 2019) or resilience-based risk-informed decision-making tools for community leaders and policy makers.

2. COMMUNITY MODELING

The west part of Norman, OK, USA, with an area of 14.5 km by 12.9 km was studied herein which includes more than 90% of Norman's population. The residential sector (RS) in this area includes 41,254 houses among which 37,785 are occupied and 3,469 are unoccupied. The number of occupied and unoccupied houses, population, median house value, median household income, median family income, the percentage of unemployment, as well as the number of students in each school level were derived from census data (City-Data, 2016). Moreover, the city has fifteen elementary schools (ES), four middle schools (MS), and two high schools (HS) which host 4,829 students, 3,671 students, 3,460 students, respectively. Also, the city's total population is 110,844. For the business sector (BS), 53,890 people work in the modeled part of Norman, among which, 49,848 employees live in the city and the rest (i.e., 4,042 employees) live outside the city.

The electric power network (EPN) in the community includes 4 transmission substations (TSS), 18 distribution substations (DSS), 123 transmission towers, and 1,393 sub-transmission towers. Transmission and sub-transmission towers are spaced at 310 m and 110 m, respectively. Also, a simplified water supply network (WSN), including six water towers (WT) with different capacities and one water treatment plant (WTP), was considered for Norman. In order to consider the effects of cascading failure in the analyses, dependencies among the components of each network and the cross-dependencies between components of different networks were modeled here. The cross-dependencies among networks are summarized in Table 1. The EPN provides electricity for the WSN, SN, RS, and BS. The WSN satisfies the water demand of the SN, RS, and BS. The school network hosts the students who live in the residential sector and the residential and business sectors are mutually dependent.

Table 1. Cross-dependency matrix for the networks

Network	is cross-dependent on (i.e., is supplied by):				
	RS	BS	EPN	WSN	SN
RS		×	×	×	×
BS	×		×	×	
EPN					
WSN			×		
SN			×	×	

After modeling the topology of networks and their components as well as the interaction between components, the properties of each component need to be assigned according to the studied natural hazard. In this study, the performance of community components when subjected to tornado were modeled through a set of tornado fragility curves. Additionally, a repair time associated with each damage state was assigned to each community component for investigating the restoration analysis following a simulated tornado event. For more information regarding the fragilities and repair time parameters, readers are referred to Masoomi et al. (2017), Memari et al. (2017), Koliou et al. (2017), Masoomi and van de Lindt (2016), and Lopez et al. (2009).

3. DAMAGE SIMULATION

Since Norman, OK, is a tornado-prone region, tornado hazard was selected in this study. The tornado path was modeled according to the gradient method proposed by Standohar-Alfano and van de Lindt (2014). The gradient method idealizes a tornado path with a rectangle which includes several sub-rectangles for modeling different intensities in a tornado path. Masoomi and van de Lindt (2017) discussed this method along with two other tornado path simulation methods. Based on the gradient method, for modeling a tornado path, it is needed to define the tornado path direction, length, width, and the coordinate of its center point. In this study, the tornado path direction is a random variable with a uniform distribution between 0 and π while it was assumed that any simulated path has a center point located randomly in the specified boundary of Norman shown in Figure 1. Additionally, tornado path length and width are correlated random variables and were generated based on the Gaussian copula model (the marginal distributions for path length and width are per Masoomi and van de Lindt (2018a)).

By modeling the tornado path, the tornado intensity applying on each component in the city is known. Therefore, based on the fragility parameters for each component and the wind speed corresponding to the EF-intensity acting on the component (shown in Table 2), a spatial realization of damage can be simulated. This damage which is based on the physical performance of the component defines the intrinsic failure status of the component. However, each component might have some externalities which are required for the normal functioning of the component. Therefore, after modeling the physical damage of the components, it is required to find the extrinsic failure status of the component by considering the dependencies between components of a network or cross-dependencies among the components of different network. This allows consideration of the cascading failure in the resilience assessment of communities with interdependent networks. Once, the extrinsic failure status of the component is found, then, the functionality failure status for the component is just simply the union of the intrinsic and extrinsic failure statuses. The functionality failure status of the components will be used to measure the performance of the networks and the community at different times following the event, which can be illustrated as the recovery curves discussed in the next section.

