Agent-Based Modeling Framework for Simulation of Societal Impacts of Infrastructure Service Disruptions during Disasters

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ABSTRACT

The objective of this paper is to model and examine the impacts of different levels of infrastructure service losses caused by disasters on the households' well-being residing in a community. An agent-based simulation model was developed to capture complex mechanisms underlying households' tolerance for the service outages, including household characteristics (e.g., sociodemographic, social capital, resources, and previous disaster experience), physical infrastructure attributes, and extreme disruptive events. The rules governing these mechanisms were determined using empirical survey data collected from the residents of Harris County affected by Hurricane Harvey as well as the existing models for power outages and service restoration times. The analysis results highlighted the spatial diffusion of service risks among households living in affected areas in disasters. The proposed simulation model will provide utility agencies with an analytical tool for prioritization of infrastructure service restoration actions to effectively mitigate the societal impacts of service losses.

INTRODUCTION

Natural disasters pose risks to the well-being of communities in many ways. Aside from the loss of lives and destruction of homes and properties, natural disasters create difficulty for residents of the affected areas by causing disruptions to infrastructure services. Previous studies have investigated the underlying reasons why infrastructure services fail to function in the aftermath of disasters (Nateghi et al. 2014), and the ways to improve the physical condition of infrastructure systems (Batouli and Mostafavi 2018; Rasoulkhani et al. 2017). However, the loss of services and physical damages in the aftermath of disasters are not stoppable, and the limited resources prevent building hazard-free systems. On the other hand, previous studies have shown that the effect of service disruptions is not the same among different sub-groups within a community as they have varying capabilities to tolerate the risks posed by natural disasters (Murphy and Gardoni 2006). Researchers have suggested that the socially vulnerable population are in more danger of the well-being risk. These sub-populations in the community have lower resources to tolerate the adverse impact of disasters, and it causes more hardship to this group of people (Fothergill et al. 1999). Therefore, there exists a need for developing a method to integrate the physical and social characteristics of infrastructure systems and attempt to properly allocate the limited resources to the sub-populations in the community based on their actual needs. To this end, the current paper proposed an agent-based model to investigate the effect of infrastructure service losses on the affected households based on their social attributes and the physical condition of infrastructure systems. The use of simulation-based models in disaster management is a successful technique that benefits the decision makers by providing a tool to test "what-if" scenarios and explore their consequences (Miles and Chang 2011).

CONCEPTUAL FRAMEWORK

The extent to which households experience difficulty from the service losses depends on three components: (i) natural environment, which cause damages to the infrastructure systems and affect the households living in the vulnerable areas; (ii) physical condition of infrastructure systems during the disaster; and (iii) households' tolerance level to withstand the service losses. The framework shown in Figure 1 displays the interaction between these three components. Infrastructure service disruptions occur as a result of damages caused by the disasters when the severity of the stress on the physical system is greater than its bearing capacity. Such damages to infrastructure systems lead to severe service losses that bring hardship to the residents of the affected areas. The duration of the service disruptions depends on the severity of the outages and the utility company's capacity to restore the services (Miles and Chang 2011). On the other hand, affected households, which experience the service outages, have different levels of tolerability to resist the adverse impacts of service losses. Sociodemographic characteristics of the households determine their tolerability to the service losses. There exists a service gap between the physical condition of the infrastructure systems' performance during the disasters and the household's tolerability to the service losses. This service gap influences the degree to which households will experience well-being risk in the aftermath of natural disasters. The larger the service gap between the households' tolerance to the service losses and the physical condition of the infrastructure systems is, the more their experienced well-being risk will be.

