A Digital Twin Framework for Efficient Electric Power Restoration and Resilient Recovery in the Aftermath of Hurricanes Considering the Interdependencies with Road Network and Essential Facilities

Abdullah M. Braik[a] and Maria Koliou[b*]

[a] Ph.D. Candidate and Graduate Research Assistant, Zachry Department of Civil and Environmental Engineering, Texas A&M University, College Station, TX, 77843, U.S.A., E-mail: abraik3@tamu.edu

[b] Associate Professor, Zachry Department of Civil and Environmental Engineering, Texas A&M University, College Station, TX, 77843, U.S.A., E-mail: maria.koliou@tamu.edu ([*]Corresponding author)

Abstract

The community's resilience in the face of natural hazards relies heavily on the rapid and efficient restoration of electric power networks, which plays a critical role in emergency response, economic recovery, and the functionality of essential lifeline and social infrastructure systems. Leveraging the recent data revolution, the digital twin (DT) concept emerges as a promising tool to enhance the effectiveness of post-disaster recovery efforts. This paper introduces a novel framework for post-hurricane electric power restoration using a hybrid DT approach that combines physics-based and data-driven models by utilizing a dynamic Bayesian network. By capturing the complexities of power system dynamics and incorporating the road network's influence, the framework offers a comprehensive methodology to guide real-time power restoration efforts in post-disaster scenarios. A discrete event simulation is conducted to demonstrate the proposed framework's efficacy. The study showcases how the electric power restoration DT can be monitored and updated in real-time, reflecting changing conditions and facilitating adaptive decision-making. Furthermore, it demonstrates the framework's flexibility to allow decision-makers to prioritize essential, residential, and business facilities and compare different restoration plans and their potential effect on the community.

Keywords: Community resilience, digital twin, disaster recovery strategies, electric power restoration, hurricanes, road network.

Abbreviations: AI: artificial intelligence; BN: Bayesian network; DBN: dynamic Bayesian network; DES: discrete event simulation; DT: digital twin; EPN: electric power network; IoT: internet of things; RN: road network; RW: repair worth.

1. Introduction

1.1. Motivation and problem statement

Post-hazard recovery has gained significant attention in recent years, highlighting the critical role of community resilience in effective disaster management, as it contributes to reducing losses, expediting recovery, and mitigating social and economic disruptions [1]. One key aspect of community resilience is the fast and efficient restoration of electric power, which holds immense importance for emergency response, economic recovery, and the proper functioning of essential lifeline and social infrastructure systems [2]. While the interest in community response to hurricanes dates back at least half a century [3], and despite the extensive research dedicated to enhancing the resilience of the community in general and the electric power network (EPN) in particular, the restoration and recovery of the EPN after hurricanes still face significant challenges [4]. This is mainly due to the size and complexity of the EPN, coupled with its vulnerability to natural hazards, and is further exacerbated by the deregulated nature of the profit-oriented electricity market, which provides a minimal incentive for investing in community resilience through preparedness and preplanning ([5]; [6]).

The main objective of post-disaster EPN recovery is to restore electricity to the maximum number of customers as fast as possible, considering their significance in maintaining community resilience [7]. Over the past decade, the reliability, hardening, and risk assessment of the EPN in the face of strong-wind hazards have been extensively studied (e.g., [8]; [9]; [10]; [11]; [12]; [13]; [14]; [15]; [16]; [17]; [18]; [19]). Moreover, many studies analyzed the post-hurricane performance and recovery of the EPN and its spatial and socio-economic distribution (e.g., [20]; [21]; [22]; [23]). Other studies proposed various methods to perform predictions and model the response and restoration of the EPN in the face of hurricanes. These methods can broadly be classified into two categories: (i) physics-based approaches, where hazard and fragility analysis are coupled with network analysis (e.g., [24]; [25]; [26]; [27]; [28]; [29]; [30]) , and (ii) data-driven approaches, which involve utilizing statistical models and machine learning (e.g., [31]; [32]; [33]; [34]; [35]).

Physics-based methods play a crucial role in pre-hazard mitigation and preparedness, where sophisticated hazard and structural damage models are developed using numerical and finite element techniques. These methods offer strengths such as a solid physical foundation, interpretability, scenario testing capabilities, and the ability to model probabilistic and uncertainty factors. However, their static probabilistic outputs may be limited in post-disaster scenarios due to significant epistemic and aleatory uncertainties inherent in natural hazards and their interactions with structures. Furthermore, these methods often lack the capability to update prior estimates during the restoration process. On the other hand, data-driven methods rely on post-disaster reports and surveys, offering advantages in adaptability, efficiency, and handling complexities. However, they encounter challenges during immediate emergency response phases due to the time required for data collection and analysis. Moreover, the large volume of data needed is often unavailable shortly after the disaster. Therefore, an integrated framework that combines the strengths of both physics-based and data-driven methods is essential to extend the applicability of the risk assessment framework to post-disaster emergency response. This integration can facilitate adaptive decision-making and guide the restoration process effectively.

Amid the data revolution and the enormous advancements in artificial intelligence (AI) and the Internet of Things (IoT), data-driven methods have advanced significantly, motivating researchers to expand their use to collect and analyze real-time data to generate insights into current events during and after the hazard occurrence. Therefore, the capabilities of the models can extend beyond offline (pre-disaster) predictions toward online (post-disaster) learning. This can be achieved through a digital twin (DT), which provides a virtual model integrated with the real system through real-time data transfer. Hence, researchers have recently proposed visions to integrate DT in disaster management (e.g., [2]; [36]; [37]; [38]). When applied at the community level, the DT has the potential to enhance disaster management and significantly improve its resilience. By utilizing high-fidelity models and dynamic simulations that are updated in real-time, decision-makers can make informed choices based on the actual conditions and take proactive measures to mitigate the impact of disasters.

A DT is considered as an essential step toward smart cities [39]. A smart city DT relies on physical and other types of sensors driven by the enormous advancements in the IoT and the fifth generation of wireless systems [40]. Therefore, various studies have proposed DT frameworks for the management and operation of the EPN (e.g., [41]; [42] [43]; [44]). These methods combine the technologies of cyber-physical systems, smart grids, and the IoT to provide continuous real-time data that is used to update the initial state estimates of the network. However, these methods rely on the availability of large amounts of data and hence are suited for scenarios with limited disruptions and the availability of almost complete information. Consequently, their direct applicability in disaster management, where extensive damage is widespread across multiple lifelines and social infrastructure systems including the physical sensors, and immediate knowledge is often limited, may be constrained.