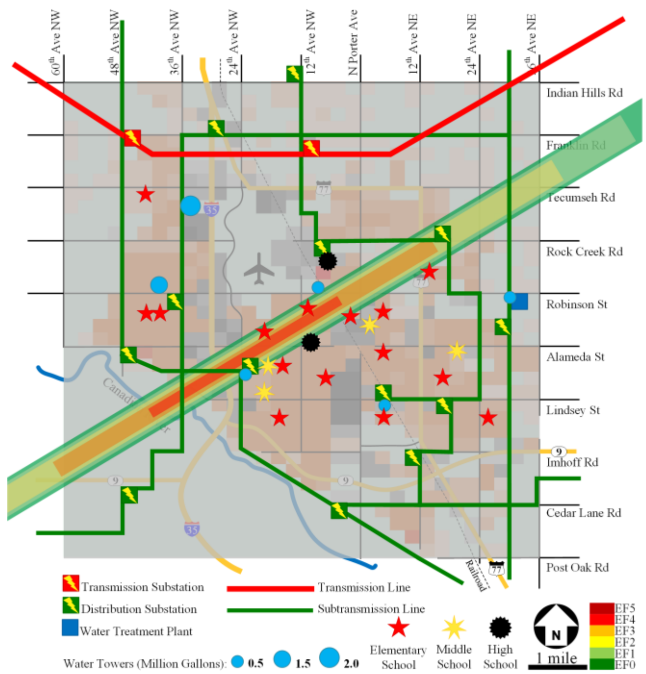

Figure 1. A simulated tornado path along with the modeled networks of Norman

Table 2. Wind speed for each EF scale

EF Scale	3-Sec Gust Wind Speed, m/s (mph)	
	Wind Speed Range (McDonald and Mehta, 2006)	Mean Value
EF0	29-38 (65-85)	34 (75)
EF1	39-49 (86-110)	44 (98)
EF2	50-60 (111-135)	55 (123)
EF3	61-74 (136-165)	67 (150)
EF4	75-89 (166-200)	82 (183)
EF5	>89 (>200)	101 (225)

4. RECOVERY ANALYSIS

The discrete event simulation (DES) method was used in this study for doing the recovery analysis. The flowchart for the recovery analysis is shown in Figure 2. For the recovery analysis, a recovery sequence list of the damaged components is first made for each network based on some priority rules/policies in that some components might be more critical than others and needs to be recovered as soon as possible. Then, the available recovery resource units are assigned to the damaged components in the recovery sequence list. Once a damaged component is repaired, the corresponding recovery resource unit moves to the next damaged component in the list until all components are repaired.

