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PROBABILISTIC QUANTIFICATION OF COMMUNITY RESILIENCE USING DISCRETE EVENT SIMULATION

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Abstract. *This paper puts forward a comprehensive framework for probabilistic quantification of community resilience considering multiple interdependent infrastructure systems. The proposed framework integrates various dimensions of resilience including technical, organizational, social, and economic. To this end, first the post-hazard status of the components of the community, e.g., infrastructure systems, is determined through casualty and damage models. Next, discrete events simulation is employed to quantify the recovery of the community, and the infrastructures thereof. For this purpose, the community restoration capacity, comprising workforce, material, and equipment, is assigned to the damaged components, which produces repair events. Once a component restored, the status of all components is updated considering interdependencies. At this point, the framework quantifies the costs incurred by the community comprising direct costs, i.e., restoration and relocation costs, and indirect costs, i.e., business interruption and socioeconomic costs due to absence of services, during the pre-repair period. Thereafter, the released restoration capacity is reassigned to another unrestored component, producing another event. This process continues until all components reach the intended functionality. The total community cost, which is the accumulated cost over the entire recovery period, is regarded as an indicator of the community resilience. The functionality of different infrastructure systems as well as different dimensions of resilience is incorporated in this single global indicator. This, in turn, provides the ability to determine the importance of each component based on the extent of contribution to this indicator. Therefore, the proposed framework provides decision makers with a decision support tool to identify the optimal resource allocation strategy to achieve a resilient community. The proposed framework is showcased by an application to a community with a building portfolio, commercial units, transportation network, healthcare facilities, and a power distribution network.*

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1 INTRODUCTION

Resilience is rapidly becoming a major area of research in academia and an important discourse in engineering practice [1]. Resilience encompasses various tracks of research. For example, a number of studies have focused on defining and quantifying the resilience [2-4], while some others have worked on modeling the different aspects and dimensions of resilience, such as infrastructure interdependencies [5, 6]. In addition, some studies have defined performance metrics for resilience assessment of infrastructures and communities [7, 8].

There are several definitions for the notion of resilience in different scientific disciplines ranging from environmental engineering to materials science, psychology, sociology, and economics [2]. Among all of these studies, two key aspects of resilience are defined as strength and flexibility. Bruneau et al. [2] proposed a comprehensive description of resilience, which expands the definition to 11 different aspects. Renschler et al. [9] proposed a framework for defining and measuring resilience at the community scale, dubbed PEOPLES. This framework accounts for seven dimensions of the community, namely, Population and demographics, Environmental/Ecosystem, Organized governmental services, Physical infrastructure, Lifestyle and community competence, Economic development, and Social-cultural capital, hence the acronym PEOPLES.

The next challenging issue in the context of resilience is the interdependency of infrastructures. According to Rinaldi et al. [10], dependency is defined as a relationship between two infrastructures through which the state of one infrastructure is correlated to the state of the other. This phenomenon is a critical characteristic of any infrastructure system, since the failure of one infrastructure can propagate through the system and result in cascading failures in other infrastructures. Therefore, it is crucial to consider this interdependency. Several studies in the literature have focused on modeling this interdependency and the resulting cascading failure [5, 6].

The next challenging issue is the coincidence of multiple hazards and the ensuing multiple consequences. In fact, the occurrence of one hazard may increase the consequences of another hazard. For example, the occurrence of an earthquake after a heavy snowfall may result in more severe consequences, since the accumulation of snow on the structures results in increasing the mass of the structure and amplifying the P-Δ effect. Ouyang et al. [11] proposed a methodology to model the concurrent hazards. It considers the double, triple, and generally k-combination of hazards and subsequently computes the associated probabilities and consequences.

This paper puts forward a comprehensive probabilistic framework to quantify the community resilience, considering multiple interdependent civil infrastructures and multiple consequences. This framework employs Monte Carlo sampling. In each sample, a hazard event with a random intensity is generated by a probabilistic intensity model. Thereafter, the performance of infrastructures is quantified considering prevailing uncertainties. Consequently, the loss of functionality of the infrastructures in the aftermath of the hazard event is quantified in terms of the incurred damage, economic losses including downtime and business interruption, social losses including death, casualties, reduced quality of life, and socioeconomic losses. This results in an estimate of the robustness of the infrastructures in the face of the hazard event, and is quantified using risk analysis approaches, such as FEMA-NIBS [12] and the framework proposed by Mahsuli and Haukaas [13, 14]. From this point forward, a novel implementation of the discrete event simulation is proposed in this paper to simulate the recovery of functionality of the infrastructures over time until the functionality reaches the desired level. To this end, probabilistic models that take into account resource availability simulate the post-disaster recovery process of communities. In particular, the community restoration capacity, including workforce, material, and equipment, is assigned to the damaged components. Once a component is restored, the status of all components is updated considering interdependencies, and the released restoration capacity is subsequently reassigned to another unrestored component. This process continues until all components reach their desired level of functionality.