Therefore, a fundamental difference exists between a DT in normal conditions and the aftermath of hazards. Integrating the concept of the DT at the community level and in the face of natural hazards still faces significant challenges [45]. Since physical sensors are susceptible to damage, and the traditional data gathering methods such as customer calls and site investigations are slow and inefficient, virtual data sensing using smart technologies such as image recognition and social sensing is an alternative method that is getting traction lately ([2]; [37]). While data-driven methods are essential parts of any DT as they provide the connection between the actual system and its digital replica, they require a large amount of data that is usually not readily available after the disaster. They also lack the generalization and interpretability of physics-based methods. Hence, the DT must also incorporate physics-based methods [38]. Still, most proposed DT frameworks for disaster management have mainly focused on data sensing in smart cities using social sensors (e.g., [46]; [47]; [48]; [49]; [36]). Another challenge is that the DT requires a model that is both highly detailed and computationally efficient. These are often two conflicting goals, and the DT must balance between them.

Recently, Braik and Koliou [45] proposed a framework for a DT of the EPN subjected to hurricanes. In their framework, a Bayesian network (BN) is utilized to generate a highly detailed network model that captures the dependencies between the various elements of the EPN. The Bayesian Network (BN) is initially constructed as a physics-based model, based on hazard and fragility analysis. It is then extended to a Dynamic Bayesian Network (DBN) over the time domain to facilitate updating with data evidence. This approach allows for the incorporation of new information as it becomes available, enhancing the model's accuracy and reliability in real-time scenarios. The proposed DBN is a hybrid physics-based and data-driven model that is both highly detailed and computationally efficient, and therefore, extends the capabilities of predictive models from offline learning to online learning where estimates are updated using real-time data. Still, applying the DT in post-disaster recovery to guide the EPN restoration remains largely unexplored.

The road network (RN) plays a significant role in post-disaster power restoration [50] and must be considered in the DT. The coupling of the EPN and RN was considered in a few previous EPN restoration studies mainly through methods such as optimization (e.g., [51]) and reinforcement learning (e.g., [52]). However, these methods are better suited for normal operation scenarios where large amounts of data are available. On the other hand, the physics-based methods following the risk-assesment framework rarely consider the interdependency between the EPN and the RN.

Hence, a significant gap is highlighted in previous studies, as there is a lack of a DT framework to guide the post-disaster restoration and repair process. Addressing this gap, this paper proposes a DT framework for EPN restoration. The DT enables adaptive decision-making, considering interdependencies between the EPN and RN. It utilizes detailed network analysis and physics-based estimates for pre-hazard preparedness, extending to post-disaster recovery by updating estimates with real-time data via DBN. The framework automates repair prioritization, accounting for uncertainties, repair times, and essential facility importance, allowing for efficient restoration and resilient recovery.

1.2. Background on digital twins and their capabilities

The DT is a dynamic and interactive digital replica of a physical system, providing continuous bidirectional synchronization of real-time data. Depending on the depth of integration between the physical and digital twins, three primary modeling levels can be identified: digital model, digital shadow, and DT. A digital model serves as a static snapshot of the real system at a specific moment, lacking any further data transfer. In contrast, the digital shadow involves unidirectional data flow, transmitting information from the real system to its digital counterpart. At the highest level of integration, we find the DT, where continuous data transfer occurs in both directions. The digital replica remains continuously updated through real-time data received from the physical system, enabling it to offer feedback and simulate scenarios to support adaptive decision-making. Ultimately, the DT can fully control the physical system [53].

DTs can be classified based on their capabilities. The supervision and operational DT represents the lowest level, providing basic visualization and monitoring features. The simulation and prediction DT surpasses this level by optimizing system performance and making predictions using algorithms and optimization techniques. Moving up, the intelligent DT incorporates machine learning techniques to learn from data in addition to the previous capabilities. Finally, the supervisory and control DT expands on all previous capabilities and encompasses decision-making. In its simplest form, human involvement is required to implement the decisions, while in its most advanced form, a fully autonomous DT is capable of making and executing decisions [54].

2. Scope

This paper proposes a DT framework for post-disaster restoration of the EPN, considering its interdependency with the RN. The scope encompasses the entirety of the DT's development process, integrating physics-based and data-driven modeling to enhance the efficiency of disaster recovery strategies. First, disaster impact assessment is addressed, incorporating data, hazard, and fragility analysis of the elements of the EPN and the RN. Then, network analysis is discussed, where the EPN is modeled utilizing the BN framework proposed by Braik and Koliou [45], while the RN is represented through an undirected graph network. A significant aspect of the restoration process is establishing a repair hierarchy sequence, where elements are prioritized based on their contribution to community resilience. Subsequently, the restoration process is analyzed, considering the interdependencies between the EPN and RN. To demonstrate the applicability and efficacy of the framework, the paper concludes with a discrete event simulation (DES) of the restoration of Galveston Island’s EPN following Hurricane Ike, showcasing its practical application in guiding resilient post-disaster recovery.

3. Methodology

Figure 1 shows a flowchart of the proposed framework. Then, the methodology’s details are discussed in the following sections.

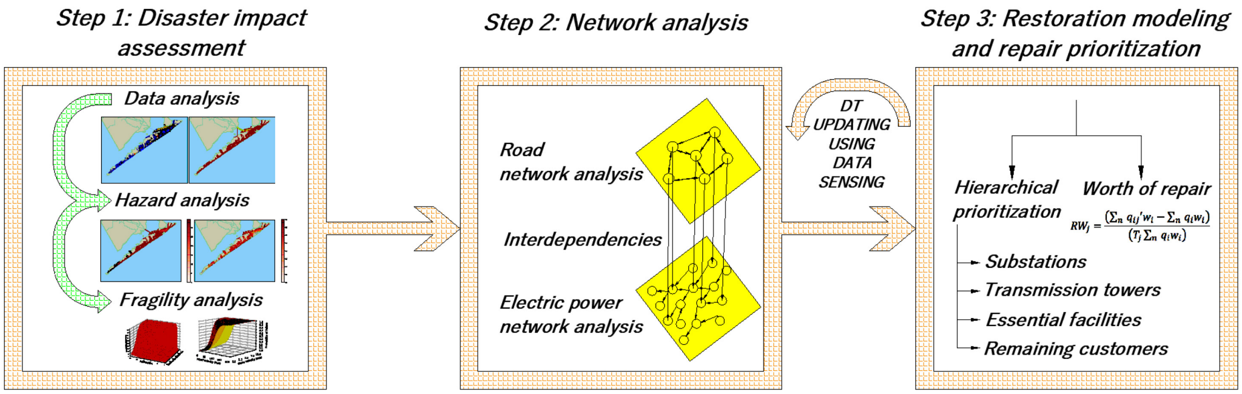


Figure 1: Flowchart showing key steps of the proposed DT framework of electric power restoration.