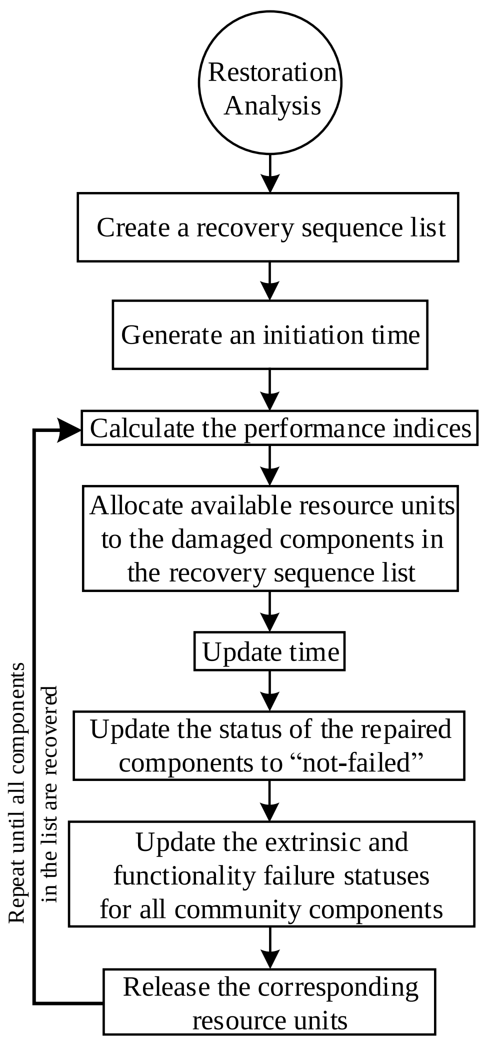

Figure 2. The flowchart for the recovery analysis

A performance index was defined for the WSN as the percentage of the community demand being supplied by the network. In order to illustrate the progress of restoration, the performance index was updated when a damaged component was repaired or when a DSS that feeds the pumping station of a WT became functional. The mean restoration curve for the WSN is shown in Figure 3 (a) for each EF-scale tornado. For example, immediately after an EF5 tornado, 64% of Norman, on average, would not be supplied by the WSN. After 14, 30, and 60 days of recovery following the event, the mean performance of the WSN is returned to 82, 90, and 95 percent, respectively.

Moreover, in order to elucidate the effect of the cross-dependencies among networks on the WSN mean restoration curve (i.e., the effect of the EPN performance loss on the performance of the WSN), the intrinsic and extrinsic performance loss were distinguished for the mean restoration curve of the EF5 tornado and are shown in Figure 3 (b). The intrinsic performance loss is the loss of performance in the WSN that resulted from the intrinsic failure of the components within the WSN, while the extrinsic performance loss is that which resulted from the extrinsic failure of the components. As shown in Figure 3 (b), the majority of the performance loss in the WSN immediately after an EF5 tornado is due to the extrinsic failures (i.e., the loss of performance in the EPN). However, the intrinsic failures last longer such that the contribution of the intrinsic and extrinsic failures are approximately equal in the performance loss of the WSN during the full restoration (i.e., 48% vs 52%). This is because the components in the WSN require a significantly longer duration to be repaired compared to the components in the EPN.

The recovery curves were developed for other networks as well (i.e., EPN, SN, RS, and BS). However, only the results for the WSN network was presented here as an example. The interested readers can refer to Masoomi (2018) for more information and the details of the recovery curves for all other networks.

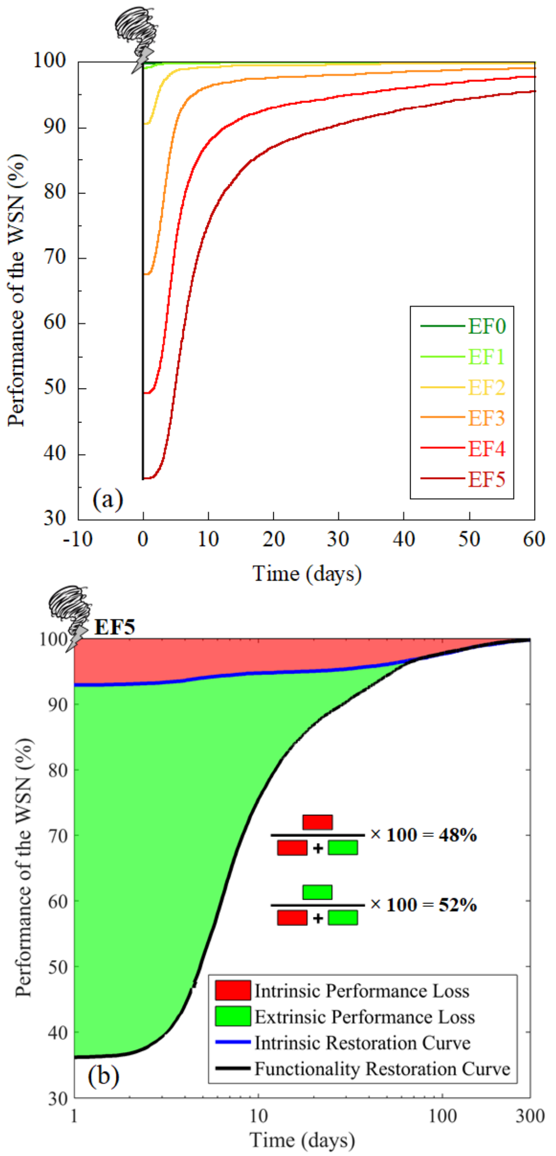

Figure 3. (a) Mean restoration curves for the WSN after each EF-scale tornado and (b) the effect of cross-dependencies on the WSN mean restoration curve after an EF5 tornado

5. POPULATION OUTMIGRATION

Masoomi et al. (2018) quantified population outmigration as a socioeconomic resilience metric that can be assessed at different level from household-level to community-level. This metric was selected in the current study as a community-level resilience metric. The population outmigration methodology calculates the probability of outmigration for each household in the city based on damage to the buildings and infrastructure, school closure, and loss of employment. Therefore, the students, employees, and other residents in a household are considered in the methodology to see if they are affected by non-functionality of schools, workplaces, and residences, respectively. the functionality of each building (i.e., residential, school, and workplace buildings) depends on the physical performance of the building as well as the availability of water and electric power.

