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Multi-agent modeling of hazard–household–infrastructure nexus for equitable resilience assessment

Amir Esmalian[1] | **Wanqiu Wang**[2] | **Ali Mostafavi**[1]

[1] Zachry Department of Civil and Environmental Engineering, Texas A&M University, College Station, Texas, USA

[2] Department of Computer Science and Engineering, Texas A&M University, College Station, Texas, USA

Correspondence
Ali Mostafavi, Zachry Department of Civil and Environmental Engineering, Texas A&M University, College Station, TX 77840, USA.
Email: amostafavi@civil.tamu.edu

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Abstract
Infrastructure service disruptions impact households in an affected community disproportionally. To enable integrating social equity considerations in infrastructure resilience assessments, this study created a new computational multi-agent simulation model, which enables integrated assessment of hazard, infrastructure system, and household elements and their interactions. With a focus on hurricane-induced power outages, the model consists of three elements: (1) the hazard component simulates exposure of the community to a hurricane with varying intensity levels; (2) the physical infrastructure component simulates the power network and its probabilistic failures and restoration under different hazard scenarios; and (3) the households component captures the dynamic processes related to preparation, information-seeking, and response actions of households facing hurricane-induced power outages. We used empirical data from household surveys from three hurricanes (Harvey, Florence, and Michael) in conjunction with theoretical decision-making models to abstract and simulate the underlying mechanisms affecting the experienced hardship of households when facing power outages. The multi-agent simulation model was then tested in the context of Harris County, Texas, and verified and validated using empirical results from Hurricane Harvey in 2017. Then, the model was used to examine the effects of different factors—such as forewarning durations, social network types, and restoration and resource allocation strategies—on reducing the societal impacts of service disruptions in an equitable manner. The results show that improving the restoration prioritization strategy to focus on vulnerable populations is an effective approach, especially during high-intensity events, to enhance equitable resilience. The results show the capability of the proposed computational model for capturing the dynamic and complex interactions in the nexus of households, hazards, and infrastructure systems to better integrate human-centric aspects in resilience planning and assessment of infrastructure systems in disasters. Hence, the proposed model and its results could provide a new tool for infrastructure managers and operators, as well as

for disaster managers, in devising hazard mitigation and response strategies to reduce the societal impacts of power outages in an equitable manner.

1 | INTRODUCTION

The objective of this study is to create a computational multi-agent simulation framework for capturing dynamic processes and interactions in the nexus of hazards, households, and infrastructure systems in order to better integrate social impacts and equity considerations in infrastructure resilience assessments. The societal impacts of prolonged disruptions in infrastructure systems are the emergent properties arising from dynamic interactions in complex socio-physical systems (Dai et al., 2020; Guidotti et al., 2019; Rasoulkhani et al., 2020; Williams et al., 2020). Therefore, there is a need for novel computational models to capture and model the dynamic processes and interactions between the complex systems of humans, hazards, and infrastructure systems. With a focus on prolonged power outages during hurricanes, this study proposes a novel computational simulation modeling framework for integrated analysis of hazard, household, and infrastructure systems to examine the societal impacts on infrastructure service disruptions. Examining the impacts of power outages on the households and assessing the effect of different mitigation strategies on the social groups is a fundamental step toward equitable resilience assessment in infrastructure systems.

Existing infrastructure resilience assessment models focus primarily on physical infrastructure but fall short of fully considering interactions between households and hazards and infrastructure (Mostafavi, 2018; Mostafavi & Ganapati, 2019). Computational frameworks properly model the failure and restoration of infrastructure systems in the face of disturbances to the systems (Guikema et al., 2014; Ouyang & Dueñas-Osorio, 2014; Ouyang & Fang, 2017; Tomar & Burton, 2021; Winkler et al., 2010). Several studies have devised ways to assess the resilience of various infrastructure systems (Batouli & Mostafavi, 2018; Gori et al., 2020; Guidotti et al., 2019; Hassan & Mahmoud, 2021; Ma et al., 2019). Particularly related to power infrastructure systems, there are studies that have developed computational models for determining the system's reliability when exposed to potential hazards with respect to topological and inherent vulnerabilities (Figuero-candia et al., 2018; Holmgren, 2006; Mensah & Dueñas-Osorio, 2016; Outages et al., 2018; Ouyang & Zhao, 2014; Reed et al., 2010). Furthermore, there are frameworks that enable modeling and optimizing the restoration of damaged infrastructure systems (Sharma et al., 2020; Sun & Davison, 2019; Xu et al., 2019). While these studies inform about the resilience and reliability of physical infrastructure systems (such as power networks and transportation systems), shed light on the interactions between hazards and infrastructure, and include modeling the restoration process of utilities, the current body of literature lacks integrated computational models and frameworks that consider households' interactions with infrastructure systems vis-à-vis the probabilistic impacts of hazards.

Recent studies highlight the need for accounting for human interaction with infrastructure systems (Simpson et al., 2020). Households do not experience the adverse impacts of natural hazards and damage to infrastructure systems equally (Jones & Tanner, 2017). Integrating household-level attributes with infrastructure systems is essential in achieving resilience goals (Ghanem et al., 2016). Household-level attributes (e.g., previous hazard experience and socio-demographic attributes) and protective actions (e.g., preparedness and information-seeking) and their integration with hazard scenarios, as well as consideration of probabilistic physical infrastructure failures, service disruption duration, and restoration possibilities, are essential components for examining societal impacts of infrastructure service disruptions. Recent studies have shown a significant disparity in the societal impacts of infrastructure service disruptions (Chakalian et al., 2019; Coleman et al., 2019; Esmalian et al., 2020b; Mitsova et al., 2018, 2021). These studies unveil risk disparities and suggest that households are heterogeneous entities as evidenced by varying levels of tolerance for service disruptions. Particularly, shelter-in-place households experience great hardship from infrastructure service disruptions. Thus, there is a need for equitable resilience assessment for infrastructure systems. This equitable resilience assessment includes: (1) examining the disproportionate impact that disruptions in infrastructure systems have on the households and (2) assessing to what extent the mitigation strategies for reducing the societal risks would benefit different social subgroups. Computational frameworks are needed to capture households' interactions with infrastructure systems. A household's decisions related to protective actions are not only influenced by its attributes, such as socio-demographic characteristics, but they are also highly influenced by perceived risk from the hazard (Lindell & Hwang, 2008), information-seeking process (Morss et al., 2016), and their social network's influence (Haer et al., 2016; Kashani et al., 2019). Capturing these dynamic processes and decisions is essential for modeling and understanding the societal impacts of infrastructure service disruptions. In addition, a households' hardship experiences are influenced largely by the duration of service disruptions, which is the result of physical infrastructure failures and the utilities' decisions regarding service restorations. Hence, the societal impacts of infrastructure service disruptions emerge from the complex interactions among various processes in the hazard, households, and infrastructure systems nexus. The current literature, however, lacks computational models that are capable of capturing and modeling the complex interactions in this nexus. Consideration of societal impacts and disparities in infrastructure resilience assessments requires novel integrated complex modeling approaches (Mostafavi, 2018). Integrated complex modeling enables capturing various processes and mechanisms related to physical infrastructure and human decision-making behaviors and their interactions using computational simulation to identify nonlinear and emergent behaviors (Reilly et al., 2017). Integrated complex modeling enables evaluating the combined effects of hazard characteristics, human decision-making behaviors and protective actions, and physical infrastructure network properties and restoration strategies. Such combined evaluation of various processes across different systems is necessary to capture emergent phenomena in civil infrastructure and urban systems, such as societal impacts and disparities due to infrastructure service disruptions.

To address this gap, this study proposes and tests a novel computational multi-agent simulation framework including three components: (1) the hazard component that simulates a hurricane with different intensities; (2) the physical infrastructure component that simulates the dynamic process of failures and restoration; and (3) the households component that captures the dynamic mechanisms related to households behavior facing power outages. The proposed modeling framework was tested and implemented for the examination of strategies to reduce the societal impacts of disruptions of power systems. The model bridges the gap in the abstraction of behaviors of system components and provides a computational implementation of households' interaction with infrastructure systems and probabilistic simulation of hazards and failure scenarios to enable examining equitable ways for reducing the societal risks.

Using the proposed multi-agent computational simulation framework, we examined strategies to reduce the societal impacts of power outages and investigated important questions such as (1) What are the proper strategies for mitigating the societal risks due to prolonged power outages? (2) To what extent are the hazard mitigation and response strategies equitable? The model enables exploratory analysis of the pathways that determine different levels of societal impacts. The model also enables assessing the extent to which different strategies for reducing the societal impacts are equitable (Williams et al., 2020). Computational frameworks and decision-making tools are needed for resilient and sustainable infrastructure systems (Rafiei & Adeli, 2016; Wang & Adeli, 2013; Zavadskas et al., 2018). The computational modeling framework would help disaster managers, infrastructure managers, and utility operators in making informed decisions that consider the specific needs and societal risks in their resilience assessments.

The remainder of the paper unfolds as follows. Section 2 outlines the multi-agent simulation framework, including the detailed description of model development and the description of agents. Section 3 presents the model implementation and model testing; furthermore, the description of model outputs and experimentation are presented in this section. Section 4 presents the results for equitable resilience assessment of power networks and discusses the effectiveness of different strategies for mitigating societal risks. Last, Section 5 discusses the contribution and major findings of the research.

2 | MULTI-AGENT SIMULATION FRAMEWORK

Multi-agent simulation modeling is a proven approach for complex modeling and analysis of coupled human–infrastructure systems (Eid & El-adaway, 2018; Nejat & Damnjanovic, 2012; Rasoulkhani et al., 2020; Reilly et al., 2017; Terzi et al., 2019). The multi-agent simulation model enables the consideration of dynamic processes and complex interactions among different entities (Gutierrez Soto & Adeli, 2017; Haer et al., 2017; Watts et al., 2019; Widener et al., 2013). Furthermore, multi-agent simulation approach has the advantage of enabling the consideration of interrelation within agents and their heterogeneity (Morss et al., 2017; Navarrete Gutiérrez et al., 2017). Therefore, multi-agent simulation provides a powerful approach for modeling the nexus of hazard–human–infrastructure. This approach also enables better incorporating equity in both impact assessment and resource allocations (Bills & Walker, 2017). For example, Gurram et al. (2019) developed an agent-based model to examine the exposure inequality related to traffic air pollution. Chen et al. (2019) created a computational framework for examining the equity in access to bike-sharing systems. Williams et al. (2020) developed an agent-based model to assess the equity in the resilience enhancement plans for smallholder farming systems. In the current study, we create a multi-agent simulation model to examine the equity in the impact and recovery of infrastructure systems, in particular power outages, in the context of natural hazards. In the context of this study, the hazard component would cause damage to the infrastructure systems and also influence the preparation time for households. The infrastructure system would be damaged due to the impacts of the natural hazard. The system's physical vulnerability and restoration decisions affect the duration of service outages. The experienced hardship due to service disruptions by individual households is a function of their susceptibility and protective actions. The susceptibility and protective actions of households are influenced by various factors (e.g., income and race) and processes and shape the level of tolerance of households to durations of service outages. Households perceive threats from the hazard, inform their social network, and make decisions about their protective actions (such as preparedness). Households in the community have unique attributes and interact with each other to inform their decision to take protective actions depending on their capabilities, perception of risks, and their immediate social network's actions. Thus, the dynamic process of information-seeking behavior and decision-making about the protective actions are integral aspects of determining the level of tolerance to power outages. In this study, we used the household service gap model (Esmalian et al., 2021) to characterize societal risks at the household level. The model examines service disruptions as threats, households' tolerance as susceptibility, and experienced hardship as an indicator for the realized impacts of risk. When the duration of service outages exceeds the tolerance level of households, they would experience hardship (which is the indicator of societal impact in this study).

2.1 | Model overview

Figure 1 depicts the underlying mechanisms and processes in the hazard–households–infrastructure nexus captured in the proposed framework. In this framework, each of the underlying mechanisms leading to the societal impacts (experienced hardship) could be captured as dynamic processes. The integration of these processes enables simulating the extent of infrastructure failures, tolerance level of households, and service restoration duration, and hence determines the proportion of households in the community that experience hardship under different scenarios of hazard intensity and response/restoration strategies. The detailed descriptions of these interactions are discussed in the following sections.

The hazard component simulates the intensity of hazard and exposure of components of infrastructure systems. The infrastructure component captures the physical vulnerability and network topology of power infrastructure systems. The extent of damage to the infrastructure system depends on the components' fragility and the network topology. The more fragile the systems' components, the greater the probability of severe damage. Furthermore, network topology influences the system's physical vulnerability due to the cascading failure and connectivity loss in the network. The extent of damage and the restoration process of the utility determines the duration of a service outage. The duration of power service outages affects the hardship experienced by households (Miles & Chang, 2011).

The household component captures the dynamic processes and interactions influencing the level of tolerance of households to service outages. In particular, this research focused on the shelter-in-place-households, as these households are vulnerable to the impacts of power outages. The rapidity of the unfolding of a hazard event affects how far in advance households are informed about the upcoming hazard event (i.e., hurricane), allowing them to take adequate protective actions. Households interact with each other to share information about the hurricane and form perceptions about the potential duration of the outages based on the information they receive and characteristics specific to the household, such as prior hazard experience. Households make decisions about their protective action to reduce the impacts of service losses. Their decisions are not solely influenced by their risk perception and socio-demographic attributes; they are also influenced by other households' decisions. A household is more likely to prepare for an upcoming hurricane if other households in their social network take protective actions. Hence, the model captures the dynamic process related to the households' information search behavior, risk perception, and decisions related to preparedness actions that determine their tolerance. The experienced hardship of households would be determined by comparing their tolerance with their experienced duration of disruptions. The model could then simulate the hardship profile of the affected communities to examine societal impacts of varying hurricane intensities based on the physical condition of the power network, restoration activities, and households' protective actions to better tolerate the disruptions.