The proposed framework is implemented in the Rt computer program [15], and is showcased by an application to a community with a building portfolio comprising residential and commercial sectors, transportation network, healthcare facilities, and a power distribution network. In this example, the serviceability of hospitals is dependent on power. Furthermore, some of the commercial sector is dependent on power to uphold their business. The commercial sector provides jobs for the residential sector, and at the same time, the residential sector is the consumer of the services and products provided by the commercial sector. This application aims at answering the following key questions through the proposed framework which will be used to evaluate the community resilience:

1) How long does it take for the entire community and each individual infrastructure to recover to its pre-disaster status?
2) What is the cost incurred by the entire community as well as the stakeholders of each individual infrastructure, directly and indirectly, to recover to its pre-disaster status?

2 LITERATURE REVIEW

In this section, a concise review of the key literature on major subjects on resilience, namely, definition of resilience, quantification of resilience, and indicators of resilience, is presented. Furthermore, the studies dealing with the modeling of the post-disaster recovery of communities have been briefly introduced.

2.1 Definition of resilience

The first definition of resilience was proposed in 1973. Holling [16] studied the resilience and stability of ecological systems. Holling defined resilience as a measure of systems to persist and absorb disturbances. On the other hand, stability is the ability of the systems to return to equilibrium after a disturbance. This definition is only focused on one aspect of resilience, i.e., the resistant capacity. The next definition, that shaped the resilience literature, was proposed in 1981. Timmerman [17] defined resilience as "a measure of a system's, or part of a system capacity to absorb and recover from a hazardous event." This definition concentrates not only on the resistant capacity but also on the ability to efficiently recover in the face of hazards. Definitions that were put forward after 1981 were mainly inspired by the one proposed by Timmerman [17]. They all emphasize on two key aspects of resilience, i.e., the ability of a system to withstand the hazards, dubbed "robustness," and to recover promptly and efficiently to functionality, dubbed "rapidity."

2.2 Quantification of resilience

In 2003, Bruneau et al. [2] provided a comprehensive description of resilience which is still the most popular one in the engineering community [1]. According to Bruneau et al. [2], resilience comprises four properties, named as four Rs of resilience: (1) robustness, defined as the ability to resist extreme events, (2) rapidity, defined as the ability to recover quickly to a high level of functionality, (3) redundancy, defined as the extent to which the components of a system are substitutable, and (4) resourcefulness, defined as the ability to identify failures, establish priorities, and allocate resources. In addition, resilience encompasses four interrelated dimensions: (1) technical, which is the ability of physical systems to perform desirably in the face of hazards, (2) organizational, which is the managerial capacity of a system to make appropriate decisions and take actions to contribute to achieving the four properties of resilience, (3) social, which is the impacts on society due to loss of critical services, and (4) economic, which is the capacity to reduce both direct and indirect economic losses against hazards. Therefore, a resilient system is one with less failure probability, less recovery time, and less consequences.

Based on the framework presented by Bruneau et al. [2], Chang and Shinozuka [18] proposed a resilience quantification framework, applicable to various infrastructure systems. In their framework, the system functionality, Q, is utilized to evaluate the performance of the system in terms of losses and recovery duration. Cimellaro et al. [19], proposed another quantification framework. In their approach, resilience is defined as the normalized area underneath the functionality curve of the system. As depicted in Figure 1, the functionality of the system remains unchanged until a hazard occurs at time t_0, which results in a sudden fall in the system performance. Next, the recovery process begins, and after the time period of T_{RE}, the system reaches the desired functionality. The control time, T_{LC}, is the duration in which the analysis is performed, is often considered as one year. According to Cimellaro et al. framework [19], resilience is quantified by the following equation, which represents the shaded area in Figure 1:

$$\text{Resilience} = \frac{1}{T_{LC}} \int_{t_0}^{t_0+T_{LC}} Q\left(t\right) dt \tag{1}$$