3.1. Disaster impact assessment

3.1.1. Data analysis

To effectively build the power restoration DT, detailed data from both the EPN and RN is required. This dataset encompasses comprehensive information about the various components within the EPN, such as substations, transmission towers, utility poles, and customers, as well as the road segments and intersections within the RN. This includes details regarding the connectivity of these elements, geographical coordinates (longitude and latitude), and essential properties necessary for fragility analysis, such as the height, diameter, age, and elevation. Then, the EPN can be modeled as a directed BN graph, while the RN can be modeled as an undirected network graph as explained in section 3.2.

3.1.2. Hazard analysis

To perform accurate fragility analysis within the DT framework, a detailed hurricane model is needed with multiple simulations performed for various hurricane return periods to capture the stochastic nature of the hazard ([55]; [56]). In this paper, the Advanced Circulation (ADCIRC) and Simulating Waves Nearshore (SWAN) hurricane models generated by Darestani *et al.* [56] and obtained from Incore [57] are used to provide detailed wind, wave, and surge maximum loads for all locations within the system. However, for simplicity, a single hazard model is used per case study, representing either the historical Hurricane Ike or synthetic hurricanes of various return periods. Hence, the hazard loads are modeled as deterministic, while the uncertainty in the damage analysis employed within the DES stems from the fragility functions, as discussed in the next section. Future research could focus on comprehensive hurricane probabilistic analysis to enhance the prior load estimates.

3.1.3. Fragility analysis

A fragility function is a mathematical model that quantifies the probability that a system or component will reach or exceed a specified damage state given a certain level of demand. Given hazard intensity measures, fragility functions can be used to calculate the conditional failure probabilities of various EPN and RN elements. In this paper, the fragility functions obtained from Darestani *et al.* [58]; Darestani *et al.* [14]; Sánchez-Muñoz *et al.* [59]; and Darestani *et al.* [56] are utilized to calculate the probabilities of failure of wood utility poles, transmission towers, substations, and RN segments respectively, as shown in Equations 1-4, where σ(y) is the standard logistic function. V_W is the wind speed (m/s), θ_W is the wind direction (radians), V_F is the water velocity (m/s), H_S is the surge height (m), H_W is the significant wave height (m), H_p is the pole height (m), t_P is the pole age (years), A_C is the conductor's effective area (m^2), F is the flood height (m), D_s is the distance from shore (m), and I_F is the flood duration (hours). The coefficients (a_0: a_7, α_0: α_3, γ_0: γ_1, β_0: β_2) can be obtained from existing literature adopted in this study (see references above).

$$P_{failure-pole} = \Big(1 + \exp\Big(-\big(a_0 + a_1 V_W + a_2\big(H_p - H_S - H_W\big) + a_3 V_F H_S + a_4 V_W \sin(\theta_W) + a_5 V_W A_C + a_6 max(t_P, 25) + a_7 H_W\big)\Big)\Big)^{-1} \qquad (1)$$

$$P_{failure-tower} = 1 - [1 - \sigma(\alpha_0 + \alpha_1 V_W \sin(\theta_W))][1 - \sigma(\alpha_2 + \alpha_3 V_W \cos(\theta_W))] \quad (2)$$

$$P_{failure-substation} = \Phi\big((ln(F) - \gamma_0)/\gamma_1\big) \quad (3)$$

$$P_{failure-road} = \big(1 + \exp\big(\beta_0 + \beta_1 ln(D_s) + \beta_2 ln(I_F)\big)\big)^{-1} \quad (4)$$

The EPN incorporates isolator elements, positioned upstream of each line, to enable isolation in response to disruptions [60]. This has been utilized by previous studies to aggregate EPN elements into lines (e.g., [10]; [13]). Therefore, this allows aggregating elements within a line into nodes in the BN proposed herein. For a line of m poles or towers, each having a probability of failure q_{i}, the line's probability of failure P_L can be calculated using Equation 5 [45].

$$P_L = 1 - \prod_{i=1}^{m}(1 - q_{\mathrm{i}}) \quad (5)$$

3.2. Network analysis

3.2.1. EPN analysis

The DBN DT framework proposed by Braik and Koliou [45] is adopted in this study. The EPN network is modeled using a BN, where each element is assigned two nodes: a physical node representing the physical state of the element (failed or not failed) obtained from the fragility analysis, and a performance node representing the operational state of the element (outage or restored). Figure 2 shows a sample DBN, where F and P stand for physical and performance nodes respectively, while $S, T, D,$ and C stand for substation, transmission line, distribution line, and customers. When evidence is received about the physical state (failure or survival) of transmission tower T_1, the probabilities of downstream nodes at time t_0 (BN$_0$) are updated. The updated physical node probabilities are then passed to the Bayesian Network at the next time step t_1 (BN$_1$). Similarly, if evidence is received regarding the performance state of customer C_3, the probabilities of the entire BN1 are updated and subsequently passed to the next BN at time step t_2 (BN2). This process continues, with the DBN being updated at each subsequent time step t_x.

The BN's ability to update prior estimates using data evidence distinguishes it from approaches such as fault-tree analysis, where node states are sampled using Monte Carlo Simulation (MCS) [61], and hence allows for extending the applicability of the risk assessment framework from pre-hazard mitigation and preparedness toward post-disaster emergency response. The first step to constructing the BN is to estimate the failure probabilities via fragility analysis. These represent the marginal probabilities of the upstream physical nodes. Then, logical dependency rules between nodes are established using conditional probability tables. Thus, the consideration of power flow is based on the connectivity of EPN nodes, given the direct link between system failure and physical damage to EPN components. For example, in Figure 2, the performance state of upstream nodes like PS_1 depends solely on the state of the physical node of the same element FS_1. On the other hand, the performance state of intermediate nodes like PT_1 depends on both the state of the physical node FT_1 and that of the upstream performance node PS_1. Once the BN is constructed, forward propagation can be used to calculate the probability of power outage for every performance node in the network. Then, the BN can be updated in real-time using data by extending the BN toward a DBN [45]. This data can be obtained via various data sensing methods (discussed in Section 1). The algorithm for building the EPN BN and then updating the DBN with data evidence is summarized in Table 1. Details on performing forward propagation for the BN and updating the conditional distributions can be found in Darwiche [62].