2.2 | Hazard component

The hazard component of the proposed model considers the failure of the power network due to damage by severe windstorms to components not designed to withstand strong winds. It is important to mention that the damages to components of the power network are not limited to those induced by intense winds; other risks such as debris flows and potential flooding could also cause damages to power networks. However, wind-induced damages are the most prevalent causes of damage during hurricanes as

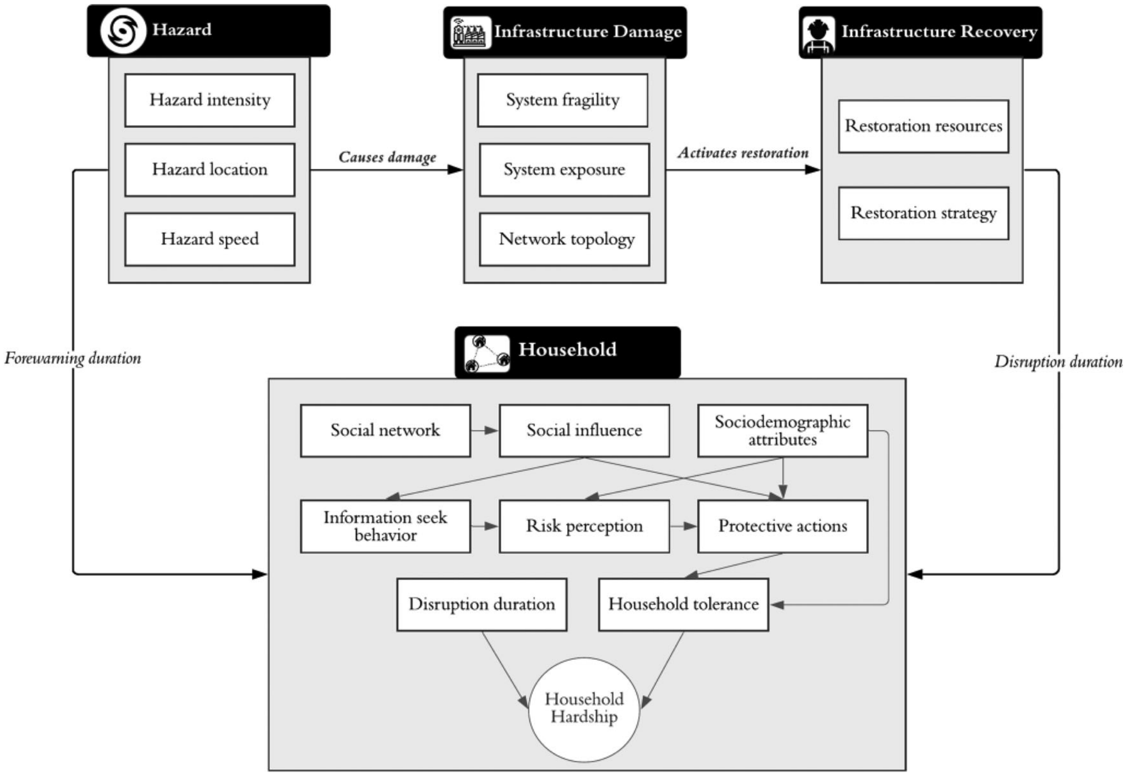

FIGURE 1 Human–hazard–infrastructure nexus framework for equitable resilience assessment of power systems

suggested by a review of the literature (Dunn et al., 2018; Panteli et al., 2017).

The hazard component simulates different hurricane categories and also includes the historical wind speed of Hurricane Ike and Hurricane Harvey in Harris County. The wind speed model is obtained from the HAZUS-MH wind model (Vickery et al., 2006). The wind model probabilistically generates the full profile of wind speed during the duration of a hurricane event with various return periods. The generated hurricane scenarios are grouped based on the maximum gust wind speed in the county. This model generates wind speed values for each census tract across the study area. Then, the generated hurricane scenarios are used to simulate the hurricane hazard in the multi-agent model. The wind gust speeds for different coordinates are implemented for the fragility analysis of the power network.

2.3 | Power network agent

2.3.1 | Network structure

The hurricane wind model poses stress on the power network and could cause multiple damages to the power network. The power network is a connected grid consisting of elements such as generators, substations, transmission lines, poles, conductors, and circuits. The data for modeling actual power networks within an area are either unavailable or difficult to access due to security issues. Therefore, the power network in this study is modeled by using a synthetic power network introduced by Birchfield et al. (2017) and Gegner et al. (2016). The implemented synthetic power network is a near-real representation of the power network in the study area, which matches the topological characteristics of the actual network in Harris County. The synthetic power network determines the geographic coordinates of the synthetized generations and loading substations based on the required loads and the publicly available power plant data in the study area. Then, the substations and generators are connected by transmission lines through a network that has structural and topological properties of an actual network and a converged power Alternating Current (AC) flow.

The distribution network consists of distribution poles and conductors. The number of distribution poles is estimated based on the population of each tract, assuming each pole serves 40 customers (Ouyang & Dueñas-Osorio, 2014). In the presence of actual data, the assumed values could be updated to provide context to the model outputs. The poles are directly linked via a distribution line to the distribution pole. Similarly, each distribution pole is con-

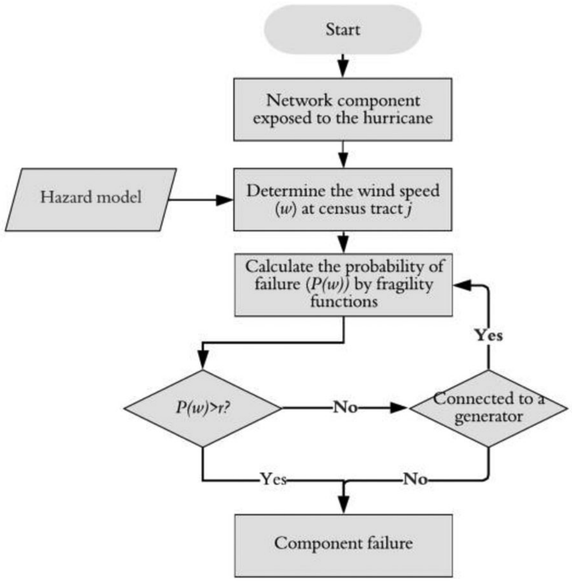

FIGURE 2 Schematic overview of the process for modeling the power system failure

nected to households through conductors. This methodology enables investigating damage to the power network in the absence of real data to model the actual system. Components of the power network, including power generators, substations, transmission lines, the distribution network, and their linkages are captured in the modeled synthetic power network.

Failures in the power network occur not only due to the direct damage to the power network components due to wind forces, but connectivity loss and cascading failures also cause disruptions to the network. Figure 2 shows the overview of the failure-modeling process in a power infrastructure network. The model includes two elements capturing the failure of the network from its exposures to a hurricane: (1) *component damage*: Failure in the power network components, which is modeled by incorporating fragility functions. The fragility functions help determine the probability of damage to the network components based on hazard intensity; (2) *connectivity disruptions*: The failure of a network component may lead to a series of consecutive connectivity losses. We used connectivity analysis of the network to model such cascading failures in the power network. The following describes the detailed modeling approach.

2.3.2 | Component damage

Fragility curves are used to model the failure in the components of the power network. Fragility curves are commonly used for modeling damages to infrastructure systems in response to natural hazards (Winkler et al., 2010). Fragility curves, in this model, determine the failure probability ($P(w)$) based on the imposed wind speed. To this end, the failure probability would be compared to a random variable $r \in [0, 1]$ from a uniform distribution in each iteration (Figure 2). A component, such as a power pole, would fail if the failure probability becomes greater than the generated random number (r). In this model, we consider the failure in the critical components of the power network: substations, transmission lines, distribution poles, and conductors. Damage to power plants by hurricanes, being highly unlikely, was not being considered as structural damage (Ouyang & Dueñas-Osorio, 2014).

Substations
The damage to substation loads is modeled by implementing the aggregated fragility functions developed in HAZUS-MH 4 (FEMA, 2008). The fragility functions provide failure probability based on the local terrain, wind speed at the area, and the structural characteristics of the substation. Equation (1) shows the general form of the fragility function. In this equation, the probability of failure (P_f) is related to the exposed wind speed (x). The two parameters, mean (μ) and variance (σ^2) are used to define the lognormal fragility curve. The fragility curves used for modeling damage to the substations are plotted in Figure B4 in Appendix B:

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

Transmission elements
Transmission elements include the transmission lines and the transmission towers, which support the lines. The length of the transmission lines is determined based on the specific latitude and longitude of the generators and substations loads in the synthetic network. The number of necessary transmission towers is estimated by assuming 0.23 km between two consecutive towers. Similar to the fragility function in Equation (1), we implemented a lognormal fragility function for determining the (P_f) of the transmission towers. The implemented fragility curves for modeling damage to the transmission tower are shown in Figure B2 in the Appendix. Damage to transmission towers is modeled so that towers fail independently of one another (Panteli et al., 2017); therefore, the total failure probability for the transmission element due to damage to the support structure between two substations that have n towers would be calculated using the following approach. In Equation (2), $P_{T(w)}$ is the probability of failure in the transmission element, $P_{k,w}$ represents the probability of failure of an individual tower between substations, and N

is the number of required towers for supporting the lines:

$$PT\,(w) = 1 - \prod_{k=1}^{N} \left(1 - P_{k,w}\right) \tag{2}$$

Extreme weather conditions could cause great damage to transmission lines; thus, separate fragility curves are used to model such damage. Following the approach proposed by Panteli et al. (2017), a linear fragility function (interpolated linearly), as shown in Equation (3) and Figure B2 (Appendix B), is implemented for calculating the probability of failure for the transmission lines.

$$PL\ (w) = \begin{cases} 0.01, & \text{if } w < w_{\text{critical}} \\ PL, & \text{if } w_{\text{critical}} < w \leq w_{\text{collapse}} \\ 1, & \text{if } w \geq w_{\text{collapse}} \end{cases} \tag{3}$$

This equation considers three conditions. First, if the wind speed is below a certain level of "good weather condition," the probability of failure is small (0.01). Here, w_{critical} is the wind speed at which the transmission lines can sustain damage, and w_{collapse} represents a situation when the survival probability of the component is very small. Then, the component's probability of failure (PL) is calculated by considering a linear relation in the intermediate phase between w_{critical} and w_{collapse}. These wind speed thresholds are assumed to be between 30 and 60 m/s following empirical studies (Murray & Bell, 2014; Panteli et al., 2017). In the presence of data from utilities, the equations and thresholds could be adjusted to reflect the real behavior of the components; pseudo algorithms are presented in Table A1 in Appendix A.

Distribution elements

The synthetic distribution network considers the failure of the conductors that connect the households to the power network and the poles that support the conductors. The empirical damage models, developed by Quanta Technology and implemented by Quanta (2009) and Mensah and Dueñas-Osorio (2016) are used in the absence of field data. The fragility equation for modeling the failure to the conductors is shown in Equation (4). This equation (also see Figure B3) draws the relationship between the wind speed (w) and the probability of failure to the conductors ($PC(w)$) in the distribution network.

$$PC\ (w) = 8 \times 10^{-12} \times w^{5.1731} \tag{4}$$

Last, the fragility function for modeling failure in the distribution poles is implemented in the model. Several studies have developed fragility equations for the distribution poles depending on their material, age, and maintenance (Salman & Li, 2016; Salman et al., 2015; Shafieezadeh et al., 2014). The fragility equation developed by Shafieezadeh et al. (2014) is used in this study to model the failure in the distribution poles. An example of the fragility curves is shown in Figure B3 in Appendix B.

2.3.3 | Connectivity disruption

The failure of a component in the power network may propagate through the network and lead to connectivity loss (also called cascading failures; Winkler et al., 2010). The model also considers the cascading failures due to the interdependencies among the components of the power network. For example, when a substation experiences damage, if the distribution network elements connected to the damaged substations are no longer connected to a power generator through other network components, these subsequent distribution networks would also be removed from the power network (Mensah & Dueñas-Osorio, 2016). Therefore, at each iteration of the model, the connectivity of the subsequent network component to a generator will be assessed. The pseudo-codes of the developed algorithm are shown in Table A2 in Appendix A.

2.3.4 | Restoration process

Restoration activity takes place after the hurricane passes through the affected area. After the failures in the power network are detected, the utility repairs damaged components of the power network. The downtime of different system elements depends on three main factors: (1) the extent of damage to the power network, (2) the available resources to the utility for restoring service, and (3) the utility's strategy for restoring the power (Duffey, 2019; H. Liu et al., 2007). Severe hurricanes pose more danger to the infrastructure elements and make it difficult for the utilities to restore services. The number of crews and the spare equipment in place also affect the restoration time (Xu et al., 2019). Finally, the priority of restoration activities influences the duration of outages. For example, restoration in more populated areas may sometimes be prioritized to meet the needs of a higher number of affected households (H. Liu et al., 2007). The pseudo algorithms are shown in Table A4 in Appendix A.