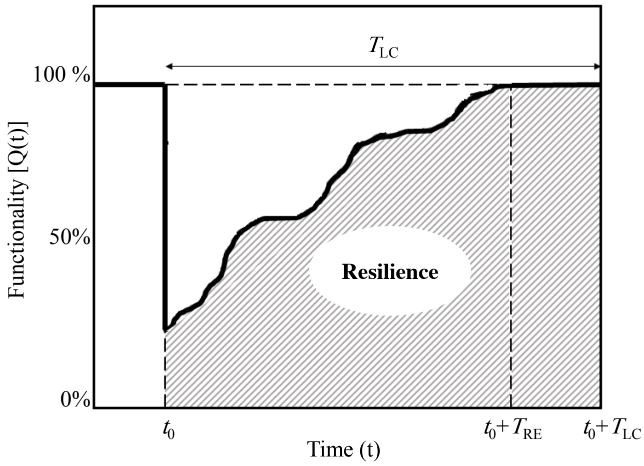

Figure 1. Graphical representation of resilience

In 2012, Ouyang et al. [11] proposed a three-stage resilience analysis framework. These three stages are resistant capacity, absorptive capacity, and restorative capacity. In their framework, network betweenness [5] is considered as the performance metric of the system. To this end, random scenarios for occurrence of hazards during a time span of one year are generated and the system's performance under each is evaluated. Thereafter, the annual resilience is quantified as the mean ratio of the area underneath the real performance curve to the area under the target performance curve during a year. Other methodologies have been also utilized for quantification of resilience, such as graph theory, fuzzy inference, probabilistic methods, and entropy theory [20].

2.3 Indicators of resilience

Due to the multifaceted nature of resilience, which includes physical, social, organizational, and economic dimensions, there are several indices that address each aspect [21]. For the case of technical resilience, based on the type of infrastructure under investigation, several metrics have been proposed. For example, Miller-Hooks et al. [22] quantified resilience of transportation networks as the maximum expected system throughput. Shinozuka et al. [6] considered the power supply as the resilience metric of power systems. For social resilience, there are also several metrics, such as social vulnerability index [21], number of dead or injured during and after the hazard event [19], and number of households without power [6]. Organizational resilience has been measured by several different approaches. Shinozuka et al. [6] considered the restoration duration, while Cutter et al. [23] proposed fire, police, emergency relief services, and temporary shelters per 1000 population as the metric of evaluating organizational resilience. For the case of economic resilience, loss estimation models are typically utilized to measure property loss and business interruption as the resilience metrics [18]. For example, Shinozuka et al. [6] considered Gross Regional Product (GRP), while Norris et al. [4] and Cutter et al. [21] proposed median household income as the economic resilience metric. The next challenge is to aggregate these indices into a single composite indicator to make it more comprehensible for the general public and the policymakers [24]. The first solution at hand is to assign subjective weights to each index and sum them up in to a global index [24].

2.4 Modeling the post-disaster recovery

The most basic way to model the recovery process of the infrastructures is to assume a subjective pattern. Cimellaro et al. [19], proposed three recovery patterns for the infrastructures, namely, linear recovery, trigonometric recovery, and exponential recovery. Each pattern has its own justification, e.g. the exponential recovery function is used when, due to the initial abundant resources, the recovery rate is high but decreases as it reaches the end. The trigonometric function, on the other hand, is used when the community is not well prepared for the hazards. The linear function is used when there is no information about the degree of preparedness of the community against hazards.

The use of discrete event simulation methodology in simulating the post-disaster recovery have been addressed in few studies. Cagnan and Davidson [25] utilized this method to simulate the post-earthquake restoration process for electric power systems. Moreover, Luna et al. [26] applied discrete event simulation to model the post-earthquake recovery of water distribution system. Huling and Miles [27] employed SimPy to simulate the disaster recovery of buildings. SimPy is a discrete event simulation framework which is specifically written for the Python programming language.

3 PROPOSED FRAMEWORK

In this section, the proposed framework for evaluating resilience is presented in a stepwise manner.