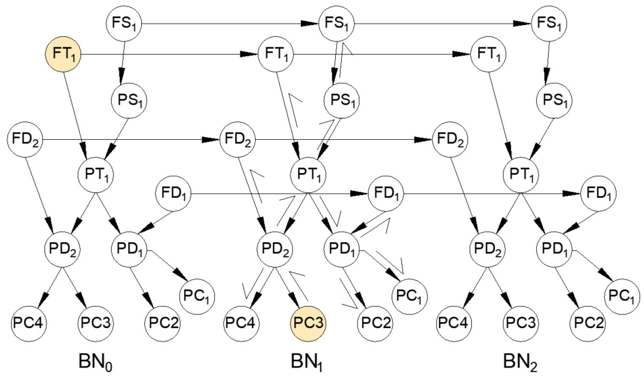


Figure 2: Sample EPN DBN

Table 1: Algorithm for building the BN and updating the DBN

Algorithm for building the BN and updating the DBN:
1. Input: Probabilities of physical damage to EPN elements from hazard and fragility analysis, Connectivity data of the EPN elements, data evidence $[d_1, d_2, ..., d_T]$ obtained at times $[t_1, t_2, ... t_T]$
2. Construct the BN nodes and edges using connectivity data and build the conditional distribution tables based on logical dependencies
3. Populate the prior estimates of the upper (physical) nodes using probabilities obtained from hazard and fragility analysis
4. Perform forward propagation to calculate the outage probabilities of performance nodes conditional on physical nodes and upstream performance nodes. This will generate the prior BN_0 at time t_0
7. Define Function $DBN(BN_i, d_i)$:
8. Update all physical and performance nodes probabilities conditional on d_i to generate BN_{i+1}
9. Return the posterior BN_{i+1}
10. $BN=BN_0$
11. for d in $[d_1, d_2, ..., d_T]$:
12. BN=DBN(BN, d)

3.2.2. RN analysis

The RN can be modeled using a non-directed weighted graph network, where segments of the graph represent the edges connecting the nodes, while the time of travel between two adjacent nodes, which can be calculated as the length of the segment divided by the average travel speed, is the weight of the edge within the graph. Ertugay *et al.* [63] suggested reducing the estimated travel speed in proportion to the probability of road closure, and hence, the travel time (weight of the edge within the graph) in this paper is divided by $(1 - P_{f-r})$ to consider the effect of road closure following hurricanes, where P_{f-r} is the probability of failure of the road segment estimated using the fragility functions. Moreover, as long as the road segment is flooded, the travel time is assumed to be infinity. Hence, the travel time through any road segment, which represents the weight of the segment's graph edge, depends on its probability of failure P_{f-r} and the flood duration. This allows for estimating the minimum travel time between any two nodes within the RN [64]. Therefore, based on these assumptions and by constructing the graph network, the minimum travel time can be calculated for various states of flooding and damage to the RN segments. Then, real-time data obtained about the actual states of the segments and travel times can be used to update the physics-based estimates.

It is important to acknowledge that, in this framework, the initial physics-based estimates of the RN post-disaster conditions only consider the damage and flooding states. Therefore, the RN model focuses mainly on connectivity and accessibility to estimate the repair unit's ability to reach failed elements. On the other hand, the effect of the traffic flow is not considered. Up to date, most post-hazard RN proposed models use pre-hazard traffic demand (e.g., [65]; [66]). Therefore, the high computational cost of these models won't necessarily enhance the accuracy of the estimations. Recently, some studies have been proposing methods to estimate the traffic demand resulting from the evacuation process (e.g., [67]). Such models can be further enhanced if coupled with agent-based modeling (e.g., [68]; [69]; [70]). Hence, a more comprehensive RN analysis that considers both the topology and the traffic flow could be incorporated within the proposed DT framework in future studies.

3.2.3. Interdependencies between the EPN and RN

The interdependencies between the EPN and RN are considered by connecting each node within the EPN to its closest RN node. Consequently, when an EPN repair crew unit completes repairs in one element and needs to move to another, the travel time between these two is modeled based on the distance between the nearest pair of RN nodes. This is explained using Figure 3, where the travel time between EPN nodes E1 and E2 will be calculated using the travel time between RN nodes R1 and R2, while the travel time between E1 and E3 will be calculated using R1 and R3.

However, it is important to note that this paper does not account for other interdependencies, such as the impact of damaged utility poles on the RN or the consequences of traffic signal outages and it is acknowledged as a potential limitation.

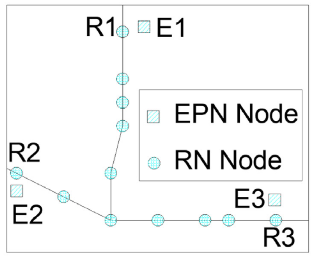


Figure 3: Interdependencies between the EPN and RN nodes

3.3. Restoration modeling and repair prioritization

To maximize the efficiency of the restoration process, the repair and restoration of the EPN elements during post-disaster outages follow a hierarchical process. This is consistent with the principles outlined in the literature and industry practices for power restoration in utility networks, where the priority sequence starts with repairing damaged substations and transmission towers and then distribution lines serving essential facilities. After that, repairing the remaining utility poles is based on restoring power to the largest number of customers as fast as possible ([71]; [72]; [73]; [74]).