To determine restoration duration, the model determines the duration of the power outages by considering the dynamic repair process (Figure 3). The process involves multiple steps (Sharma et al., 2020). First, the priorities are given to the power restoration in different areas to implement repair and restoration strategies. Then, for each damaged element, the required resources and time to repair

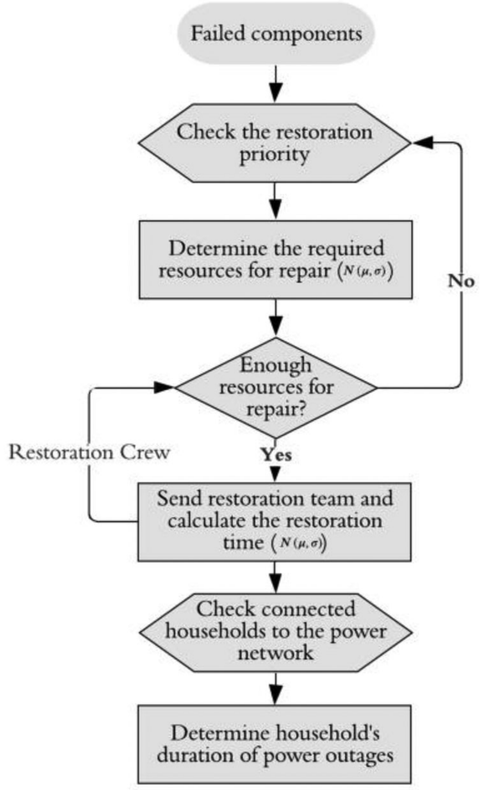

FIGURE 3 Schematic overview of the process for modeling the restoration activity

will be calculated based on Table B1 (Appendix B). The time to restore each element is calculated by considering a normal distribution and checking for non-negativity, $N(\mu, \sigma)$, with specific mean and standard deviation (Mensah, 2015). The resources in this model are crews, materials, and machines. The number of teams needed for the repair task is given in Table B1. The utility could have a finite number of resources in place, but then these resources could be augmented daily by assistance from other utilities through Regional Mutual Assistance Groups and collaborations (Edison Electric Institute, 2016). A linear relationship is assumed for the increase in repair resources (Figure B1) based on the results of previous studies (Ouyang & Dueñas-Osorio, 2014). The model inputs resources and initially implements 800 teams increasing by 15 teams per hour for a week as the base case scenario.

2.3.5 | Restoration strategies

Based on a review of the literature, there is no standard way of restoring power when a severe weather event damages a power network (Applied Technology Council, 2016). Some utilities would prioritize the restoration of the service areas with greater populations; however, this restoration strategy might favor residents living in a larger metropolitan area and might adversely affect people in rural areas (H. Liu et al., 2007). Other strategies mainly focus on physical characteristics, such as prioritizing the components with a high criticality, such as failed substations and transmissions (C. Liu et al., 2021; Ouyang & Dueñas-Osorio, 2014). The model uses priorities assigned to the components in the network to generate the different repair strategies.

In this study, we tested the influence of three main strategies for restoring the power for residents, *component-based restoration*, *population-based restoration*, and *social vulnerability-based restoration*. In component-based restoration, the model prioritizes the restoration of critical components, such as failed substations and transmissions. The critical components are those that require more resources and serve a large number of users. After the repair of these components, the model initiates the repair of the damaged distribution network comprising conductors and poles in a random sequence. Restoration based on population and the social vulnerability index (SVI) focuses on the prioritization of the repair of the components, which serve areas with larger populations or higher social vulnerability scores informed by census data and an SVI (Flanagan et al., 2011). Depending on the selected strategies, the ranges of service restoration duration would vary in different areas. Therefore, in this model, households would experience varying levels of power outage durations due to the differences in the restoration duration, which is a function of the extent of damage and the utility's restoration strategy.

2.4 | Household agent

Households have varying levels of tolerance for withstanding power outages. Empirical data from household surveys collected in the aftermath of three major hurricane events (Harvey, Florence, and Michael) together with theoretical decision-making models were implemented to simulate the underlying mechanisms that influence households' tolerance. The tolerance depends on households' decisions about protective actions and their inherent needs for the service (Baker, 2011; Coleman et al., 2020; Esmalian et al., 2020b). The model includes the process through which households know about the event and form perceptions about the risks. Then, empirical models developed based on the survey data used in conjunction with decision-making processes are used to determine the probability of a household taking protective actions. This probabilistic characteristic of the households' behaviors enables consideration of the uncertainties regarding the individual's behavior in the model. Finally, the household's hardship status would be determined based on tolerance and the

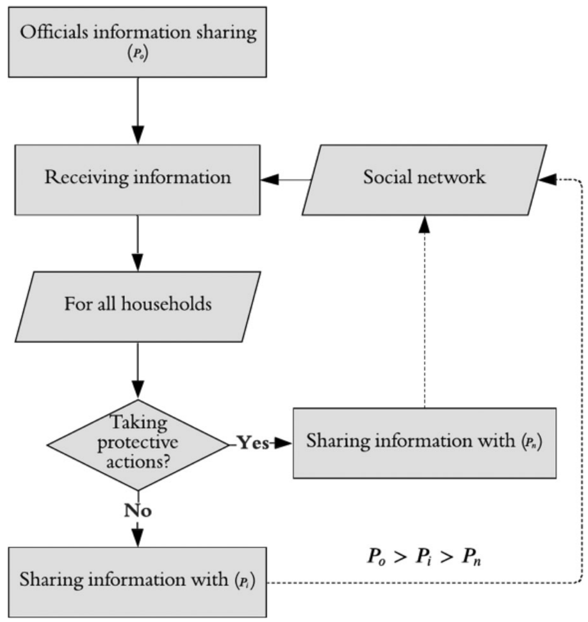

FIGURE 4 Schematic overview of the information seek/share behavior

duration of outages. The pseudo algorithms are shown in Table A3 in Appendix A.

2.4.1 | Information propagation process

Two information propagation processes are considered in this model (Figure 4). First, we modeled information-sharing through official sources (such as mass media). In the days before hurricane landfall, officials disseminated information about the upcoming hurricane, which is modeled by implementing a probability of receiving the information by the households through officials (P_o). In addition, those who receive the message might also share the information with their immediate social network, depending on how important they perceive the risks of the hazard, and then take protective action themselves. Hence, two probability values of (P_i) and (P_n) are considered for implementing the information-sharing process by households. Those who perceive great risk from the hazard and take protective actions (P_i) are more likely to share information with their social network than those who do not take protective actions (P_n). These probabilities are determined using the empirical data and considering a higher value for the probability of receiving information from the officials.

2.4.2 | Household agent's social network

Agents interact with each other and influence the decisions of others through their social networks. The social network of the agent would not only influence the information propagation process; it would also affect other agents' decisions regarding protective actions (Anderson et al., 2014; Tran, 2012). Multiple network structures—random network, small-world (SW) network, scale-free (SF) network, and distance-based network—characterize how households are connected with each other. These network structures are present in real-life social settings. For example, the literature suggests that information-sharing through online social media, which follows an SF network structure, could expedite information propagation (Nocaj et al., 2015; Schnettler, 2009). Therefore, we considered multiple network structures to account for various modes through which households could interact and share information, and we tested the impact of such structures on the overall impact of the hazard on the communities. The social network would affect both the information propagation process and the household decision-making on the protective actions through peer effect.

2.4.3 | Household agent's risk perceptions

Household agents form a perception about the potential duration of the power outages. We analyzed data collected from the household surveys to determine households' expectations of the disruptions; the summary statistics of household survey data could be found in Esmalian et al. (2020b). Households' expectation of the duration of the disruption affects their decisions regarding taking protective actions. Those with higher expectations of the disruptions are more likely to take protective actions (Coleman et al., 2020; Lindell & Hwang, 2008). The expected duration of disruptions was measured by the number of days a household expected the power outages. This variable is positive and a count data; thus, a Poisson regression model was selected for modeling the expected duration of the outage. Equation (5) shows how the mean value of the duration of the expectation (μ) is related to the predictors through a *log* link by implementing a Poisson regression model. In this model, x_f refers to the forewarning duration of the event (measured by the number of days), x_i captures if the households receive the information about the hurricane (binary variable), x_o is home ownership, x_a captures whether the head of the household is elderly, x_m captures if any of the household members have a mobility/disability issue, and x_{fz} refers to if the households live in a flood zone:

$$\mu = exp\left[1.74700 + 0.30471 log\left(x_f + 1\right) + 0.12369 x_i - 0.27720 x_o - 0.21065 x_a - 0.51210 x_m - 0.28153 x_{fz}\right] \tag{5}$$

2.4.4 | Household agent's socio-demographic characteristics

Households' demographic characteristics influence their perceptions of the risk, decisions regarding the protective actions, and consequently their tolerance for the disruptions (Baker, 2011; Coleman et al., 2019; Horney, 2008). In this model, households' demographic characteristics are considered by developing a sample of agents based on publicly available census data. A population is sampled by considering the probability of being from a specific segment of a community by using the actual proportions in the census data. In particular, data about income level, race, age, education, mobility/disability conditions, and type of housing of the households were collected. In addition, to determine whether a household was in a flood zone, their location was plotted against a 500-year flood map.

The demographic characteristics of households not only influence their decisions on protective actions, but they also affect households' level of need for the service. The level of need is modeled through the use of empirical data. In the surveys, this variable is measured with an ordered five-level Likert scale; therefore, a cumulative logit model is developed for determining the level of need (Equation 6). The model relates the effect of predictor x on the log odds of response category j or below by coefficient β (Agresti, 2007). This type of modeling helps in determining the probability of Y (the level of need) falling below a certain level (Equation 7). Then, as the summation of each probability level (π_j) equals 1, the probability of each level could be determined. Appendix B outlines the models for estimating the level of needs:

$$\text{logit}\, P\,(Y \leq j) = \alpha_j + \beta x \tag{6}$$

$$\text{logit}\ [P\,(Y \leq j)] = \log\left[\frac{P\,(Y \leq j)}{1 - P\,(Y \leq j)}\right]$$
$$= \log\left[\frac{\pi_1 + \cdots + \pi_j}{\pi_{j+1} + \cdots + \pi_J}\right], \qquad j = 1, \ldots, J-1 \tag{7}$$

2.4.5 | Household agent's protective action process

Households take protective actions to reduce the impacts of power outages in two ways. First, the general preparedness behavior of households in terms of obtaining food, water, and emergency kit supplies helps them to better cope with the outages. Second, some households might take further actions by purchasing a generator. We modeled the protective action process of households by implementing the diffusion model developed by Banerjee et al.

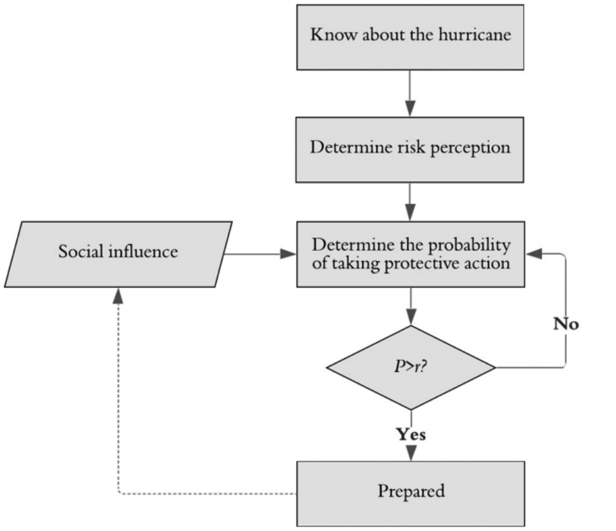

FIGURE 5 Schematic overview of taking protective actions by households

(2013). As shown in Figure 5, households are first informed about the hurricane through the information propagation of officials or their immediate social network. Second, an initial number of households decide to take protective actions depending on their decisions' probability (P_p). Households' probability of taking protective actions (P_p) depends on the households' personal characteristics, such as demographic characteristics, risk perception, and peer influence. Equation (8) shows the implemented logistic function to model this process. Third, those who decide to take protective actions influence their social network by passing the information regarding their protective actions. Fourth, the newly informed households now decide if they want to take protective action. This process initiates as soon as the officials detect the hurricane and ends after (f) days of forewarning:

$$\log\left(\frac{P_p}{1 - (P_p)}\right) = X_i\ \times \beta + \lambda \times F_i \tag{8}$$

In this model, β is the vector of the coefficients that relates the personal characteristics (X_i) to the log-odds ratio of the protective action decisions. F_i is the fraction of the household's social network that had decided to take protective actions divided by the total number of household's social network. The unit-less parameter of λ represents the change in the log-odds ratio of protective actions due to peer influence. A value of zero for λ describes the case in which households make their decision independent of their social network, while larger values of λ refer to a situation when households affect the decision of their social network. The empirical models were implemented to determine the β, and the model has been tested to determine the range of λs. Details related to the factors considered for developing these models are presented in Appendix B.