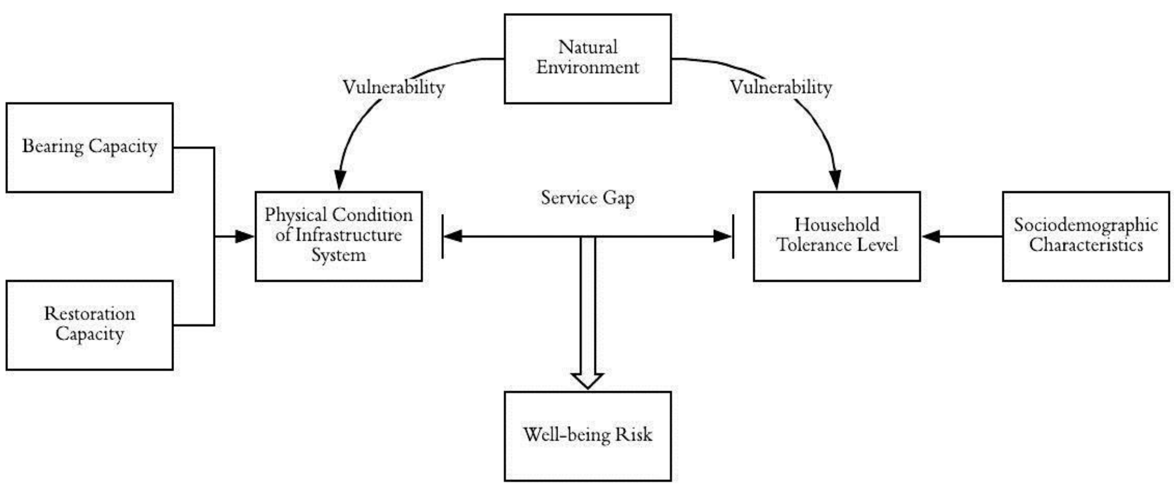

Figure 1. The conceptual framework for the assessment of households' well-being risk during infrastructure service losses

In this paper, specifically, the impacts of power outages on households' tolerance in the aftermath of hurricane disasters were examined. Power outages are among the destructive impacts of hurricanes causing significant hardship to the residents of the affected areas (Davidson et al. 2003). In this study, the failure of the power systems due to severe windstorms were investigated; in fact, severe winds during hurricanes cause failure to power distribution systems which have not been designed to experience strong winds. It is worthwhile to mention that not all the damages to power systems during a hurricane are caused by the severe winds; however, a review of the literature suggests that most of the damages were a result of the windstorms (Dunn et al. 2018; Panteli et al. 2017). The power service will be restored by the utility companies based on the extent of damages to the power infrastructure and available restoration plans and resources (Liu et al. 2007; Miles and Chang 2011). Households living in the affected areas will experience varying levels of hardship from power outages based on their tolerance level to withstand the service loss. This tolerance level is defined as the amount of time that a household can tolerate infrastructure service losses in a disaster. Based on the tolerance level of households and the duration of service losses that households experience, the buffer from the risk would be defined as the safe zone which is available to households for tolerating the service losses. The buffer is a measure of the well-being of households, which is specified according to the tolerance level and the level of service loss. The more buffer available to the households, the less their hardship from the service losses will be.

AGENT-BASED MODELING

Agent-based modeling (ABM) is a powerful modeling technique that focuses on the individual active components of a system (Bonabeau 2002). In ABM, active components (e.g., human entities) are characterized as agents, each with a set of social capabilities and goals, values, and preferences (Mostafavi et al. 2015). In the context of this study, the use of ABM would enable: (i) discovering what factors and mechanisms drive households' tolerance level; (ii) juxtapose the well-being buffer of various households with the range of disaster severity to determine the distribution of expected hardships; and (iii) explore effective intervention strategies to protect households' well-being during disasters. In addition, the use of ABM enables the construction of a theoretical space that includes a range of community profiles in terms of sociodemographic, social capital, resources, previous disaster experience, and other factors. ABM has been successful in studying complex behavior of households (Azar and Menassa 2012; Rasoulkhani et al. 2018; Rasoulkhani and Mostafavi 2018) as well as disaster management (Mustapha et al. 2013). Hence, ABM was adopted in this study to evaluate the underlying mechanisms affecting households' tolerance for disaster disruptions.

COMPUTATIONAL REPRESENTATION

The creation of a computational representation for the proposed ABM theoretical framework entails constructing mathematical models and algorithms to capture the theoretical logic representing the tolerance level of households for disaster-induced disruptions. An object-oriented programming platform, AnyLogic 8.3.3, was utilized to create the computational ABM. The proposed ABM incorporates two agent classes, including households and service area. Household agents in a service area experience hardship from power outages based on their sociodemographic characteristics. The service area agent includes two main components: (i) natural environment, which initiates disruptive events; and (ii) power infrastructure, which determines the failure of the system and duration of power outages. Figure 2 depicts the Unified Modeling Language (UML) class diagram of the computational ABM and summarizes the information regarding the attributes and functions implemented. The following subsections represent the mathematical implementation for the model agents, their attributes and components, and relationships between them.