During post-hurricane scenarios, the assessment of utility poles becomes challenging due to their large numbers within the EPN compared to substations and transmission towers, making it harder to evaluate their significance and monitor their conditions with limited information available. Ouyang and Dueñas-Osorio [72] proposed a formula to estimate the repair worth (RW) for distribution lines in the EPN as the ratio of the number of customers served by the line to the repair time required. However, this formula doesn’t consider the uncertainties in the physical and performance states of the lines, and hence requires a near-complete knowledge of each line's condition, which is rarely attainable in post-hurricane scenarios. Moreover, it doesn't allow for giving different weights to customers based on their importance for community resilience and recovery. It also does not incorporate factors such as travel time to reach the line or the accessibility of the road segments, which are important considerations in prioritizing repair efforts and optimizing the restoration process in post-disaster scenarios. Therefore, in this paper, a modified RW formula is proposed, building upon the formula proposed by Ouyang and Dueñas-Osorio [72] per equation (6), where RW_j is the RW of distribution line j, n is the total number of customers in the system, and T_j is the total time for repair of line j, including both the repair time and the travel time. Moreover, q_i is the probability of power restoration of customer i before the repair, and ${q_{ij}}'$ is the probability of power restoration of the same customer if line j is repaired. q_i and ${q_{ij}}'$ can be calculated using the BN via the forward propagation variable elimination algorithm [45]. Therefore, q_i represents the marginal probability of restoration, while ${q_{ij}}'$ represents the conditional probability of restoration conditioned on updating the physical node of element j to be repaired. Finally, w_i is the weight assigned to the customer i based on its importance for community resilience.

$$RW_j = \frac{\left(\sum_n {q_{ij}}' w_i - \sum_n q_i w_i\right)}{\left(T_j \sum_n q_i w_i\right)} \tag{6}$$

While a single forward propagation run of the BN is computationally efficient as demonstrated by Braik and Koliou [45], equation (6) requires running the algorithm to compare hundreds of elements, and hence, it can become computationally expensive. Therefore, it is important to utilize conditional independence within the BN [62] to prune the network and hence reduce its complexity without affecting the mathematical accuracy of the results. This can be explained using Figure 2, where repairing distribution line 2 (updating the state of FD_2 to "repaired") only affects the state of customers PC_3 and PC_4, while the states of the remaining customers are conditionally independent of FD_2. Hence, when applying equation (6) to FD_2, the BN can be pruned to include only $FD_2 \rightarrow PD_2 \rightarrow (PC_3, PC_4)$, while q_{ij}' for the other customers will be equal to q_i. As the computational cost of the BN is proportional to its size [75], this will considerably reduce the run time while resulting in equivalent mathematical results.

Therefore, once substations and transmission towers are checked and repaired, a weight of 1.0 is given to the essential facilities (such as fire stations, police stations, hospitals, and major water structures including water pumps and elevated tanks) and zero to the remaining customers. Then, the lines feeding the essential facilities are prioritized for check and repair based on equation (6). This can be utilized to further reduce the computational costs, as in this stage, only lines serving customers with non-zero weights need to be compared, while the remaining lines and the customers they feed can be pruned from the BN, as their computed RW using equation (6) will be zero. Table 2 summarizes the algorithm for pruning the BN and prioritizing element for repair using equation (6).

Table 2: Algorithm for BN pruning and prioritizing EPN elements for repair

Algorithm for BN pruning and selecting the EPN node with the maximum RW:

```
Input: n: number of customers, w_i: weight of customer i for all i in [1:n], e: number of upstream non-repaired EPN nodes,
T_j: total time of repair of line j for all j in [1:e], BN: The full constructed BN
Define Function Prioratize_Element_for_Repair_Based_on_RW_max(n, list of w_i , e, list of T_j , BN):
        Calculate the outage probabilities q_i for all i in [1:n] using the full BN
        for j in 1:e:
                Prune the BN to BN', which includes only customers C' (with size h<=n) downstream of the EPN node j
                if (w_k=0 for all k in [1:h]) or (T_j=∞):
                        RW_j =0
                else:
                        Update the probabilities of of the pruned BN' conditoinal on repairing the EPN node of j
                        for i in 1:n:
                                if customer_i is in C':
                                        calculate the outage probability q_i' using the pruned BN'
                                else:
                                        q_i'=q_i
                        caluclate RW_j using Equation (6)
        Return the EPN node corresponding to the maximum RW value
```

Once all essential facilities are restored, the remaining customers are given weights according to their importance per stakeholder priorities, and the lines feeding them are checked and repaired in order based on equation (6). The assignment of weights to customers is a crucial task that falls upon decision-makers, and therefore, simulation analysis using techniques like DES is employed in this paper to estimate the impact of different weights that can assist decision-makers in understanding their effects. A formal definition and details of applying the DES to model the restoration of the EPN are provided in Section 4 below. While some decision-makers may prioritize residential customers, considering the significant role of prompt power restoration in individuals and families' recovery, it is important to recognize that neglecting business and industrial customers can have detrimental effects on them ([76]; [77]; [78]), resulting in long-term consequences on the overall recovery and resilience of the community.

3.4. DT for disaster management

The electric power restoration framework proposed in this study allows for combining and leveraging the advantages of both physics-based and data-driven modeling approaches. The physics-based damage analysis and network modeling allow for a highly detailed model capable of making predictions before the hazard occurrence. This enables decision-makers to test various restoration scenarios to help in preplanning and preparedness and provides a basis to immediately guide post-disaster investigation and repair. Then, the proposed framework allows for real-time updating of the initial physics-based estimations with data. By utilizing a DBN, receiving data on the state (physical or performance) of any element within the network can be used to update the prior belief of the entire network while remaining within the true physical nature of the system. Hence, the restoration process can be monitored and updated in real-time, reflecting changing conditions and facilitating adaptive decision-making. Thus, the framework in this paper is proposed as a DT, with the digital model being continuously updated using real-time data sensing and can influence the real system through adaptive decision-making.

The proposed DT possesses a range of capabilities, starting with supervision based on the visualizations and models it generates. It also performs simulations and makes predictions utilizing DES . Additionally, it incorporates the intelligence of the DT by updating the DBN and learning from collected data. Furthermore, it is capable of controlling the real system through adaptive decision-making and directing the restoration processes. However, it is essential to acknowledge that in disaster management, achieving a fully autonomous DT is unlikely in the near future. Some level of human involvement will still be necessary to apply and implement the decisions made by the DT. For instance, repair crews would be responsible for executing repair decisions suggested by the DT.

4. Application study using discrete event simulation

To showcase the practicality of the proposed framework, an illustrative application study utilizing DES is conducted.

4.1. Galveston testbed

In this application study, the Galveston Island testbed in conjunction with the Hurricane Ike model is utilized. A comprehensive dataset compiled from various sources, including Darestani and Padgett [79], SPDCPB [80], Incore [57], and GalvestonGIS [81], provides the location, type, properties, and connectivity of EPN components such as poles, towers, and substations. Additionally, it provides details regarding the location and type of electricity receiving customers, as well as the spatial distribution and connectivity of road segments and intersections within the RN. This compiled dataset is used to build a high-fidelity model of the EPN and RN, as summarized in Table 3. The EPN elements, RN elements, buildings, and essential facilities of Galveston are shown in Figure 4. To reduce the size of the BN as recommended by Braik and Koliou [45], the poles are aggregated into 2,718 distribution lines, while the transmission towers are aggregated into 1 transmission line. Moreover, the residential, commercial, and industrial buildings are clustered into 2,102, 1,108, and 248 building clusters, respectively where the buildings in each are assumed to share a common electricity feeder. Furthermore, this dataset includes the results of Hurricane Ike simulations needed for fragility analysis, providing spatial variations of wind speed and direction, wave speed, direction, and height, highest flood depth, and flood duration across the island.