2.4.6 | Household agent's protective action process

Households have different levels of tolerance for withstanding prolonged power outages (Esmalian et al., 2019). This is why even a similar outage duration would cause varying levels of hardships in different households (Coleman et al., 2019). Households' tolerance for power outages is a function of their protective actions and inherent needs for the service. Household tolerance is determined by implementing accelerated failure time (AFT) models, which are a type of survival analysis approach for the time-to-event data (Dale, 1985). This type of modeling was found to best describe the model and to have the lowest prediction error when compared to generalized linear models (Poisson family and negative binomial regression) and ensemble learning methods (random forests and boosting; Esmalian et al., 2020a). Using AFT models, we can directly relate tolerance to the predictors with a linear relationship as shown in Equation (9):

$$\log \mu_i = x_i^T \beta + \varepsilon_i \tag{9}$$

where μ_i represents the mean tolerance, x_i^T denotes the vector of predictor, β is the vector of parameters, and ε_i is an error term that is assumed to be independently distributed. In this model, three main predictors were used for determining tolerance: households' level of need for the service, their preparedness for the event, and if they obtain a generator to withstand the power outages. The protective actions of the households are determined through a probabilistic approach outlined in the previous sub-section. The level of need is determined based on their socio-demographic characteristics to be considered in calculating the tolerance level.

In the last step, the households' experienced hardship is determined by integrating the results from the restoration process with households' tolerance. Households experience different levels of the duration of disruptions and experience hardship when the duration of the outage exceeds their tolerance. Figure 6 presents the process for determining the households' experienced hardship from service disruptions.

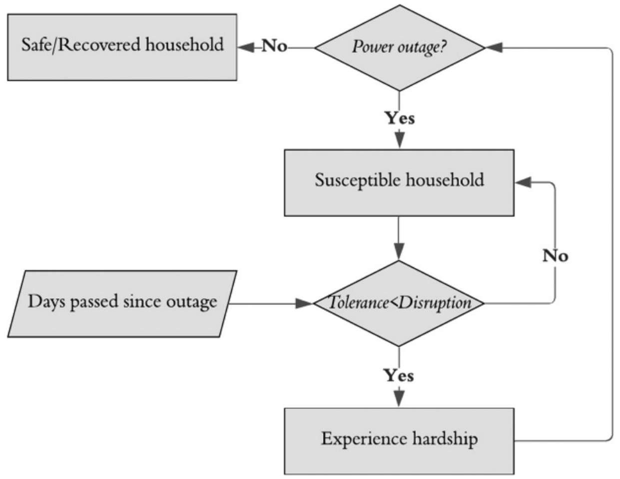

FIGURE 6 Schematic overview of household hardship experience process

3 | MODEL IMPLEMENTATION AND SIMULATION EXPERIMENTS

3.1 | Computational implementation

Computational representation of the proposed multi-agent modeling framework includes developing and implementing algorithms and mathematical models to capture the theoretical logic representing the experienced hardship of households due to disaster-induced disruptions. The computational model is created by using an object-oriented programming platform, AnyLogic 8.3.3. Figure 7 depicts the Unified Modeling Language diagram of the model, which shows the class of the agents, agents' attributes and functions, and their relationships. A sample of 2500 households based on the demographic characteristics of Harris County was generated and placed in the census tracts. The sample is statistically representative of the households in Harris County with a 95% confidence level and a 2% margin of error. The synthetic power network includes a total of 97 substations, 242 transmission elements, and 1433 distribution elements located in Harris County based on latitude and longitude coordinates as described in the power network agent section.

3.2 | Verification and validation

The model is verified and validated through a systematic and iterative process to ensure the quality and credibility of findings. Various internal and external approaches were conducted to verify the data, logic, and computational algorithms in the simulation model (Bankes & Gillogly,

FIGURE 7 Unified Modeling Language class diagram of the multi-agent simulation model

1994; Mostafavi et al., 2016; Rasoulkhani et al., 2020). First, the internal verification of the model was ensured by using the best available theories and standard approaches for implementing the models' logic and rules. Second, we used reliable empirical data collected in the aftermath of three major hurricane events to develop the model. Furthermore, we conducted a component validity assessment for ensuring the model components' completeness, coherence, consistency, and correctness. The extreme conditions were tested to examine the model's ability to generate reasonable outcomes. External verification of the model was ensured by examining the causal relationships among the model components. The behavior of these subcomponents under different values was traced to ensure the external verification of the model. The model logic and functions were examined to discover any unusual patterns to ensure that logic and assumptions in the model are correct.

For validation, the generated patterns in the model outputs were compared against the empirical data to validate model behavior. The mode of each simulated output was used to determine the system's behavior, then the generated patterns from the model were compared with the actual household behaviors from the empirical survey data and similar studies and reports. The developed multi-agent simulation model integrated the processes leading

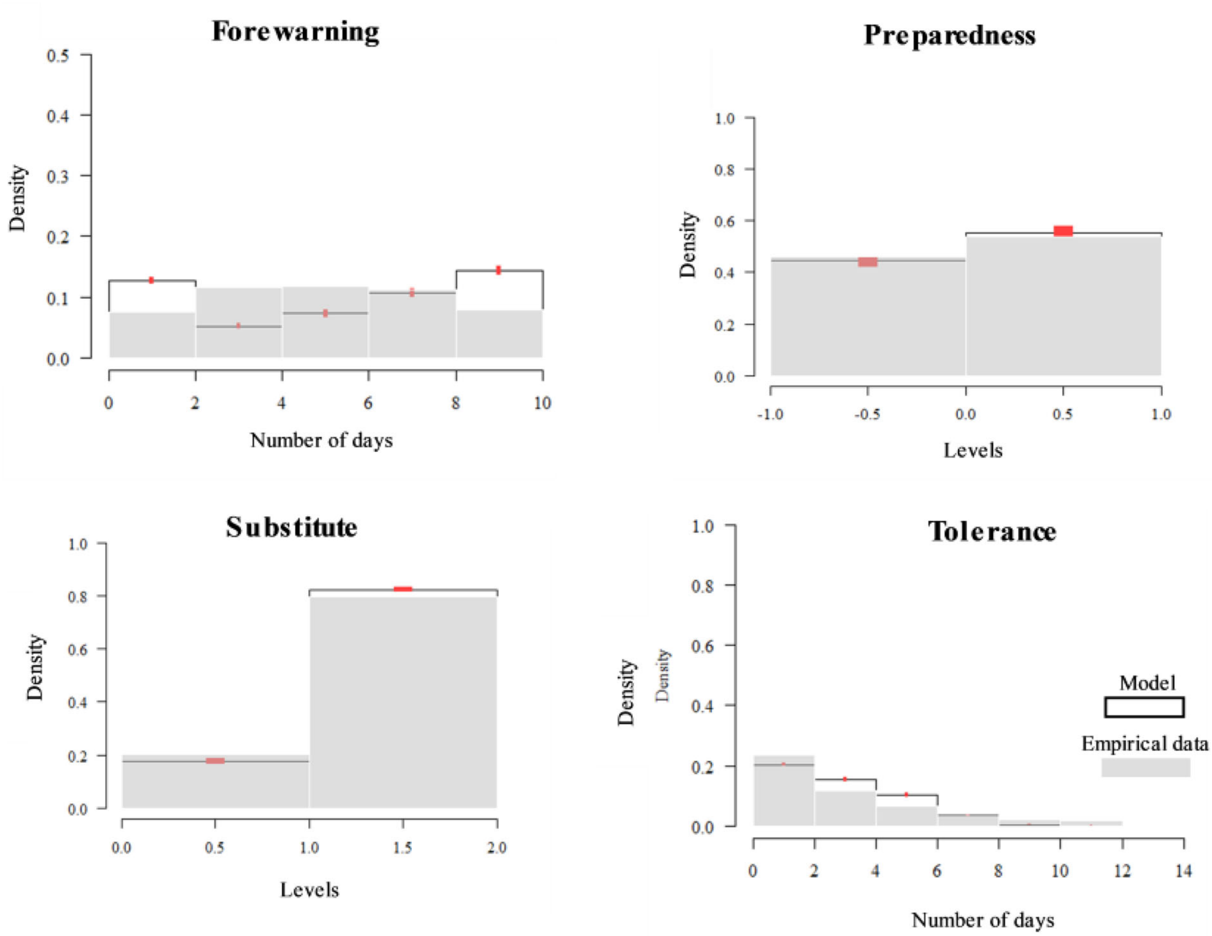

FIGURE 8 Comparing values generated by the model with empirical data. Red whiskers show the model replications' 5% and 95% values

to the generated patterns. These generated patterns were compared against the distribution of parameters of interest to check if the model is able to generate correct behavior. In this study, the intent of the model was to examine the strategies to reduce societal impacts of power outages. In particular, emergent behavior patterns of the outputs were of interest. Furthermore, results from similar studies and reports on the impact of hurricanes on the power networks were used to validate the model's output for the physical system (Mensah & Dueñas-Osorio, 2016; Ouyang & Dueñas-Osorio, 2014). The model is capable of generating patterns and values similar to the empirical data (Figure 8). The model outputs capture the Hurricane Harvey scenario in Harris County, Texas, in 2017 (Figure 8). For example, the generated proportions of households that prepare and obtain substitute energy sources (generators) are similar to those values from empirical data. Some differences arise in the model results for large and small values of the forewarning time; however, the distribution of tolerance is close to the empirical values. It is worth mentioning that the primary objective for the creation and use of multi-agent and agent-based models is not a prediction but rather to generate examples of the probabilities of various possibilities for robust decision-making under uncertainty (Mostafavi et al., 2016).

3.3 | Model output description

The percentage of households experiencing hardship from power outages is recognized as an indicator of the societal impacts on the community. When a households' duration of power disruption exceeds their tolerance, they experience hardship. This indicator includes both the physical impact and the societal susceptibility of the households for the risk posed. This dynamic measure is calculated for all households based on their location and their tolerance during the time without service. Figure 9a shows how the dynamic profile of hardship could be implemented to assess the effectiveness of various strate-

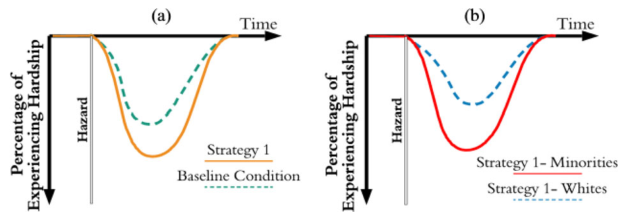

FIGURE 9 Schematic dynamic profile of hardship. (a) Comparison of the effect of strategies, and (b) comparison of the impact of strategies on different social groups

gies in reducing the societal impacts of power disruptions. Different scenarios could be tested to find ways to mitigate the societal risks of disruptions to power networks.

In addition to examining the societal impact on the community, the model enables examining the impact on various sub-populations (Figure 9b). This capability of the model enables an understanding of whether system restoration strategies are equitable. For example, while one strategy might reduce the societal impact on the community as a whole, it is possible that the strategy is in favor of certain demographics in the community. Thus, strategies would be examined to determine how they improve the condition of different social groups in the affected community.

3.4 | Simulation experimentation

The developed simulation model enables testing scenarios through various variables such as household characteristics, household social network structure, forewarning duration, hurricane category, and restoration units and strategy. The user could choose the values related to each of these variables in an interactive user interface (Figure 10a). The model outputs the various values related to different variables, including household protective actions and tolerance, the extent of damages to the different components of the power network, and the households' profile of hardship. In addition, as shown in Figure 10b, the model visualizes the spatial distribution of households' states by color-coding them depending on their states. Households who experience the power outages are shown in orange, those whose tolerance becomes less than their duration of disruption and experience hardship are shown in red, and the color changes to green when the power is restored for these households.

We performed Monte Carlo experimentation in the scenario testing to account for the stochasticity in the model. The primary variable of interest in the model experimentation was the percentage of the households who experienced hardship from the power disruption. Therefore, experiments were replicated as many times as the mean value of proportional of households experiencing hardship reached 95% confidence interval with 5% error (Hahn, 1972). The experiment scenarios were designed by changing the input values of each scenario and replicating iterations for each of the experiments.

3.5 | Scenario analysis

The model is implemented for scenario testing aiming at (1) identifying the combination of the strategies that would lead to the lowest societal impact due to the power outages, and (2) examining the extent to which the strategies are equitable. In this study, we examine three main strategies to reduce the societal impacts of power outages. First, the power utility's restoration strategy would be evaluated to examine its influence on the hardship levels. In this regard, three strategies of restoration based on the importance of the components, population size, and SVI would be evaluated. SVI is a widely adopted measure for examining the susceptibility of populations in disasters. Second, the influence of the forewarning time on the experienced hardship of the households could be examined. Early warning about the upcoming hazard can reduce the societal impacts (Panakkat & Adeli, 2009; Rafiei & Adeli, 2017) by influencing the protective decisions of households (Cremen & Galasso, 2021; Watts et al., 2019). This assessment would determine the effectiveness of identifying an impending hurricane and communicating critical information with the population. Third, the impact of the social network of the households on their experienced hardship would be evaluated. This assessment would show the value of using alternative social networks (such as social media) for disseminating hazard information. Social media platforms, for example, have distinct network characteristics, which enable quicker information-sharing without spatial boundaries (Watts et al., 2019; Zhang et al., 2019). Therefore, the type, density, and weight of the social influences would be examined to explore their effect on reducing the impacts of power outages on the households. The combination of these strategies to lower the hardship experienced by the households was also examined. In addition, the equitable resilience assessment in this study is being implemented by examining the disproportionate impact and effect of strategies on racial groups, while there are other social dimensions in equitable resilience. A similar approach could be implemented for understanding the equity aspect for other social groups; however, this study mainly focused on one group as an example of equitable resilience assessment.