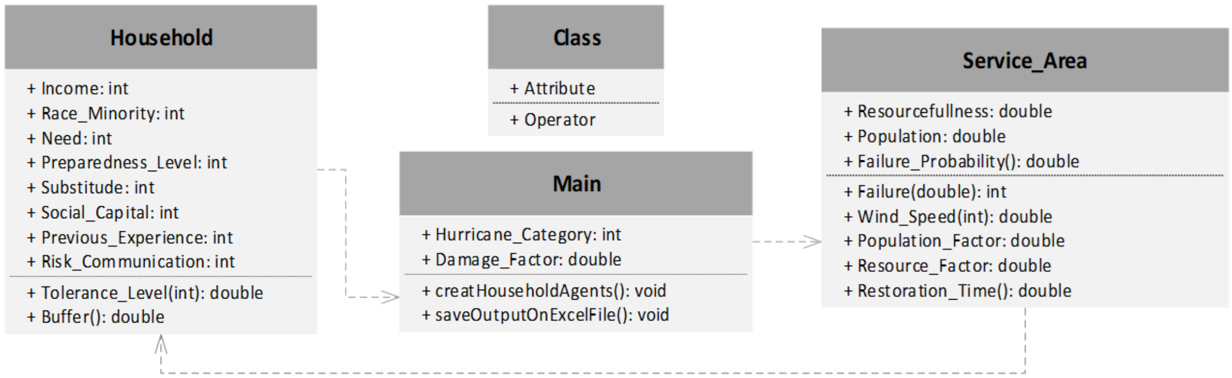

Figure 2. UML class diagram of the model

Service area agent: The first component in this agent is the natural environment initiating hurricanes as disruptive disasters. Hurricanes were modeled based on the level of wind speed in the service area. As shown in Table 1, Saffir-Simpson scale classifies the hurricane into five categories based on their maximum wind speed. For each category of hurricane, a wind speed was assigned from a uniform distribution with specified intervals shown in Table 1.

Table 1. Saffir-Simpson Hurricane Category Classes

	One	Two	Three	Four	Five
Speed (mph)	74-95	96-110	111-129	130-156	≥157

The second component of this agent includes the power infrastructures exposed to the hurricanes. This component includes two sub-models. The first sub-model is implemented for predicting the damages to power systems. Fragility curves were used to predict the power outages; using fragility curves is a standard approach for modeling the failure of the infrastructure systems in responses to natural hazards (Stein et al. 2010). In this model, fragility curves provided the probability of failure based on wind speed. In each iteration of the simulation the probability of failure (p_f) would be compared to a uniformly distributed random variable $r \in [0,1]$. The system would fail if the probability of failure is larger than the randomly generated number. The general form of the fragility curve is given in Equation 1, here probability of failure (p_f) in each service area is determined based on the experienced wind speed (x), and the lognormal fragility curve is defined based on the two parameters mean (μ) and variance (σ^2). In this model, all service areas experience the same level of wind speed, and the same fragility curve is used to calculate the probability of failure. However, as the model is modular, these components could be changed based on the physical characteristics of different locations in the presence of proper data.

$$p_f\left(damage|w=x\right)=\int_x^{-\infty}\frac{1}{\sqrt{2\pi\sigma}}exp\left(\frac{-\left(\ln(x)-\mu\right)^2}{2\sigma^2}\right)d_x \tag{1}$$

The second sub-model is used for calculation of the duration of the outages in each service area. The restoration time of the power outages is considered to depend on three aspects: 1) the severity of hurricane, 2) the resources available to the company to restore power, and 3) the population of the service area. Severe hurricanes pose more damages to the infrastructure services and make it difficult for the companies to restore the services; in addition, the road closures and flooding make the restoration process even more complicated (Miles and Chang 2011). The resources that a company has in place for the repair affect the restoration time. Finally, the population of the service area influences the priority of restoration activities. Companies would usually prioritize the restoration process in the densely populated areas to meet the needs of a higher portion of the affected residents (Liu et al. 2007). Equation 2 is used to calculate restoration times. The restoration time was assumed to be 15 hours in the normal condition. Then, the hurricane intensity factor (f_h), the resource factor (f_r), and the population factor (f_p) modify restoration time.