Table 3: Summary of EPN, RN, customer, and essential facilities quantities

Component	**Utility pole**	**Transmission tower**	**Substation**	**Residential building**	**Commercial building**	**Industrial building**
Count	13,207	52	9	24,756	2,681	357
Component	**Fire station**	**Police station**	**Hospital**	**Water facility**	**Road segment**	
Count	7	1	21	22	5,035	

Hence, by using the infrastructure data and the hazard analysis, fragility analysis is performed for both the EPN and RN, which concludes step 1 of the methodology through disaster impact assessment. Further discussion on the results of the fragility analysis is presented in Section 4.3. Subsequently, utilizing the connectivity data, network analysis is performed in accordance with step 2 of the methodology, facilitating the establishment of interdependencies between the EPN and RN. The progression to step 3 of the methodology, restoration modeling and repair prioritization, is demonstrated through the application of DES. The physics-based predictions derived from hazard and fragility analysis serve as the prior estimates and initial conditions of the DES. Subsequently, stochastic simulation is employed to model the entire restoration process. The assumptions of the DES are explained in Section 4.2, while the results are elaborated upon in Sections 4.3 and 4.4.

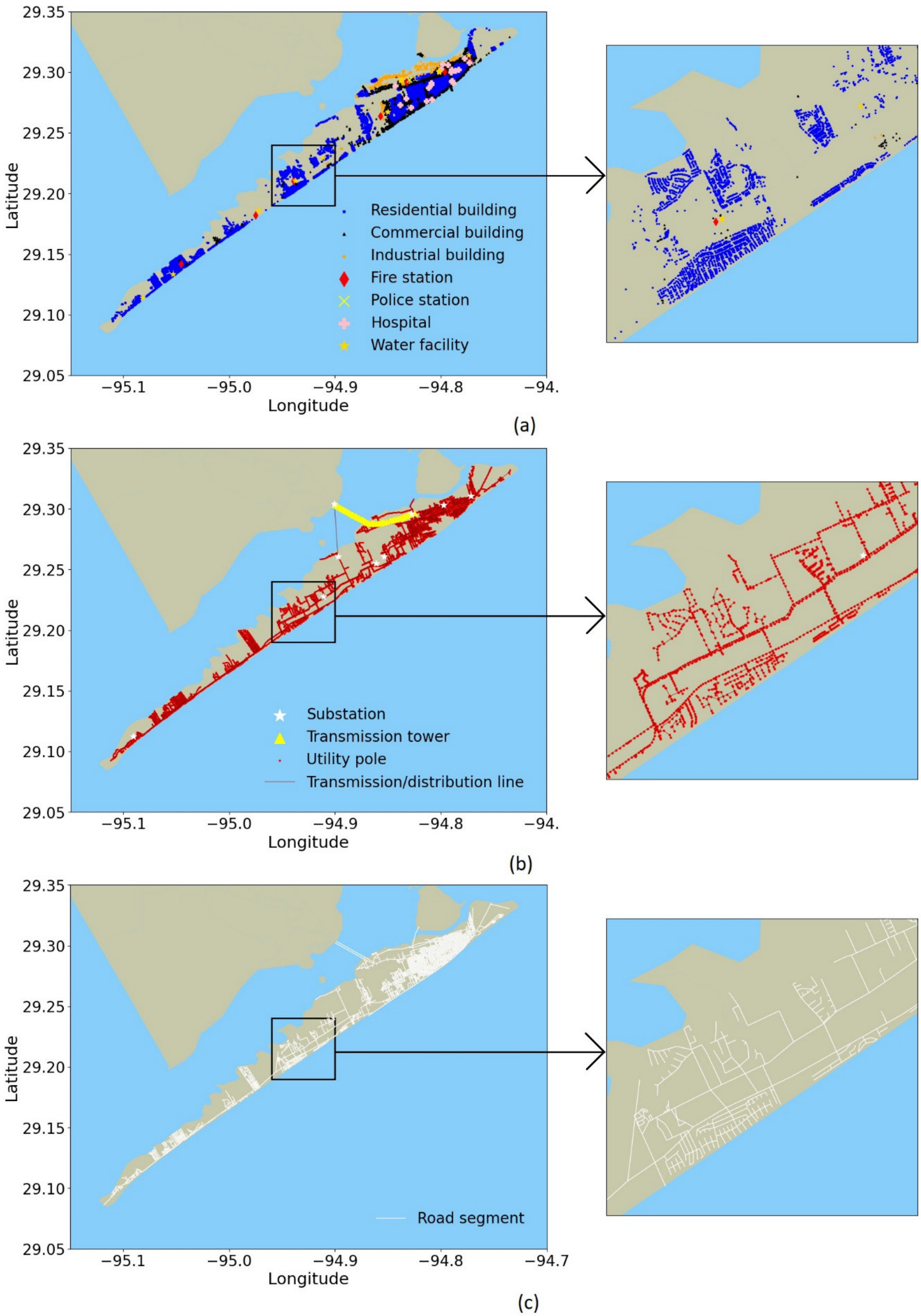


Figure 4: Graphic view of Galveston Island's: (a) Building and essential facilities map (b) EPN map (c) RN map

4.2. Discrete event simulation assumptions

DES is a computational method that models the behavior of complex systems as a discrete sequence of events [82]. In this study, the events triggering a change in the state of the system are the occurrence of hazards, leading to damages, outages, and flooding, as well as the subsequent repair and drainage of the EPN and RN elements. The repair activities are conducted by repair crew units, while the drainage is assumed to naturally occur following the estimations of the hazard analysis. It is assumed that a fixed number of repair crew units is available for both the EPN and RN and that these units possess equivalent capacities, with each capable of handling one task at a time. Furthermore, the crew members within the unit will operate in shifts to ensure continuous work throughout the simulation.