Once the probability of outmigration is calculated for each household in the city, the probability can be aggregated for the households at each grid to estimate population outmigration (PO) at the grid level or be aggregated for all households in Norman to estimate PO at the community level. In this study, population outmigration analysis was performed for Norman subjected to tornadoes with different intensities and the mean percentage of population outmigration at the community-level is shown in Figure 4 as a function of time after the event for each EF-scale tornado. In the case of an EF5 tornado (with the tornado path center located within the area of pseudo-Norman), 6.96% of the Norman's population (approximately 7,700 people) out-migrate, on average, as a result of physical-socio-economic disruptions in the community.

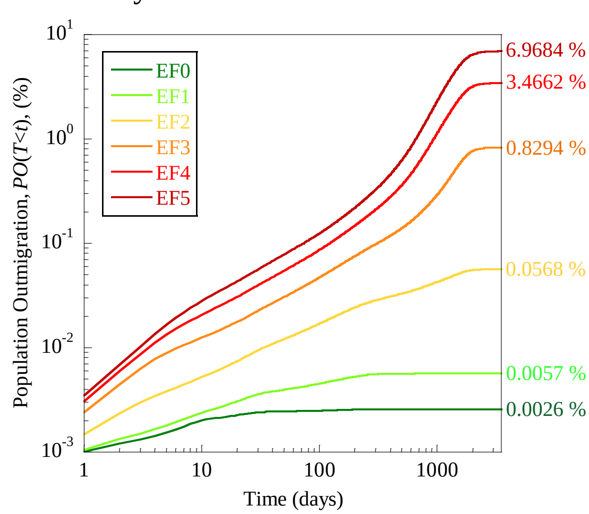

Figure 4. Mean population outmigration in Norman after each EF-scale tornado

6. FATALITIES AND INJURIES

The number of tornado-induced injuries and fatalities were estimated for a simulated tornado to serve as a community-level life-safety metric in this study. Masoomi and van de Lindt (2018b) developed several models to predict tornado-induced injuries and fatalities based on a dataset of historical tornadoes in the United States.

For example, the Basic Model in Masoomi and van de Lindt (2018b) was applied to Norman to estimate casualties for a simulated tornado in Norman. The mean values for the expected number of injuries are 0.08, 0.16, 2.03, 11.41, 35.49, and 150.89, respectively, after an EF0 to EF5 tornado in Norman and the corresponding mean values for fatalities are 0, 0, 0, 0.56, 2.48, and 18.52, respectively.

7. COMMUNITY-RESILIENCE-BASED DESIGN

A community-resilience-based design (CRBD) methodology was proposed here based on population outmigration and tornado-induced casualties as community-level metrics, which is shown in Figure 5. The CRBD methodology along with a multi-objective optimization algorithm can be leveraged to disaggregate community-level objectives into a required performance target for the specified components of the built environment. Four resilience actions (i.e., robustness, redundancy, resourcefulness, and rapidity) can be considered to define the decision variables in the optimization problem in this methodology. For example, in order to improve robustness, the fragility curves can be enhanced. Redundancy can be boosted by changing the dependencies in the community modeling or by providing back-up components for the critical facilities such as hospitals. Furthermore, resourcefulness and rapidity can be improved in the recovery process by applying better policies for resource allocation or restoration prioritization.