FIGURE 10 Screenshots of the developed simulation model

4 | RESULTS AND DISCUSSION

The hardship experience of households from scenario analysis was used for exploratory analysis of societal risks of prolonged power outages. The analysis included: (1) examining strategies for reducing the societal impacts; (2) examining to what extent these strategies, including restoration strategies, forewarning, and social networks, are equitable; (3) robustness of the strategies for reducing the societal impacts under different scenarios; (4) identifying pathways that lead to low societal impacts. To this end, a base scenario similar to the Hurricane Harvey context was used with a forewarning of 9 days, component-based restoration by utility, and an SF social network between households. Scenarios were then modeled and compared with the base-case scenario through Monte Carlo simulation. In the simulation results, day zero is the time when an impending hurricane is identified by the officials as a threat, and the information is communicated with the residents.

4.1 | Simulating community-scale societal impacts

A baseline scenario of societal impacts of power outage disruption in a community similar to Harris County affected by a category 4 hurricane is shown in Figure 11. Figure 11a shows the mean proportion of households experiencing hardship each day. The results suggest that at maximum, around 50% of the community experienced hardship from the outages, and it took roughly 20 days for the community to fully recover (recovery is determined by having power restored for all households). The impact, however, was not equal among the subgroups in the community. Racial minority groups experienced a higher hardship from disruptions. Figure 11b shows the overall probability of experiencing hardship for each group. Analysis of variance (ANOVA) test showed that the difference between the two groups is statistically significant at 0.05 confidence level (p = .018). This result suggests that racial minority groups are more likely to experience hardship from power outages in comparison with others in the base-case scenario. The results overall show the model's capability to capture the societal impact of the disruptions on communities and also reveal the inequities in the impacts of prolonged power outages on vulnerable populations (e.g., minority groups).

4.2 | Examining strategies for reducing societal impacts

4.2.1 | Restoration strategy

Results for comparing different strategies for restoring the power (Figure 12) show that while under the component-based strategy, the maximum proportion of hardship in a day is around 54%. This value would be decreased to around 47% under the population- and SVI-based restoration strategies. The results show that overall, a community similar to Harris County, Texas, would benefit from prioritization of the areas with a higher vulnerable population. In this case, the probability of experiencing hardship for the nonvulnerable population increases and becomes greater than the vulnerable population (p = .003); however, the reduction in the probability of experiencing hardship for the socially vulnerable groups leads to an overall reduction in the societal impacts. In addition, giving priority to the areas with a higher population result in the reduction of overall societal impacts on the affected community, while the vulnerable population still faces a greater probability of experiencing hardship (p = .003). These findings suggest that overall, the prioritization of areas with a higher social vulnerability level and also with a higher population could lead to the reduction of societal impacts in the affected community.

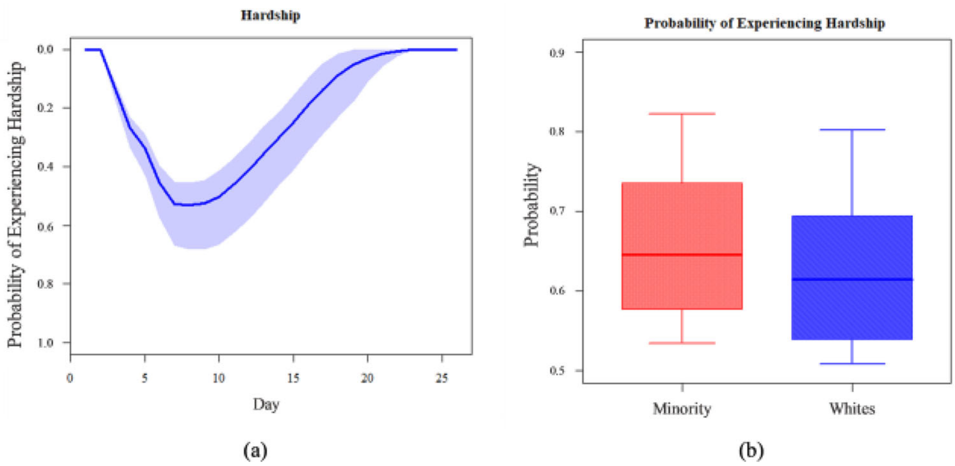

FIGURE 11 Societal impacts of disruptions from power outages in the baseline scenario. (a) Average daily proportion of households experiencing hardship and the 10% confidence intervals, and (b) boxplots and mean lines for the probability of racial minorities and whites experiencing hardship

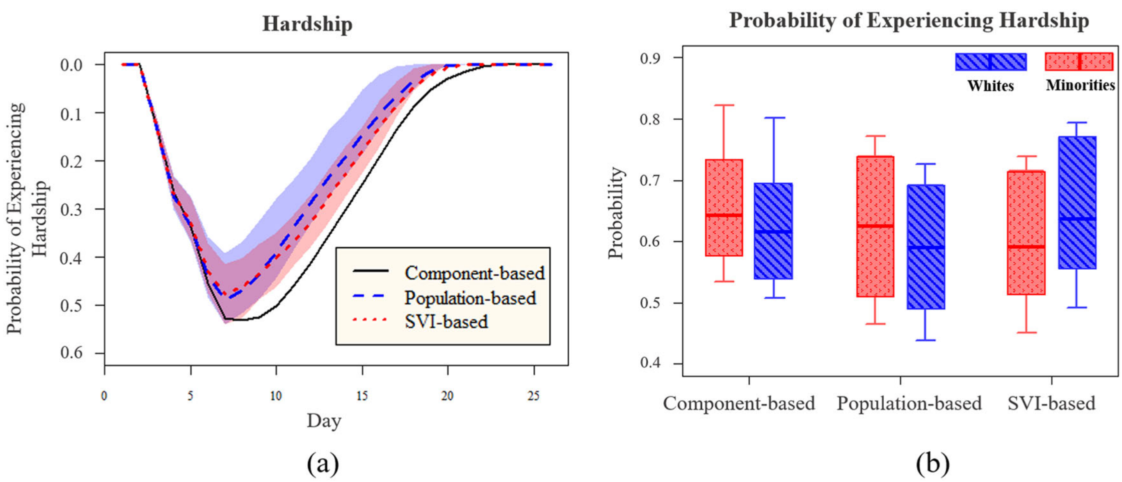

FIGURE 12 Comparing different power restoration strategies. (a) Dynamic patterns of the proportion of households experiencing hardship under each strategy, with shaded areas indicating the 0.25 and 0.75 percentile of the values, and (b) probability of experiencing hardship for different racial groups under each restoration strategy

The results comparing the effect of different prioritization strategies on racial groups are shown in Figure 13. The charts juxtapose the probability of experiencing hardship for two social groups under different restoration strategies. In the SVI-based recovery, the probability of experiencing hardship decreases by 8% for the socially vulnerable groups, while it would increase by 4% for the nonverbal group. The population-based recovery, however, decreases the probability of experiencing hardship by 2% and 4% for the vulnerable and the nonvulnerable groups, respectively. The results suggest that the population-based restorations while improving the overall societal risks, do not favor minority groups. On the other hand, the SVI-based recovery, while increasing the risks for the Whites, reduces the overall societal impact. While the population-based restoration and SVI-based would reduce the overall societal impacts, an SVI-based approach seems to be more equitable.

4.2.2 | The effect of increasing the forewarning period

Providing a longer forewarning to the communities reduces the societal impacts of power outages. As expected, the longer duration of the forewarning helps the households to better prepare for the impacts of the power outages and take protective actions to reduce the impacts

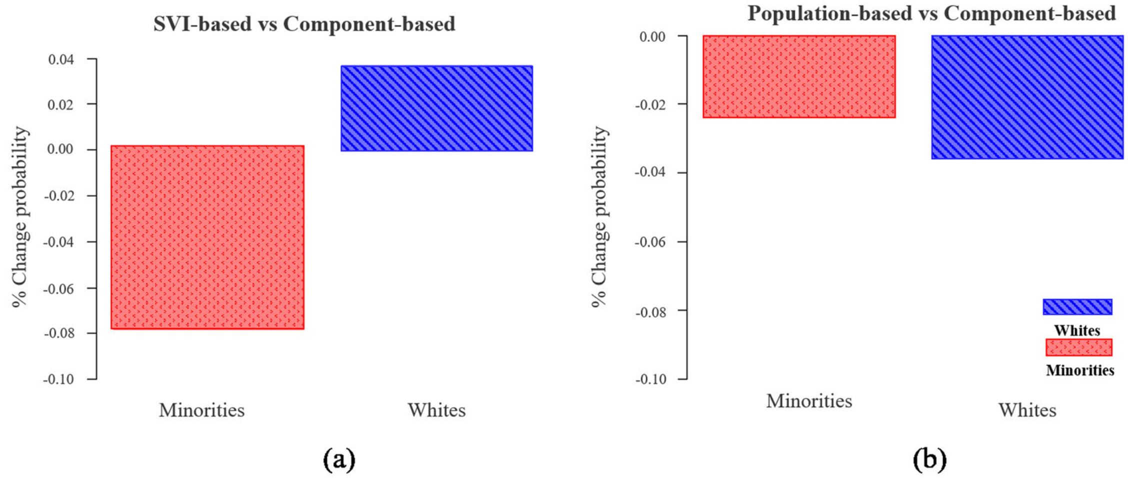

FIGURE 13 Comparing the probability of experiencing hardship for the racial groups under each restoration strategy

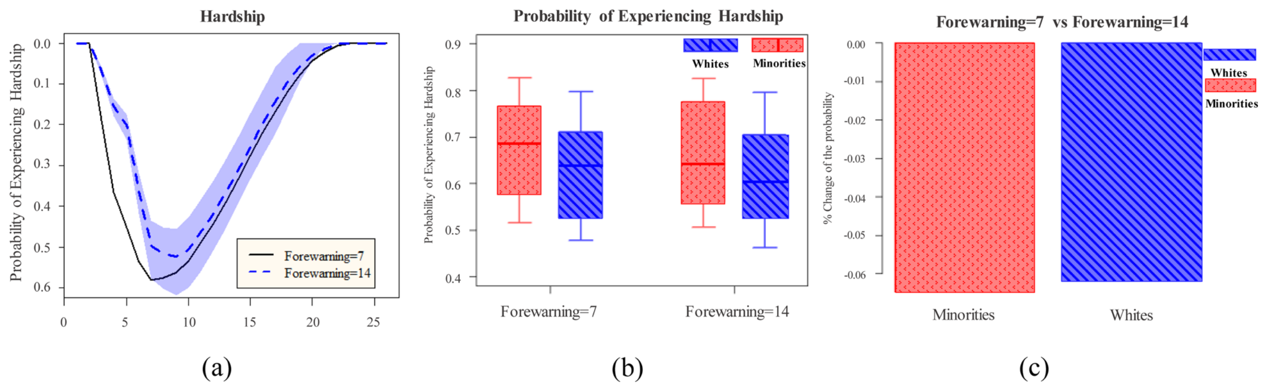

FIGURE 14 Comparing different forewarning levels. (a) Dynamic patterns of the proportion of households experiencing hardship under each forewarning level. The shaded areas show the 0.25 and 0.75 percentile of the values, (b) probability of experiencing hardship for different racial groups under each forewarning level, and (c) change in the probability of experiencing hardship for the racial groups under improvement of the forewarning level

of power outages on their well-being. Comparing an event with a week of forewarning with a scenario in which the household had 2 weeks of forewarning, the results suggest that this early identification of a hazard is very effective for reducing the impacts for the communities (Figure 14). The maximum proportion of households experiencing hardship in a day would decrease around 8% when increasing the forewarning time from 7 to 14 days. With rapidly intensifying hurricanes (such as Hurricane Ida, 2021), the forewarning period is becoming shorter, and hence the results show the effect of shorter forewarning periods on the experienced societal impacts of power outages. Investments in making advancements in predicting and tracking the hurricane pass, and proper communication with households could significantly reduce the societal impacts of power outages. However, the enhancements in providing longer forewarning would not necessarily reduce the societal impact for socially vulnerable populations. In both the base scenario and the enhanced strategy, minorities show a statistically significant higher probability of experiencing hardship (p-values are respectively .002 and .001 for forewarning of 7 and 14), Figure 14b. While the enhanced strategy shows to reduce the impact for the minority groups slightly more than other groups, this strategy seems to treat everyone equally and does not necessarily be in favor of improving the equity in the impact.

4.2.3 | The effect of hazard information dissemination and social network types

The social network type has implications regarding which social network people receive information. The two structures of social networks, namely, SF and SW, are compared as each provides certain characteristics in the propagation of information through the community. For example, as

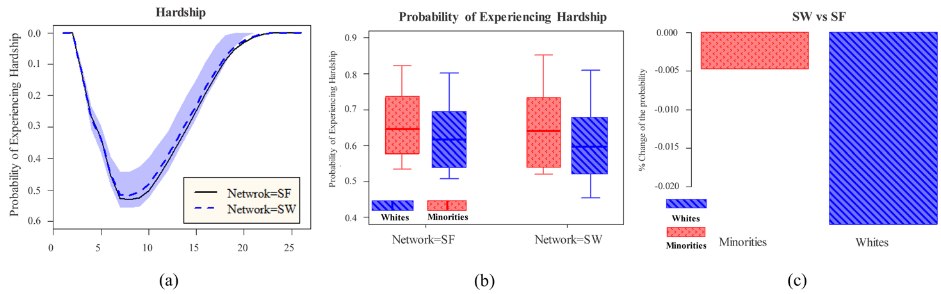

FIGURE 15 Comparing scale-free and small-world social networks. (a) Dynamic patterns of the proportion of households experiencing hardship under each forewarning level. The shaded areas show the 0.25 and 0.75 percentile of the values, (b) probability of experiencing hardship for different racial groups under each network structure, (c) change in the probability of experiencing hardship for the racial groups under a change in the social network structure

discussed earlier, communication among close friends happening offline (in person or on the phone) is through an SW network, and communication on social media is through an SF network (Nocaj et al., 2015; Schnettler, 2009). The results from Figure 15 show that there is a slight difference in the societal impacts of power outages on the community when comparing the two network structures. One reason is due to the delays in acting upon the information received by the social network for taking protective actions. Results suggest that the probability of experiencing hardship is greater in the small-work structure. Both cases show a greater probability of experiencing hardship by the vulnerable population, with *p*-values being .018 and .001, respectively, for SF and SW structures. The change in the network structure from SF to SW seems to have a greater impact on the nonminority group. This means that lack of information communication through social media could have more impacts on minority groups, compared to White households.