Assumptions of the repair times of the EPN and RN elements are based on average times obtained from the literature. An average repair time t_{avg} of 72 hours is assumed for a single substation or transmission tower, while the repair of a damaged utility pole takes an average of 5 hours [24]. Therefore, a line consisting of m poles or towers each having a predicted probability of failure q_i will have an expected number of failed elements of $m' = \sum_{i=1}^{m} q_i$. Hence, the expected repair time will be m' times the average time of repair of a single element within the line. On the other hand, the average time to repair a 1-km length road segment is assumed to be 1 day, if the probability of damage to the road segment is less than 0.2, 7 days if it is more than 0.8, and 2 days for all other cases [83]. However, it should be noted that the reliance on deterministic average repair times might result in underestimating the uncertainties in the restoration process.

While the method proposed in this paper allows for updating the estimations based on various types of evidence data as demonstrated by Braik and Koliou [45], it is assumed in the DES that the only source of evidence is the feedback of repair crews. Therefore, once a repair crew reaches the selected line, the state of its elements is stochastically sampled based on their probabilities of failure to give either failed or not failed, and the simulated time of repair is the number of damaged elements times the average time of repair of a single element. Therefore, if a line contains m poles or towers, the simulated number of damaged elements m'' is stochastically sampled following m independent non-identical Bernoulli (INB) trials [84], where the probability for each trial is equal to the probability of failure of the element estimated through the fragility analysis. Even if no element is failed, it is assumed that the minimum checking time t_{check} is 0.5 hours for distribution lines and 5 hours for substations and transmission lines. Therefore, $t_{repair-j}$, the time of repair of a line j, is sampled using equation (7), where t_{check}, t_{avg}, and m'' are the minimum checking time, average repair time, and simulated number of damaged elements, respectively, as defined above, and $q_1, q_2, \ldots, q_m$ are the failure probabilities of poles or towers within the line j.

$$t_{repair-j} = \max\left(t_{check}, m''. t_{avg}\right), Where\ m'' \sim INB(q_1, q_2, \ldots, q_m) \tag{7}$$

The EPN units are assumed to start working 4 hours after the hurricane [85], while the RN units are assumed to start working only after all roads are drained. Both EPN and RN units start from the road node in the mainland before the Galveston bridge. An average travel speed of 25 mph (11.2 m/s) is assumed through an undamaged and drained road segment. This speed is reduced based on the probability of failure of the road as elaborated in Section 3.2.2. This reduction in travel speed is capped at a minimum of 2.5 mph (1.12 m/s), ensuring that even in the presence of substantial damage, travel remains possible but significantly slowed. In the case of flooded roadways, repair units are expected to face impassable conditions, except for access to substations, where it is expected that given the high value and significance of the substations, access will be made possible even in the event of flooding.

The repair prioritization follows the criteria discussed earlier, with substations and transmission lines taking precedence for repair. Subsequently, distribution lines are prioritized based on their RW, where Equation (6) is used to assign each EPN crew unit an element to repair. Since any downstream line cannot operate unless all its upstream lines are repaired, the upstream lines are compared for prioritization at each step. Initially, priority is given to restoring essential facilities, indicated by assigning them a weight of one, while assigning a weight of zero to the rest of the customers. Subsequently, attention shifts to the remaining customers, who are then assigned non-zero weights. The road segment with the highest probability of damage is given the highest repair priority.

4.3. Supervisory and control DT

In Figure 5, a dynamic dashboard is presented, tracking the progress of electric power restoration. In this application study, equal importance is assigned to the restoration of residential, commercial, and industrial buildings. Additionally, allocation has been made for 8 repair units for the EPN and 5 units for the RN. Figure 5 (a) displays the initial state of the EPN immediately after the hurricane's impact. As no data has yet been collected, the estimates are primarily based on the prior physics-based analysis and show a significant failure of EPN components, resulting in a nearly complete power outage across the island. Furthermore, most RN segments are flooded, with damage concentrated near the shoreline.

Figure 5 (b) portrays the intermediate state of the EPN on the sixth day following the hazard occurrence. At this stage, the restoration of essential facilities and a substantial portion of the remaining customers has been achieved. Additionally, the RN has been drained, and repairs are being undertaken for damaged segments. Notably, significant recovery has been experienced in the upper half of the island, while the other half still faces a widespread outage. This underscores the importance of visualizing spatial variations, allowing for the identification of overlooked areas. Finally, in Figure 5 (c), the fully repaired and restored state of the EPN on day 16 is shown.

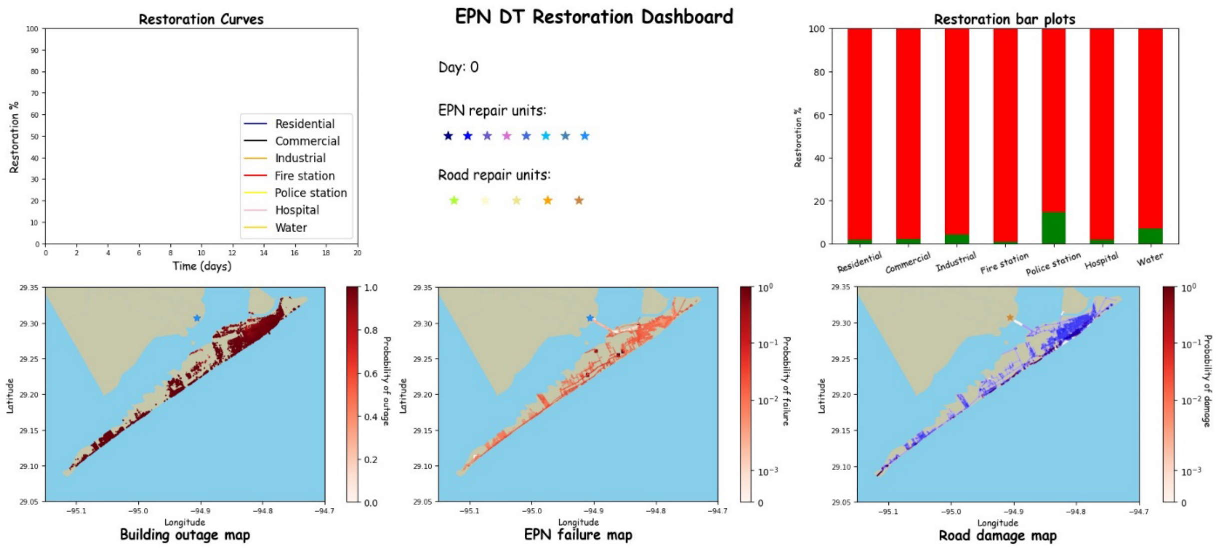
As discussed in Section 3.4, the proposed DT exhibits a versatile range of capabilities, from supervision to intelligent decision-making. The DT provides dynamic and detailed visualizations that allow decision-makers to assess the damage and performance of the EPN components and their effect on customers, in addition to the state of the RN segments and their effect on the mobility of repair units. It extends its capabilities further through simulation and prediction, as demonstrated by the DES application study and the resulting estimates. One of its standout features is its intelligent capability, achieved through the BN updates. By collecting data on specific nodes within the EPN, the entire network can be updated. Therefore, predictions for other nodes that share upstream connections with the nodes we have monitored can be enhanced. This adaptive learning ensures the DT's ability to provide more accurate predictions following real-time data sensing. Moreover, by prioritizing elements for repair through the RW calculations, the DT can be used in adaptive decision-making and to direct and control the restoration process. Furthermore, it allows decision-makers to intervene at any point in time and redirect the restoration strategies and the distribution of resources. Hence, the proposed DT possesses the full capabilities of a supervisory and control DT.