As an example, a full analysis of Norman was done to find a predefined goal for each population outmigration and the number of tornado-induced injuries and fatalities after an EF3 tornado. For simplicity, the percent change in the median of fragility curves of the residential buildings in Norman was considered here as a decision variable while a myriad combination of decision variables can be assumed in an overarching analysis. As shown in Figure 6, after an EF3 tornado in pseudo-Norman, the mean population outmigration, the mean number of injuries, and the mean number of fatalities are equal to 919, 68.3, and 4.6, respectively. The values for these community-level metrics can be decreased to 266, 35.7, and 2.1, respectively, by a 25% increase in the decision variable. They can be further reduced into 167, 12.9, and 0.8, respectively, if 50% increase is chosen for the decision variable. These values can be checked with a predefined community-level goals defined by policymakers or community leaders to find if they are satisfactory. In order to increase the flexibility of the problem, the decision variables can be considered different for different parts of the city.

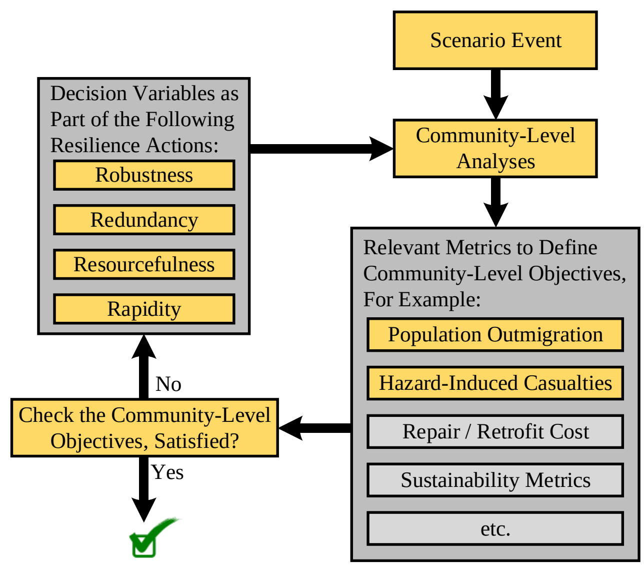

Figure 5. Community-resilience-based design (CRBD) methodology

8. CONCLUSIONS

In this study, a framework was proposed and explained for community-resilience-based design (CRBD) of the components of the built environment within a community. The purpose of the CRBD methodology is to disaggregate several prescribed community-level objectives (including resilience objectives such as population outmigration) into a set of required performance targets for specified (or all) components of the built environment. The proposed methodology can be further implemented to find an optimized recovery policy or to master-plan a new community or network.

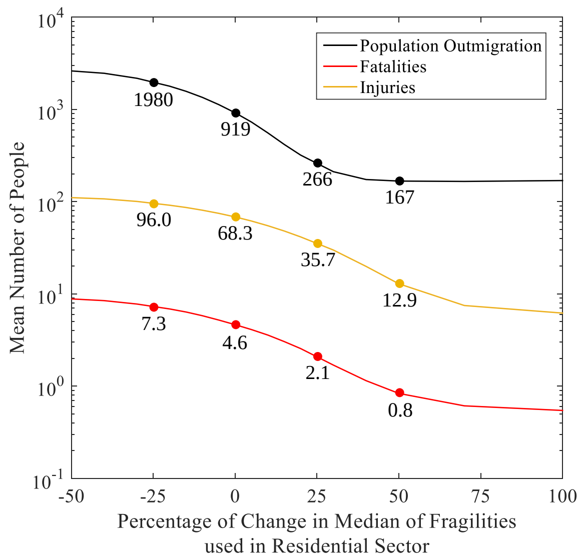

Figure 6. Mean population outmigration, mean number of fatalities, and mean number of injuries after an EF3 tornado in Norman for different performance changes of the buildings in the residential sector of Norman

9. REFERENCES

Alexander, D. E. (2013). "Resilience and disaster risk reduction: an etymological journey." *Natural Hazards and Earth System Sciences*, 13(11), 2707-2716.

Bruneau, M., Chang, S. E., Eguchi, R. T., Lee, G. C., O'Rourke, T. D., Reinhorn, A. M., Shinozuka, M., Tierney, K., Wallace, W. A., and von Winterfeldt, D. (2003) "A framework to quantitatively assess and enhance the seismic resilience of communities." *Earthquake spectra*, 19(4), 733-752.

Cimellaro, G. P., Renschler, C., & Bruneau, M. (2015). Introduction to resilience-based design (RBD). In *Computational Methods, Seismic Protection, Hybrid Testing and Resilience in Earthquake Engineering* (pp. 151-183). Springer International Publishing.