$$T = 15 \times f_h \times f_r \times f_p \tag{2}$$

In this equation, f_h is determined based on the wind speed following Panteli et al. 2017. Here, $f_h = 1$ when wind speed is less than 45 mph, $f_h \sim U(2,4)$ when wind speed is within 45 mph to 90 mph, and $f_h \sim U(5,7)$ when wind speed is higher than 90 mph. Resource factor (f_r) is calculated by considering the resourcefulness of the company in the service area. The values for f_r are determined based on three resource levels of low=1, medium=2 and high=3. Finally, the population factor (f_p) is calculated based on the number of people living in the service areas, where $f_p = 2$ when the population is less than 15000, $f_p = 1.5$ when the population is within 15000 and 30000, and $f_p = 1$ when the population is higher than 30000.

Household agent: Households have varying levels of tolerability for withstanding the power outages based on their sociodemographic characteristics. A negative binomial model was proposed for predicting the tolerance level of households. The response variable in this model is a count data of the number of days that the household could tolerate the outages; Poisson regression models and negative binomial models are two common ways for modeling the count data (Long, 1997). One of the properties of the Poisson random variables is the equality of the mean and the variance. However, in modeling the tolerance level, a significant difference was observed between the two parameters; thus, the negative binomial model was preferred to the Poisson regression model. The model for predicting the tolerance level is given in Equation 3.

$$\mu = exp\begin{bmatrix} 2.854 - 0.365x_s - 0.369x_e - 0.113x_i + 0.098x_n - 0.094x_p \\ -0.163x_{sc} + 0.027x_{in} - 0.113x_r \end{bmatrix} \tag{3}$$

In this equation, x_s is a parameter accounting for having a substitute for the power outages, x_e is whether the households have a previous experience with natural disasters, x_i is the reliability of the information that the household received about the outages, x_n accounts for the level of need of the household to the power service, x_p is the level of preparedness of the household for the power outages, x_{sc} accounts for having a social capital, x_{in} is the annual income of the household, and x_r is whether the household is a racially minority. Finally, the buffer for each household was determined based on the difference between the tolerance level of the household and their experienced power interruption duration.

$$Buffer = Tolerance - Interruption \tag{4}$$

VERIFICATION OF COMPUTATIONAL REPRESENTATION

The computational model was verified by a systematic and iterative process. Use of standard methods and the best available theories for governing the logic and rules in the model ensured the internal validity of the model. The model was tested under extreme conditions to check its ability to produce reasonable results. Finally, component validity assessment was conducted to ensure the completeness, coherence, consistency, and correctness of the model components.

NUMERICAL EXAMPLE

In this section, we show through a hypothetical example, how the simulation model can be used for the scenario testing. In this example, fifty households were generated and divided into five regions. Each of these households has its own sociodemographic characteristics which determine their tolerance level to power outages. The regions contain information on the power distribution system and the company's restoration capacity. The hurricane type will be given to the model as an input, and the model would predict the potential outages and the related restoration times for each region. Then, the tolerance to the power outages for the residents living in each service area will be compared to their experienced duration of power losses to determine the well-being state of the households and the buffer that the household has to tolerate more service disruptions. The proposed simulation model was used for experimentation processes. In the first set of experiments, the spatial distribution of the affected households was investigated. Figure 3 depicts the map displaying the condition of the households in the aftermath of the category-four hurricane. First, some households would lose power based on the condition of the service area and wind speed; these households are depicted by yellow in Figure 3.a. Then, those households that the experienced interruption level has exceeded their tolerance level are distinguished by red in Figure 3.b. These households have a zero buffer and are in need of external help to withstand the risks. For example, some household in region 1 would directly turn into the normal condition (green state) without experiencing severe hardship from the power losses as shown in Figure 3.b and 3.c, while all the residents in region 4 have experienced the red condition before truing into the green state. Finally, all households would go back to the normal condition after the power was restored as depicted in Figure 3.d. These maps help to identify the most affected areas in advance of hurricanes and can be used by the utility companies for the resource allocation plans.