4.3 | Combined effect of strategies for reducing the societal impacts

4.3.1 | Robustness of restoration strategy to different hurricane categories

The effectiveness of implementing different strategies for restoring power to reduce the societal impacts varies depending on the intensity of the hurricanes. Figures 16a,b show the probability of experiencing hardship for each strategy and the dynamic impact under the four hurricane categories. While there is no significant advantage for implementing population-based and SVI-based strategies during low-impact events such as hurricane category 1 (*p*-value equal to .297), these strategies seem to over-perform the component-based restoration during hurricane categories 2 and 3 (with *p*-values for ANOVA test being .001 and $<$ .001). The largest difference is related to hurricane category 3, with population-based restoration leading to the mildest societal hardship. However, the difference between the societal impacts of implementing the population-based and SVI-based with component-based, while being statistically different (*p*-value of .01), decreases in hurricane category 4. This result suggests that the effectiveness of the improved restoration strategy may not increase linearly as the intensity increases. When the intensity increases to hurricane category 4, the SVI-based strategy seems to perform slightly better than population-based and component-based restoration. This trend is due to the increased gap between the vulnerable population and others when the intensity increases as the intensity of the hurricane increases. Figures 16c, d compare the probability of experiencing hardship for the racial groups for population-based and SVI-based relative to component-based, respectively. While the population-based recovery seems to improve the condition for both social groups, this strategy seems to be slightly in favor of the nonvulnerable population. However, the SVI-based restoration reduces the societal impacts for the vulnerable population more than others. Therefore, when the intensity increases to hurricane category 4, this strategy reduces the overall hardship even slightly better than the population-based restoration.

4.3.2 | Robustness of forewarning to different hurricane categories

The extent of reduction in the societal impacts of power outages by providing a longer forewarning time varies depending on the hurricane category. The probability of experiencing hardship for different forewarning levels is not equal in different hurricane categories (*p*-values are $<$ .001). The reduction of societal impacts showed significant changes for the forewarning time of more than 6 days

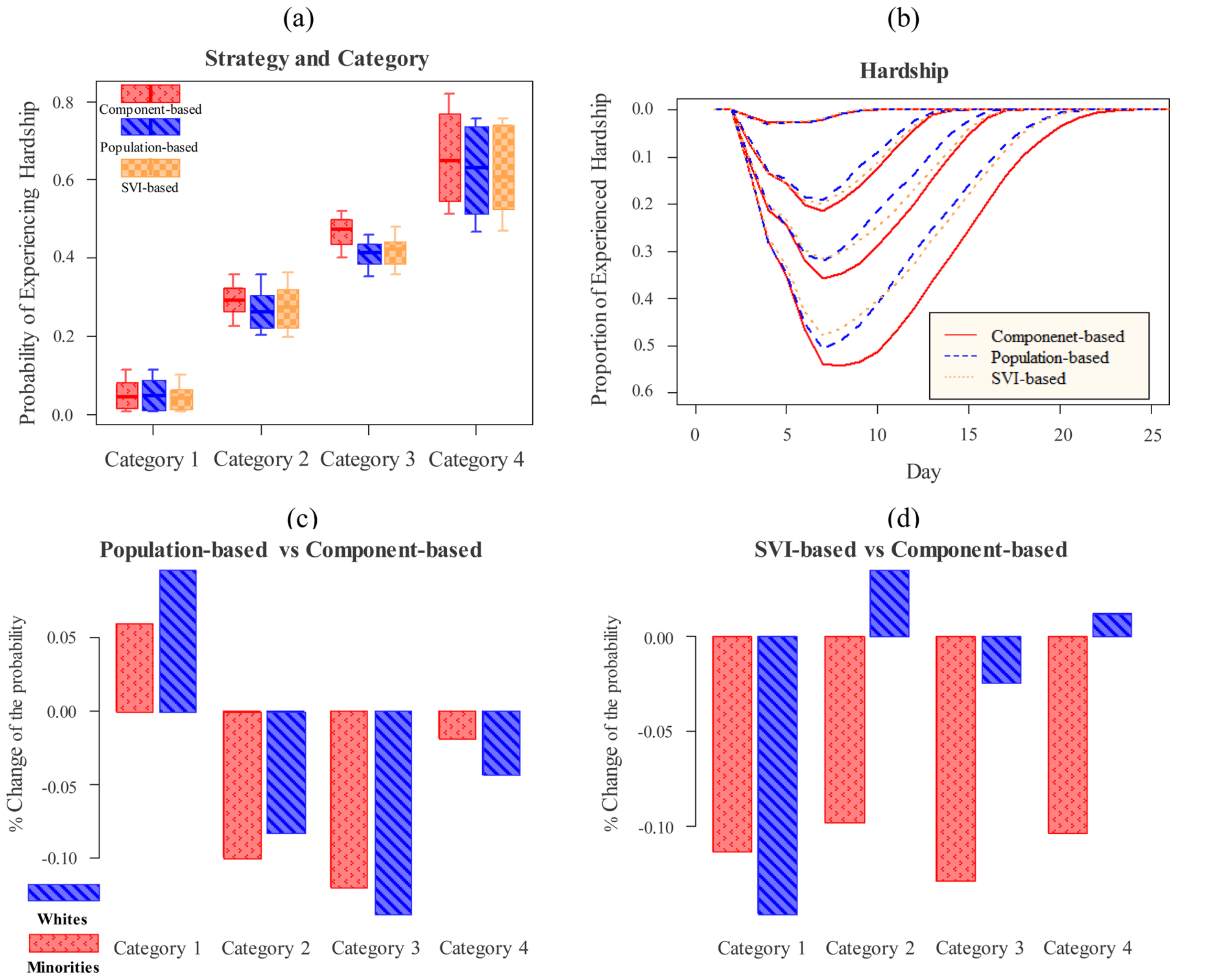

FIGURE 16 Effect of restoration strategy on the societal impacts of power outages under various hurricane intensities. (a) Histograms of the probability of experiencing hardship for each scenario, (b) displays the average daily experienced hardship for each scenario, (c, d) percentage difference of the probability of experiencing hardship for the racial groups under each scenario

(Figure 17a,b). These figures show that both the probability of experiencing hardship and the daily experienced hardship sharply decline when forewarning time increases to more than 6 days. The results explain the major impact of rapid onset hazard events (such as fast-moving hurricanes) on the affected communities. Figure 17c compares the probability of experiencing hardship for scenarios increasing by 3-day increments of forewarning. This result suggests that providing longer forewarning is mainly an effective strategy for low-intensity hurricanes. The effect of providing a longer forewarning in categories 3 and 4 hurricanes seems to diminish. Thus, implementing this strategy may not solely reduce the societal impacts of high-intensity hazard events. Last, Figure 17d shows the percentage of reduction of the probability of experiencing hardship for racial groups if the forewarning increase from 6 to 12 days. The result shows that increasing the forewarning duration does not seem to benefit certain groups. While minorities experience a decrease in the experienced hardship under hurricane categories 1 and 2, the difference does not seem to be significant, especially for the more intense hurricane events.

4.4 | Pathways to different levels of societal impacts

A combination of scenarios was used to create the scenario landscape (Figure 18) and to evaluate the combination of strategies that lead to the least onerous societal impacts of power outages. To this end, classification and regression tree (CART) analysis was implemented to examine the effect of different variables for reducing the societal impacts under various scenarios (Breiman et al., 1984). CART is a tree-based classification technique that explains how a target variable could be determined based on the

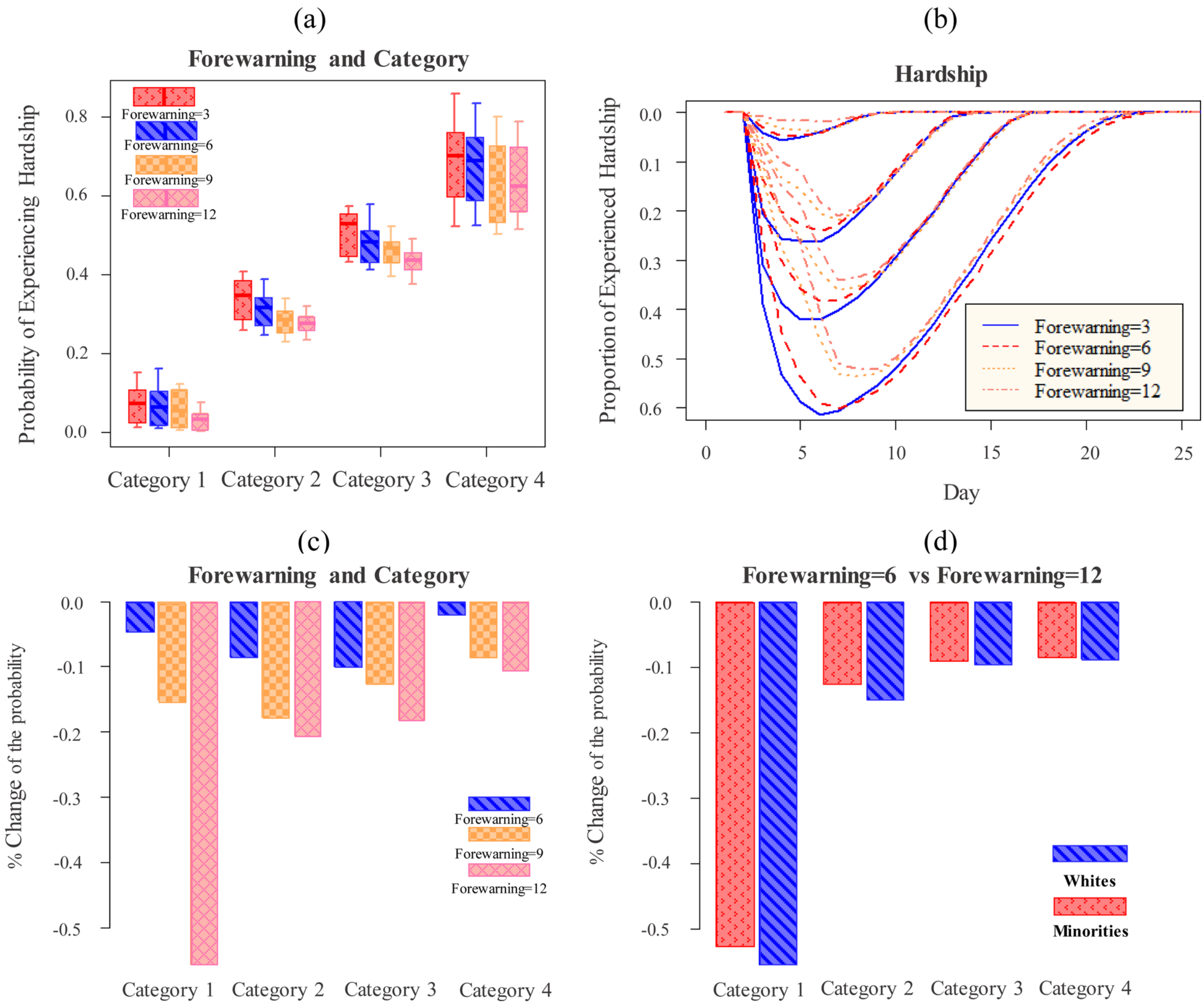

FIGURE 17 Effect of providing longer forewarning on the societal impacts of power outages under various hurricane intensities. (a) Histograms of the probability of experiencing hardship for each scenario. (b) average daily experienced hardship for each scenario, (c) percentage change of the reduction in the probability of experiencing hardship for each scenario compared to the forewarning equal to 3 days, and (d) percentage difference of the probability of experiencing hardship for the racial groups under each scenario

interaction among a large number of predictors. This algorithm recursively partitions into binary splits, which maximizes the homogeneity of the groups in relation to the dependent variable (Prasad et al., 2006). The higher splits show the variables with a stronger influence over changes in the dependent variable, which is the experienced hardship in the scenario landscape. CART analysis is shown to be effective in meta-modeling analysis based on simulation results (Mostafavi, 2018).