City-Data, (2016). < http://www.city-data.com/city/Norman-Oklahoma.html>.

Koliou, M., Masoomi, H., and van de Lindt, J.W. (2017). "Performance assessment of tilt-up big-box buildings subjected to extreme hazards: tornadoes and earthquakes." *Journal of Performance of Constructed Facilities*, 04017060.

Koliou, M., van de Lindt, J. W., McAllister, T. P., Ellingwood, B. R., Dillard, M., & Cutler, H. (2018). State of the research in community resilience: progress and challenges. *Sustainable and Resilient Infrastructure*, DOI: 10.1080/23789689.2017.1418547

Lin, P., Wang, N., & Ellingwood, B. R. (2016). A risk de-aggregation framework that relates community resilience goals to building performance objectives. *Sustainable and Resilient Infrastructure*, *1*(1-2), 1-13.

López, A. L., Rocha, L. E. P., Escobedo, D. L., and Sesma, J. S. (2009). "Reliability and vulnerability analysis of electrical substations and transmission towers for definition of wind and seismic damage maps for Mexico." *Proc., 11th Americas Conference on Wind Engineering*, San Juan, Puerto Rico.

Masoomi, H. (2018). *A resilience-based decision framework to determine performance targets for the built environment* (Doctoral Dissertation).

Masoomi, H., Ameri, M. R., & van de Lindt, J. W. (2018a). Wind Performance Enhancement Strategies for Residential Wood-Frame Buildings. *Journal of Performance of Constructed Facilities*, 32(3), 04018024.

Masoomi, H., van de Lindt, J. W., & Peek, L. (2018b). Quantifying Socioeconomic Impact of a Tornado by Estimating Population Outmigration as a Resilience Metric at the Community Level. *Journal of Structural Engineering*, 144(5), 04018034.

Masoomi, H., and van de Lindt, J.W. (2016). "Tornado fragility and risk assessment of an archetype masonry school building." *Engineering Structures*, 128, 26-43.

Masoomi, H., & van de Lindt, J. W. (2017). Tornado community-level spatial damage prediction including pressure deficit modeling. *Sustainable and Resilient Infrastructure*, *2*(4), 179-193.

Masoomi, H., & van de Lindt, J. W. (2018a). Restoration and functionality assessment of a community subjected to tornado hazard. *Structure and Infrastructure Engineering*, *14*(3), 275-291.

Masoomi, H., & van de Lindt, J. W. (2018b). Fatality and Injury Prediction Model for Tornadoes. *Natural Hazards Review*, 19(3), 04018009.

Memari, M., Attary, N., Masoomi, H., Mahmoud, H., van de Lindt, J. W., Pilkington, S. F., & Ameri, M. R. (2018). Minimal building fragility portfolio for damage assessment of communities subjected to tornadoes. *Journal of Structural Engineering*, 144(7), 04018072.

Nozhati, S., Sarkale, Y., Ellingwood, B., Chong, E. K., & Mahmoud, H. (2019). Near-optimal planning using approximate dynamic programming to enhance post-hazard community resilience management. *Reliability Engineering & System Safety*, 181, 116-126.

Platt, S., Brown, D., and Hughes, M. (2016). "Measuring resilience and recovery." *International Journal of Disaster Risk Reduction*, 19, 447-460.

Presidential Policy Directive (PPD), (2013). Critical Infrastructure Security and Resilience. PPD-21, Released February 12, 2013. Available at: http://www.whitehouse.gov/the-press-office/2013/02/12/presidential-policy-directive-critical-infrastructure-security-and-resil, Accessed March 07, 2018.

Reinhorn, A. M., & Cimellaro, G. P. (2014). Consideration of Resilience of Communities in Structural Design. In *Performance-Based Seismic Engineering: Vision for an Earthquake Resilient Society* (pp. 401-421). Springer Netherlands.

Salem, S., Campidelli, M., El-Dakhakhni, W. W., & Tait, M. J. (2017). Resilience-based design of urban centres: application to blast risk assessment. *Sustainable and Resilient Infrastructure*, 1-18.

Zhang, X., Mahadevan, S., Sankararaman, S., & Goebel, K. (2018). Resilience-based network design under uncertainty. *Reliability Engineering & System Safety*, *169*, 364-379.