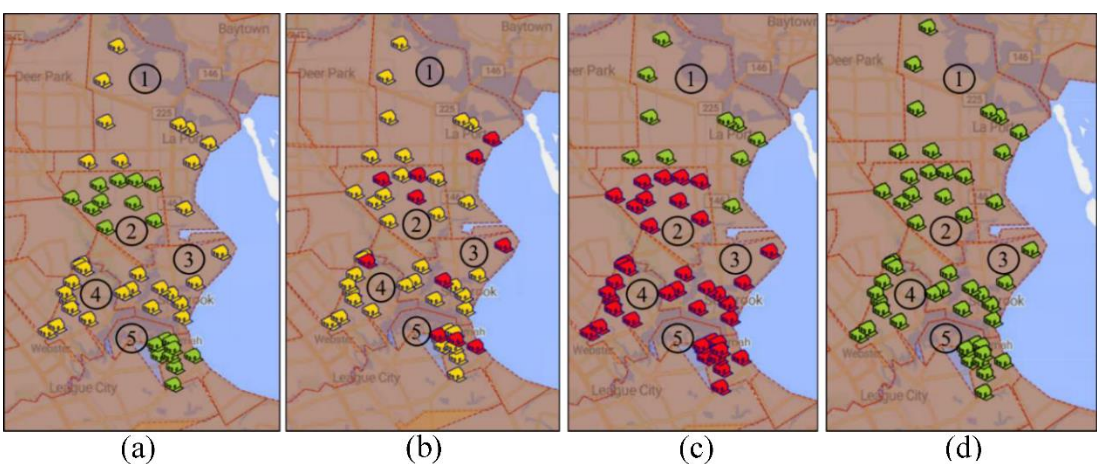

Figure 3. Spatial distribution of affected households in the aftermath of the hurricane; (a) power loss, (b) hardship experience, (c) recovery process, and (d) complete recovery

In the second set of experiments, the effect of different hurricane categories on the average buffer of households was explored. As shown in Figure 4, generally, the average buffer will decrease with the increase in the severity of the wind. Nevertheless, this trend is not similar among the hurricane types and in different regions. Category one and two hurricanes do not significantly cause hardship to the residents of the affected areas. However, a significant drop occurs in the average buffer of households under category four and five hurricanes, which suggests the need for improvements in the power system condition. Moreover, the effect of the available resources for restoring power is displayed in Figure 4; hurricane categories three, four and five put a tremendous hardship on the residents of the regions with low and medium restoration resources, while regions with high resources have a large buffer from the well-being risk under these severe wind storms.

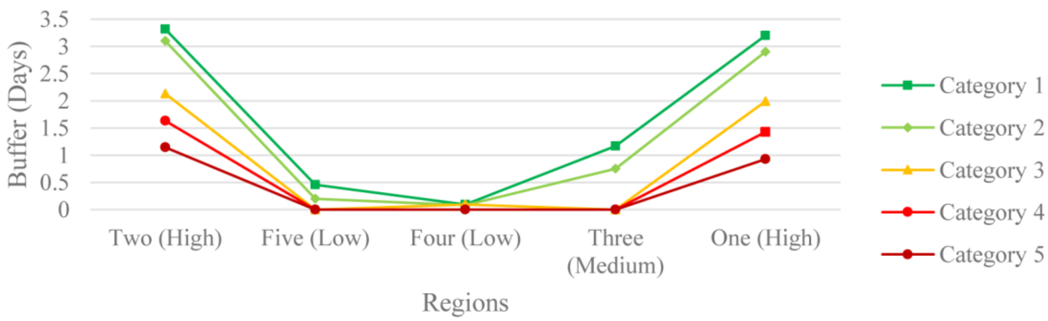

Figure 4. Trends of average buffer over different hurricane categories (resourcefulness of the regions is shown in parentheses).

CONCLUDING REMARKS

In this paper, an agent-based modeling framework was developed to explore the effect of different mechanisms on the well-being of households residing in a community affected by natural disasters. This model integrates the natural environment, physical characteristics of the infrastructure systems, and the social attributes of households to specify the extent to which the households are affected by the hurricanes. The proposed model provides users with scenario testing. The developed risk maps show the spatial distribution of the affected households based on the predicted restoration time of the service losses and each household's tolerance to withstand the service loss. These maps can be utilized by the service providers to identify the risk hotspots in ahead of the event and properly allocate their resources to meet the needs of households living in the service area. Moreover, the outcomes of the model can be implemented to test the performance of the infrastructure system to meet the societal needs under different levels of natural disasters. These findings provide utility companies with a decision-making tool to develop integrated plans for infrastructure resilience investments.

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