3.1 Identify critical infrastructures

According to the United States Department of Homeland Security [28], critical infrastructures are the ones "whose assets, systems, and networks, whether physical or virtual, are considered so vital to the United States that their incapacitation or destruction would have a debilitating effect on security, national economic security, national public health or safety, or any combination thereof." Based on that definition, 16 infrastructure sectors have been considered critical in United States, including energy sector, healthcare, water and wastewater system, transportation system, and so forth [28]. These critical infrastructures may vary depending on the characteristics of the region of interest. Therefore, the first step is to identify the critical infrastructure sectors of the region under investigation.

3.2 Identify infrastructure interdependencies

The next step is to identify the infrastructure interdependencies, which means to identify the impacts of infrastructures on each other when they are not in their normal condition. Five main categories of methodologies have been proposed in the literature [29]: empirical, agent based, system dynamics based, economic theory based, and network based approaches. In the worst case scenario, the loss of functionality of one component can propagate through the whole system, resulting in cascading failures in its clients. Therefore, modeling this interdependency provides a more realistic interpretation of the system.

3.3 Identify hazards and associated consequences

After identifying the critical infrastructures and their interdependencies, it is required to identify the hazards that affect the performance of each infrastructure. Hazards are categorized into natural and manmade based on their origin. They are also categorized into (1) extreme hazards, which happen suddenly in very short period of time, such as earthquakes, and (2) gradual hazards, which are mostly the environmental and ecological and happen over long periods of time. It should be noted that, in addition to the hazards outlined above, the incapacitation of an upstream infrastructure can also be considered as a hazard for the downstream infrastructures. Next, the associated consequences for each hazard must be identified. For example, in the case of an earthquake event, damage, casualties, relocation, and business interruption are the probable consequences. Next, the coincidence of multiple hazards must be investigated. In these cases, at first, the probability of each possible coincidence should be determined and subsequently, the associated consequences should be identified.

3.4 Develop/Adopt probabilistic models for prediction of hazards, infrastructures response, and consequences

After identifying the hazards, probabilistic models should be developed or adopted to predict the occurrence and intensity of those hazards. For example, models are needed to simulate the time, magnitude, and location of earthquake events. Next, it should be identified how each infrastructure responds in face of hazards. Therefore, probabilistic models are needed to predict the response of each infrastructure under each hazard, for instance, models that predict the maximum roof displacement of buildings in earthquakes. Next, the associated consequences for each state of infrastructures response should be evaluated. Hence probabilistic models are required to predict the associated consequences of each response state, for example, models to predict the damage and number of casualties given buildings response.

3.5 Develop/Adopt Probabilistic Models for Prediction of Infrastructures Restoration

Next, probabilistic models should be developed or adopted to predict the restoration time and cost for each consequence. For example, models are needed to predict the repair time and cost of a building, given the level of damage, or the recovery time and cost of a severely injured person. Thereafter, it is needed to determine how much restoration capacity is needed for each consequence. This capacity is the available workforce, materials, and machinery, which are utilized to restore the damaged components after the hazards. For example, it is needed to determine the labor force needed for repairing a building. Next, the restoration capacity of the community, such as the available workforce to conduct repair operations, should be determined.

3.6 Convert all consequences to cost

After identifying the consequences and restoration process, it is needed to convert all consequences in to a single positive or negative utility, such as cost. For example, fatalities are converted to cost using the notion of the value of statistical life.

3.7 Evaluate the resilience of the infrastructure system

As the previous steps completed thoroughly, all the needed tools for evaluating resilience are at hand. Figure 2 shows how previous steps are organized to configure the resilience evaluation framework. After identifying critical infrastructures, their interdependencies, and their associated hazards and consequences, a random hazard scenario is generated using the hazard prediction models. Then, the response of infrastructures under each hazard, considering their interdependencies, is evaluated. Next, the associated consequences are quantified and then converted to cost. Thereafter, based on the budgetary and restoration capacity constraints, the restoration process is simulated. As the restoration process continues, the indirect consequences, such as life quality reduction and business interruption are evaluated. At the end of the generated scenario, when all components are restored to their desired level of functionality, all computed costs are accumulated. This total system cost in an indicator of resilience for that system. Generating a host of random hazard scenarios leads to the probability distribution of the total system cost.