In this analysis, in addition to the described strategies for reducing the societal impacts (restoration activity, longer forewarning, and social network structure), also included are the hurricane category, the number of restoration resources, and the information sharing probability of the officials. The hurricane category has the greatest impact on households' experienced hardship. A longer forewarning duration seems to have a great impact on reducing the societal impacts of the power outages. This pattern is consistent for different hurricane categories, which supports the suggestion that providing a longer forewarning could effectively reduce societal impacts. The effect of the restoration strategy and increasing the number of resources varies depending on the hurricane intensity. Improving the restoration strategy to focus on the needs of the population (population-based and SVI-based) seems to more effectively reduce societal impacts than increasing the number of resources in response to high-intensity hurricanes. The effect of increasing the number of resources, however, seems to be an effective approach for lower-severity events. Last, when considering the effect of longer forewarning and information-sharing by the officials, the effect of the social network structure seems to be insignificant in reducing the societal impacts of disaster-induced prolonged power outages. The results show that

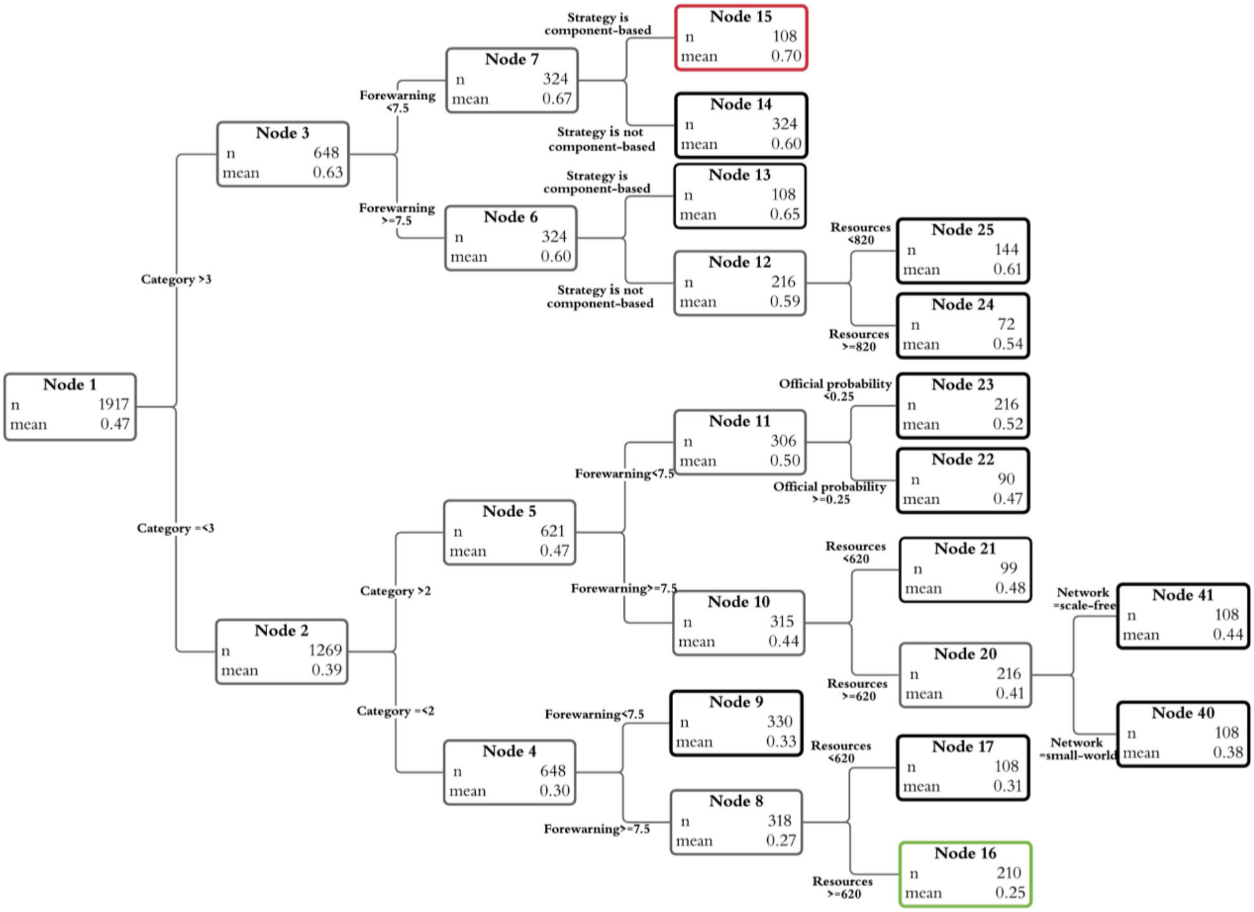

FIGURE 18 Classification and regression tree analysis for analyzing the effect of various strategies in reducing the societal impacts

hardships due to power outages during high-intensity hurricanes would be inevitable for minorities and other vulnerable populations unless power infrastructure systems are strengthened to reduce their likelihood of failure and sufficient resources, focusing on socially vulnerable populations, are earmarked for prioritizing power restoration.

5 | CONCLUDING REMARKS

This study presents a new computational simulation framework for modeling the complex hazard–households–infrastructure nexus to better integrate social equity considerations into resilience assessments. The proposed integrated multi-agent simulation model enables capturing of the complex interactions between hazard, risk and restoration process, and households' decision-making behaviors. This new computational model enables consideration of heterogeneity in the impact of infrastructure service disruption in affected communities.

The model enables a combined evaluation of the effects of hazard characteristics, population attributes and decision-making processes, and physical infrastructure network topology and vulnerability in facilitating more equitable resilience assessments. While the current literature includes various computational models for assessing infrastructure resilience, the majority of existing models focus primarily on physical systems and fail to consider the population's interactions with these systems and their services during disasters. The proposed computational framework captures and models the underlying dynamic mechanisms and complex interactions among hazard, physical networks, and household behavior in determining the societal impacts and disparities. Thus, this paper contributes to the field of computer-aided infrastructure engineering by (1) abstracting the complex mechanisms that lead to the societal impacts of hurricane-induced power outages; (2) simulating societal impacts by using theoretical models and empirical data and capturing and modeling the interactions between hazard, power network, and households' behavior; and (3) devising an approach to meet the need for equitable resilience assessment in infrastructure systems. The multi-agent simulation model enables the inclusion of the social dimension in the resilience assessment of the infrastructure system. The model is capable of assisting in resilience assessment in different contexts given the availability of similar data such as household information.

The output results would inform about the overall societal impact on the community and the distributional impact on the various segments of the community. By enabling decision-makers to conduct scenario analysis of strategies for reducing societal impacts of power outages, such as restoration strategies, forewarning time, and household social network structure, the model provides an approach to reduce overall societal impacts. The proposed model could be used by emergency and infrastructure managers and operators to better prioritize resource allocation to their hazard mitigation investments and restorations to reduce the societal impacts of infrastructure disruptions. Beyond its contribution to equitable infrastructure resilience assessment, the computational simulation model proposed in this study contributes to integrated complex modeling approaches in civil infrastructure and urban systems. Integrated complex modeling is a growingly important approach in analyzing various complex phenomena related to sustainability and resilience of urban resilience and infrastructure systems for robust decision-making, as well as developing interdisciplinary socio-technical system theories of urban infrastructure systems and disaster resilience. The integrated simulation framework that captures the complex interactions among hazard characteristics, population behaviors, and physical infrastructure network properties could provide a tool and simulated data for developing more interdisciplinary disaster resilience theories and examining complex phenomena, which could not be evaluated using empirical and observational data (Mostafavi & Ganapati, 2019).

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APPENDIX A

TABLE A1 Pseudo-algorithms for the damage from hurricanes based on the fragility equations

```
Algorithm 1 fragility curve
input: probability of failure for each element
output: element that fails
function FRAG CURVE(PoF)
    for day d in hurricane duration do
        for element e in agents do
            if e does not fail then
                R(Random) ← windspeed
                if R < PoF then
                    e fails and remove all connection link to e
                end if
            end if
        end for
    end for
end function
```

TABLE A2 Pseudo-algorithms for damage from the cascading effect

```
Algorithm 2 cascade failure
function SUBSTATION FAIL(PoF(Substation), network(ArrayList))
    if Substation s fails then
        for transmission t connected to s do
            t fails
        end for
    end if
end function
function TRANSMISSION FAIL(PoF(transmission), network(ArrayList))
    if transmissions sall connected to Substation s fail then
        s fails
        call substation fail
    end if
end function
```

TABLE A3 Pseudo-households decision-making and protective action

```
Algorithm 3 preparation
function PREPARATION(demographic features, CumulativeLogi formula,prepare lambda)
    for d in information propagation period do
        pre1 − 5 ← CumulativeLogic(demographic)
        PortionPrepare ← NeighborPrepareSum/neighborSize
        r ← Random + PortionPrepare * preparelambda
        if r < pre1 then
            prepare ← 1
        else if R < pre2 then
            prepare ← 2
        else if R < pre3 then
            prepare ← 3
        else if R < pre4 then
            prepare ← 4
        else
            prepare ← 5
        end if
    end for
```

APPENDIX B
Model development
Fragility curves and restoration resources

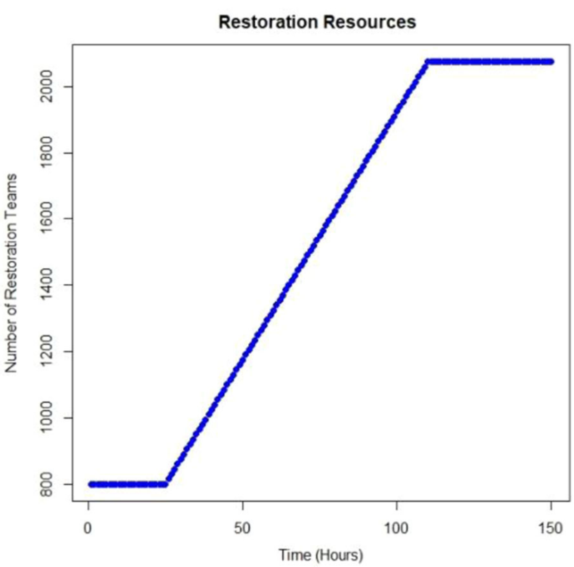

FIGURE B1 Number of added resources for the restoration activity

Household agents

Model description

In these models, the zone of tolerance would be calculated through the process and depending on the three variables. The households' zone of tolerance is a function of the household's need, substitute, and preparedness level. The following equation describes the relationships among the variables:

TABLE A4 Pseudo-algorithms for the restoration activity and prioritization

```
Algorithm 4 restoration(use population based scenario)
input: Strategy && resource
function RESTORATION(Strategy scenario,origin resource r,resource increase speed a,number of failedtracts t)
    for h in resource increasing period do
        r ← r + a
    end for
    while r > 0 and fix tracts < t do
        if r > xr then
            fix tract[x]
            r ← r − xr
            fixtracts ← fixtracts + 1
        else
            continue
        end if
    end while
    for Pole p in tract[x] do
        if p.nearest substaion(s) not fixed and r > sr then
            fix s
            r ← r − sr
        end if
    end for
    for transmission t in tract[x] do
        if t not fixed and r > tr then
            fix t
            r ← r − tr
        end if
    end for
    for Pole p in tract[x] do
        if p not fixed and r > pr then
            fix p
            r ← r − pr
        end if
    end for
    for Substation s in tract[x] do
        if s not fixed and r >sr then
            fix s
            r ← r − sr
        end if
    end for
end function
```

$$\mu = \exp\left[1.7762 - 0.5130x_s + 0.1827x_n + 0.2664x_p\right]$$

Therefore, in this model, we needed to calculate the three factors of substitute, need, and preparedness.

Need

The needed variable is inherent based on the socio-demographic characteristics of the household. Table B2 shows the influencing factors:

TABLE B1 Required resources for the damage to each component

Damaged component	Restoration time	Needed resources
Load substations	Moderate: *N*[*](72 h, 36 h), severe: *N(168 h, 84 h)* and complete: *N(720 h, 360 h)*	6 14 60
Transmission towers	*N(72 h, 36 h)*	6
Transmission lines	*N(48 h, 24 h)*	4
Distribution poles	*N(10 h, 5 h)*	1
Distribution lines	*N(8 h, 4 h)*	1

[*] *N*(*a*,*b*) refers to the randomly generated number from a normal distribution with mean = *a* and standard deviation = *b* (Mensah, 2015).

TABLE B2 Influencing factors of the households' need

Variable	Measure
Race minority	"Yes" = 1, "No" = 2
Mobility issue	"Yes" = 1, "No" = 2
Young children (age 10)	"Yes" = 1, "No" = 2
Medical	"Yes" = 1, "No" = 2

TABLE B3 Model for determining the households' need

Variable	Estimate	*p*-value
(Intercept):1	0.444	.125
(Intercept):2	1.792	<.001
(Intercept):3	3.344	<.001
(Intercept):4	4.992	<.001
Racial minority	0.896	<.001
Mobility issue	−0.519	<.001
Having children (< 10)	0.220	.050
Medical issue	−0.303	<.001

TABLE B4 Influencing factors of the households' protective action (buying a generator)

Variable	Measure
Income	"Less than $25,000" = 1, "$25,000–$49,999" = 2, "$50,000–$74,999" = 3, "$75,000–$99,999" = 4, "$100,000–$124,999" = 5, "$125,000–$149,999" = 6, "more than $150,000" = 7
Expectations	The number calculated in the previous step
Ownership	"Renter" (1), "owner" (0)
Self-efficacy	"Strongly low" = 1, "somewhat low" = 2, "medium" = 3, "somewhat high" = 4, "strongly high" = 5

Logistic regression relates the predictors to the logit based on the following equation:

TABLE B5 Influencing factors of the households' preparation

Variable	Measure
Vehicle vulnerability	"Did not have a car" = 1, "I have it" = 0
Experience	The number calculated in the previous step
Ownership	"Renter" (1), "owner" (0)
Self-efficacy	"Strongly low" = 1, "somewhat low" = 2, "medium" = 3, "somewhat high" = 4, "strongly high" = 5
Elderly	Yes (1), no (0)
Forewarning	Number of days
Distant to supermarket	Miles

Note: Distance was simulated from a normal distribution with mean 5 and variance 30.