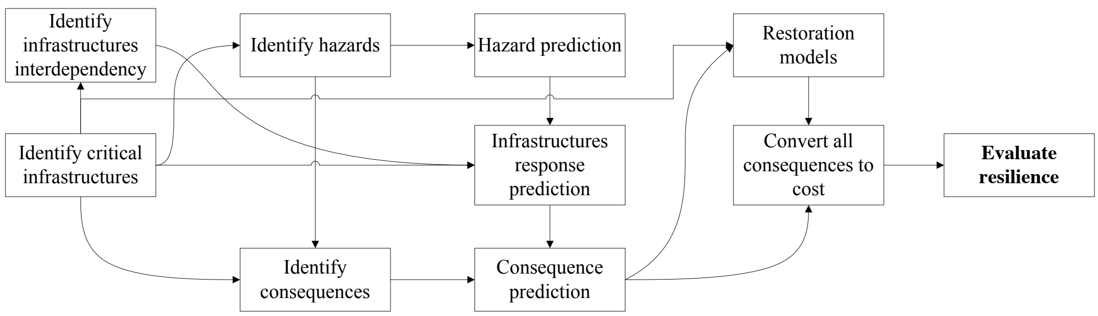

Figure 2. Resilience evaluation framework

3.8 Policy evaluation and optimization

The advantage of the proposed framework is that it aggregates all aspects of resilience into a single measure of utility. The conversion is not carried out through subjective weights unlike the existing literature [19]. Rather, each consequence is converted to cost using an appropriate measure. This facilitates the use of the said utility as an objective function in an optimization analysis to optimize the policies on resilience enhancement. For this purpose, the influential decisions should be identified. Each decision can impact one or more aspects of resilience. For example, building a new hospital is an effective policy, since it can reduce the patients' recovery time and enhance the life quality, which contributes to economic and social aspects of resilience. The next step is to identify the corresponding decision variables for each decision. For the case of constructing a new hospital, the location, time, and capacity of the new construction form the decision variables. Next, the simulation process is repeated and the risk measure that represents the resilience of the enhanced system is quantified. The cost of implementing the policy should also be added as a cost. The optimization analysis determines the optimal value of each decision variable in order to minimize the risk measure of the system and hence, results in a more resilient system. This framework makes it possible to compare and run alternative policies for the improvement of the resilience.

4 ILLUSTRATIVE EXAMPLE

In this section, a case study of a hypothetical system with five critical infrastructures is presented. These infrastructures and their interdependencies are shown in Figure 3. For example, the hospitals depend on the power system in order to function.

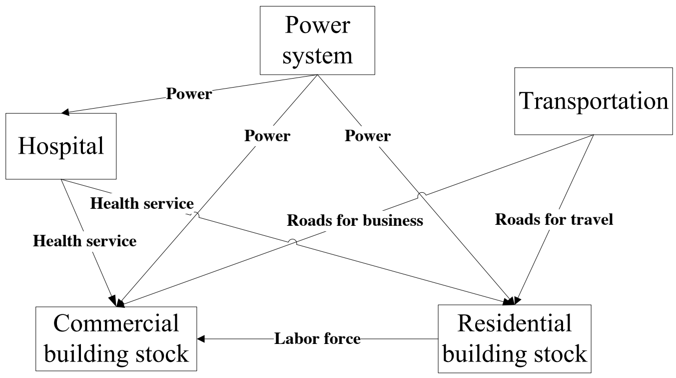

Figure 3. Example community

Figure 4 depicts the simulation process to be conducted in order to evaluate the resilience of the community. The models, software, and information required to conduct such an analysis is also tabulated in Table 1. In accordance with Figure 4, first the probable hazards and their associated consequences are identified. Thereafter, the hazards are simulated and the intensity at the location of each system component is computed. This example disregards the coincidence of hazards for simplicity. Second, the response of each component subject to each hazard event is quantified and the post-disaster status of the system is determined. This status represents the damage incurred by each component and the number of injuries and fatalities. Next, the capacity of the community to restore is assigned to damaged components on a daily basis. In particular, the analysis controls all components under repair at the end of each day to identify if they have reached the desired performance, i.e., if they have fully restored. If so, the total restoration cost of these components plus the indirect costs incurred by the system and its users is quantified and added to the total system cost. In addition, the capacity assigned to these restored components is released and then reassigned to the next unrestored component(s). When all components are restored, the duration of restoration and the total community cost are computed. This forms a single realization of the total community cost and restoration duration. The analysis continues with generating more hazard scenarios and hence, more realizations of the total community cost and restoration period until sufficiently accurate probability distributions for these random variables are obtained. Next, a risk measure is extracted from the probability distribution of the total community cost based on the attitude of the decision maker towards risk. A risk-neutral decision maker employs the mean total community cost whilst a risk-averse decision maker may utilize higher moments of cost. This risk measure will then be subjected to minimization in order to optimize the decision variables of various prescribed policies.