TABLE B6 Influencing factors of the households' level of self-efficacy

Variable	Measure
Ownership	Yes (1), no (0)
Social capital	Yes (1), no (0)
Chronic disease	Yes (1), no (0)
Medical	Yes (1), no (0)

TABLE B7 Model for determining the households' level of self-efficacy

Variable	Estimate	*p*-value
(Intercept):1	−3.191	<.001
(Intercept):2	−1.792	<.001
(Intercept):3	−0.551	.009
(Intercept):4	1.458	<.001
Ownership	0.339	<.001
Medical	−0.245	.016
Chronic disease	−0.237	.029
Social capital	0.217	<.04

The variables in the model are socio-demographic characteristics; therefore, we implemented a simulated sample of the population for determining these variables.

The cumulative logit models with proportional odds were used for modeling the parameter; here, there are

TABLE B8 Influencing factors of the households' level of experience

Variable	Measure
Having a child (age 10)	Yes (1), no (0)
Race	Yes (1), no (0)
State duration	Number of years
Elderly	Yes (1), no (0)

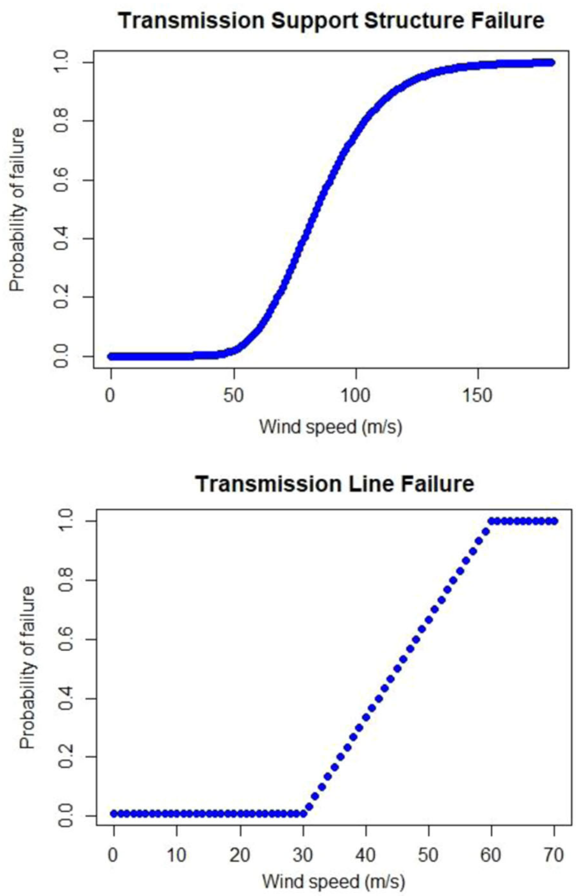

FIGURE B2 Transmission distribution network fragility curve

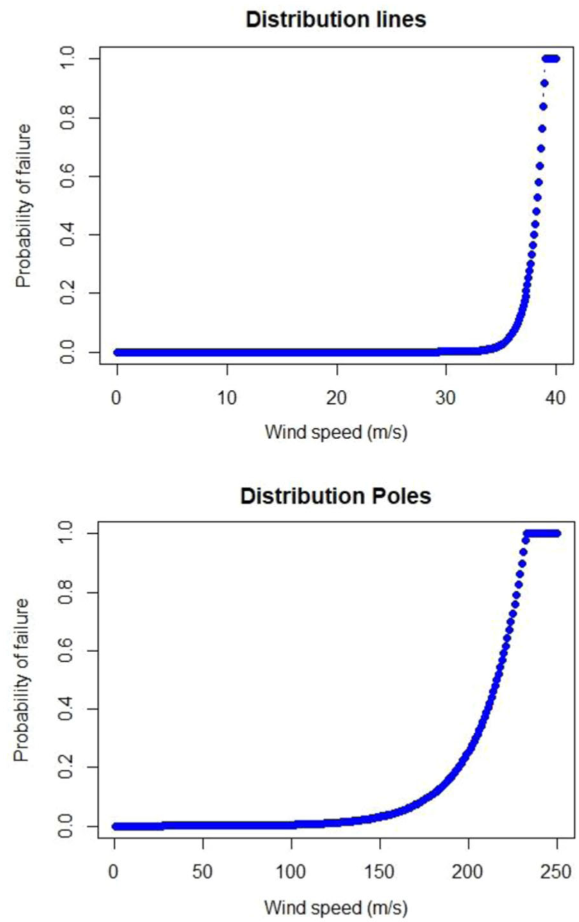

FIGURE B3 Distribution network fragility curve

four intercepts, which means there exist four equations for calculating the probability of the five need levels B3. The general equation for this model is as follows:

$$\mathrm{logit}\left[P\left(Y \le j\right)\right] = \log\left[\frac{P\left(Y \le j\right)}{1 - P\left(Y \le j\right)}\right]$$

$$= \log\left[\frac{\pi_1 + \cdots + \pi_j}{\pi_{j+1} + \cdots + \pi_J}\right], \quad j = 1, \ldots, J-1$$

Here, instead of directly calculating the probability of each level (e.g., the probability of need to be 1 ($p(y = 1)$), we will calculate the $p(Y \le = 1)$. But $P(y \le 1) = P(y = 1)$; thus, we can calculate the probability of the first level, $p(y = 1)$, by the following equation:

$$\log \frac{p\left(y = 1\right)}{1 - p\left(y = 1\right)} = 0.44441 + 0.89646x_r - 0.51914x_m$$
$$+0.21971x_a - 0.30319x_m$$

Then, the probability of ($p(y = 1)$ would be determined based on the following equation:

$$p\left(y = 1\right) = \frac{e^{[p(y=1)]}}{1 + e^{[p(y=1)]}}$$

Then, the next probability would be the probability of $p(Y < = 2)$, which is $P1 + P2$. Therefore, we can calculate the probability of the second one based on the difference between this probability and the one calculated in the previous step:

$$\log \frac{p\left(y1\right) + p\left(y2\right)}{p\left(y3\right) + p\left(y4\right) + p\left(y5\right)} = 1.79242 + 0.89646x_r$$
$$-0.51914x_m + 0.21971x_a - 0.30319x_m$$

Therefore, $p(y \le 2)$ would be calculated based on the following equation:

$$p\left(y \le 2\right) = \frac{e^{[p(y\le2)]}}{1 + e^{[y\le2]}}$$

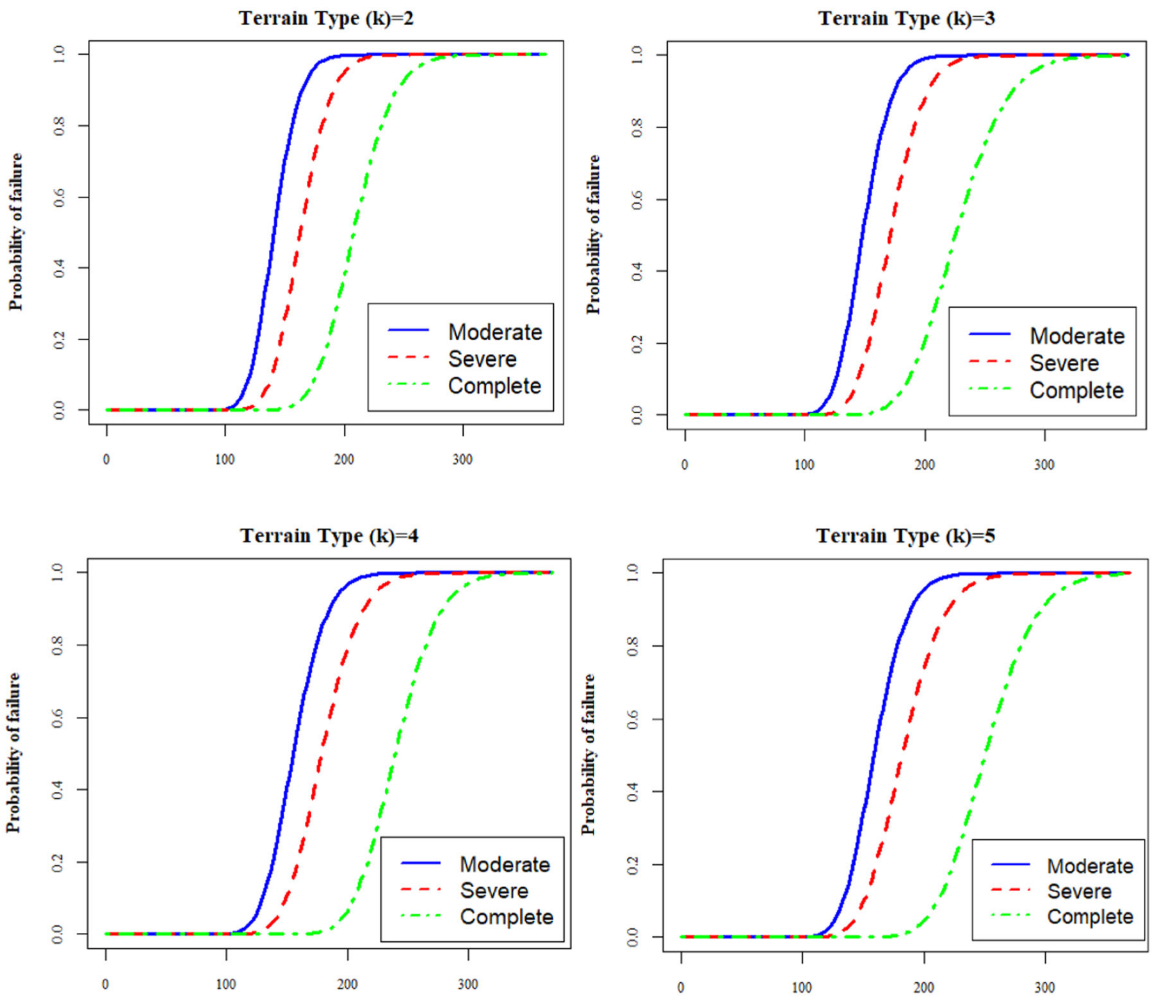

FIGURE B4 Substation fragility curve

Thus, $p(2)$ would be the difference between the two probabilities. This will be continued until we have used the third and fourth intercepts. Last, the probability of the final level $p5$ would be calculated by $1-p(y \leq 4)$. Here, $p(y \leq 4)$ is equal to the last equation using intercept 4.

Substitute

We calculate the probability of getting a generator by using logistic regression. We calculate the probability of getting a generator by using logistic regression. Here, the probability depends on the income, self-efficacy, ownership, and the household's expectations of the disruptions. Table B4 shows the variables.

$$P_s = \log\frac{p(y=1)}{1-p(y=1)} = -2.53950 + 0.07416x_i$$
$$- 0.93270x_o + 0.48647\log(x_e+1) + 0.26128x_{se}$$

Here, the log transformation was conducted on the expectation variable. Then, the probability of having a generator or $p(y = 1)$ would be determined based on the following equation:

$$p(y=1) = \frac{e^{[P_s]}}{1+e^{[P_s]}}$$

Preparation

This variable was modeled in a similar fashion as the substitute. The main variable that makes it a process variable is the forewarning. This variable depends on the following factors: having a vehicle, previous experience, being elderly, ownership, forewarning, distance to the supermarket, and self-efficacy. We calculated the probability of preparedness by using logistic regression. Table B5 below shows the variables.

Logistic regression relates the predictors to the logit based on the following equation:

$$P_p = \log\frac{p(y=1)}{1-p(y=1)} = 1.89292 - 0.58174x_v$$
$$-1.11299x_e + 0.44445x_{el} - 0.60578x_o + 0.08802x_f$$
$$-\ 0.02362x_d +\ 0.50834x_{se}$$

Then, the probability of having a generator or $p(y=1)$ would be determined based on the following equation:

$$p\,(y=1) = \frac{e^{[P_p]}}{1+e^{[P_p]}}$$

Self-efficacy

This variable defines to what extent the households believe in the effectiveness of the preparedness actions. Table B6 shows the influencing variables: ownership, having social capital, having a chronic disease, and a medical condition.

The calculation of the probabilities based on results in Table for each level should be done using the procedure explained in the need section B7.

Experience

This variable is calculated to find those with previous disaster experience. Having previous experience with a disaster depends on the duration of the time they have lived in their state, racial minority, elderly, and having a child (B8).

State duration should be simulated based on a normal distribution and mean 25 and standard deviation 15 (variance of 225). Logistic regression relates the predictors to the logit based on the following equation:

$$\log\frac{p(y=1)}{1-p(y=1)} = 1.371844 \quad + 0.020162x_{sd}$$
$$-0.656271\ x_r - 0.366558x_a + 0.272127x_e$$

Then, the probability of having a generator or $p(y=1)$ would be determined based on the following equation:

$$p\,(y=1) = \frac{e^{[-1.98711+0.12456x_i-0.71779\ x_o+0.37576\log(x_e+1)]}}{1+e^{[-1.98711+0.12456x_i-0.71779\ x_o+0.37576\log(x_e+1)]}}$$