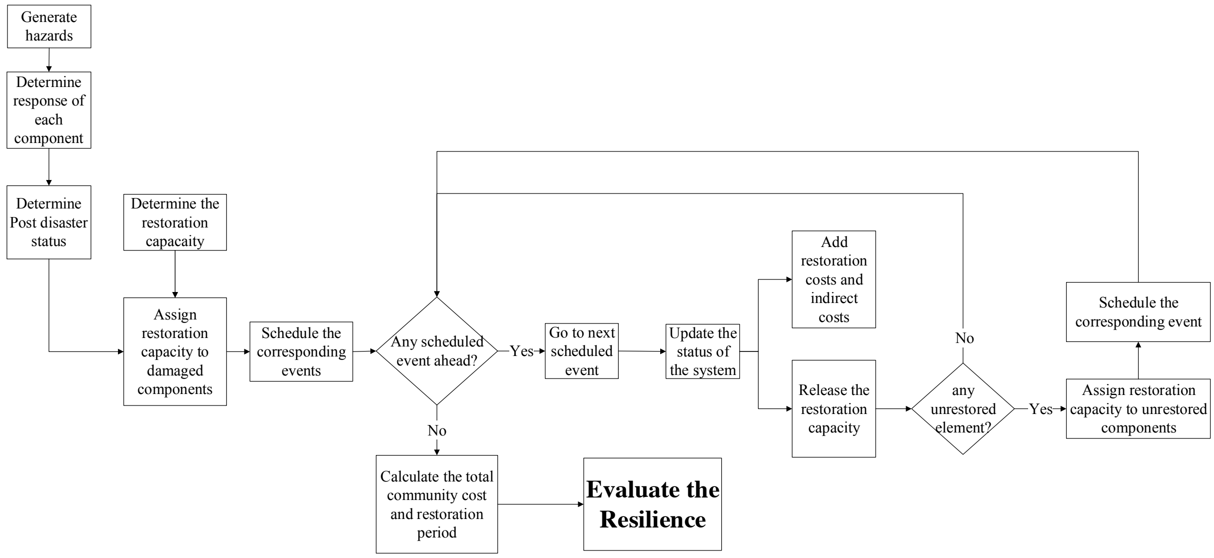

Figure 4. Simulation process for evaluating the system resilience

	Required models, software and data
Hazard	Location, severity, and duration Intensity at the location of each system component
Residential and commercial building stock	Building portfolio information Residential/commercial buildings location Response and consequence models, including damage and casualty models Relocation cost of people
Commercial complex	Average daily revenue for each complex Dependency on power in terms of reduction in revenue due to power outage Dependency on transportation in terms of reduction in revenue due to increase in travel time
Transportation	Transportation network information Transportation network analysis software Transportation components response and consequence models, including damage models
Power system	Power distribution network, including receiving stations and transmission lines Service area of each receiving station Power stations response and consequence models, including damage models Power network analysis software
Hospital	Location Patient capacity Dependency on power in terms of reduced patient capacity Hospitals response and consequence models, including damage models
Restoration process	Restoration capacity of the system Cost, duration, and needed capacity for restoration of buildings for each level of damage Cost, duration and needed capacity for restoration of transportation elements for each level of damage Cost, duration and needed capacity for restoration of receiving stations Cost, duration and needed capacity for recovery of an injured person

Table 1. Required models, software and data in the illustrative example

5 CONCLUSIONS

This paper proposes the blueprint of a comprehensive resilience evaluation framework that takes into account multiple aspects of resilience. Parameters such as power supply reduction, restoration capacity, number of fatalities, and business interruption, which represent technical, organizational, social, and economic aspects of resilience, respectively, are integrated consistently into a one global indicator. Therefore, the proposed framework facilitates conducting optimization analyses to prioritize different influential policies, and determine their optimal design in order to maximize the resilience of the system. In addition, the proposed framework determines how financial resources must be allocated to different infrastructures, as well as different aspects of resilience, to achieve a resilient community.

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