4.4. Case studies

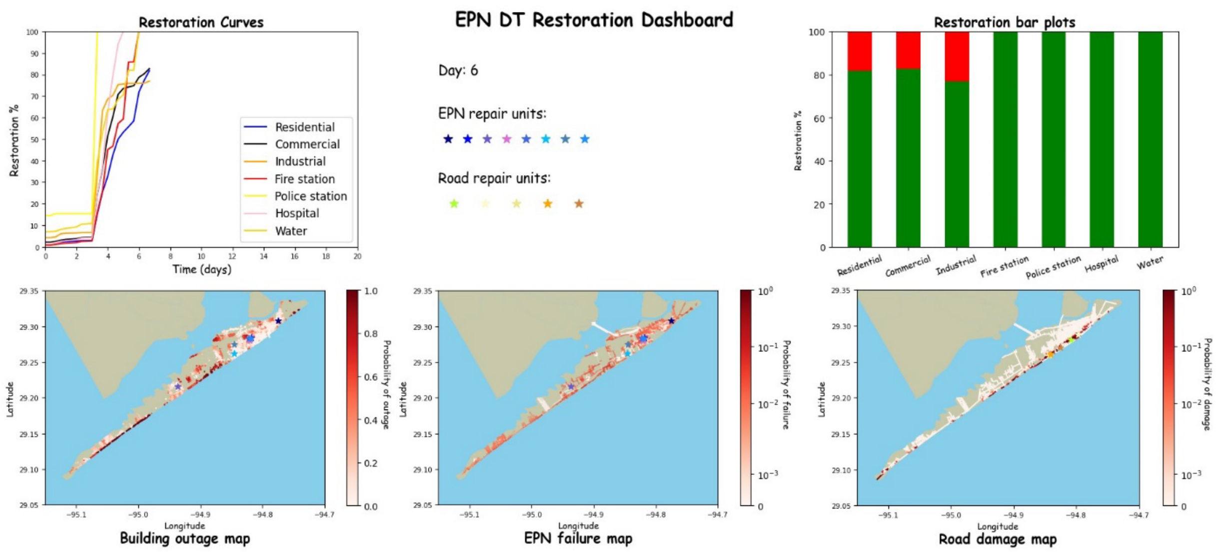
In this section, an analysis of different case studies is conducted, with a focus on the modification of prioritization strategies, the adjustment of weights, and the reallocation of resources. These are compared to the benchmark case presented in Section 4.3.

4.4.1. Sensitivity analysis

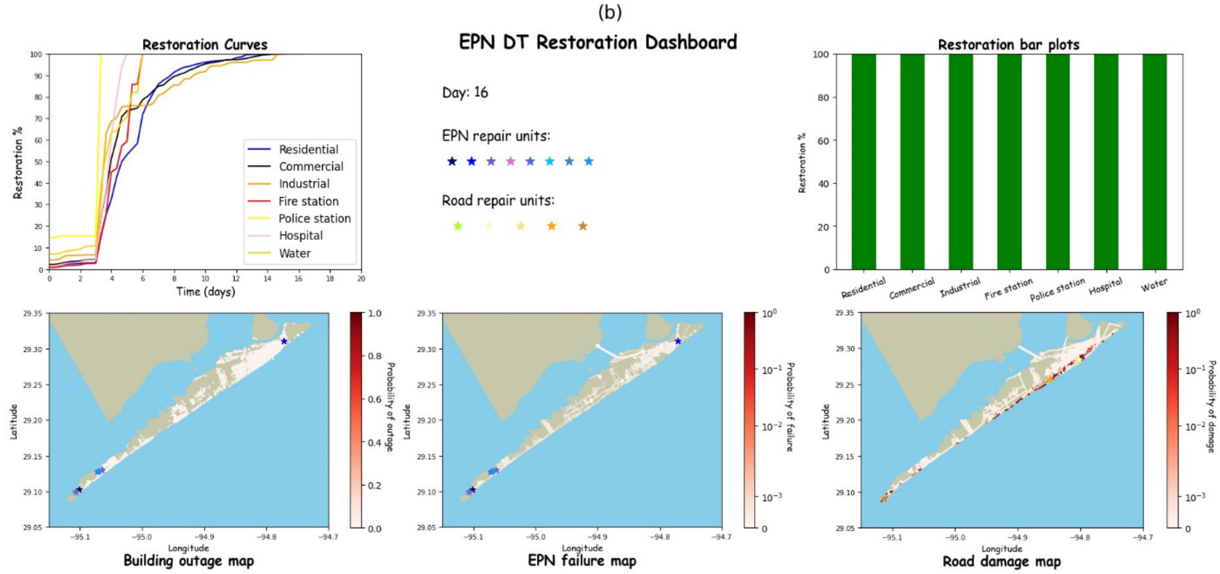
To enable a comparison between the results of stochastic simulations, MCS is utilized. Therefore, the convergence of the cumulative mean of the samples is examined, and it is subsequently used to compare different cases. Figure 6 shows the convergence of the cumulative mean of the restoration percentage for the benchmark case for days 1 to 16 after the occurrence of the hazard. Similar checks were performed in other cases and for various types of customers and essential facilities. Convergence for all cases was achieved after 40 runs, hence, the restoration plots of the mean of the 40 runs are used.


Restoration Curves
Restoration %
Time (days)
Residential
Commercial
Industrial
Fire station
Police station
Hospital
Water
EPN DT Restoration Dashboard
Day: 0
EPN repair units:
Road repair units:
Restoration bar plots
Building outage map
Probability of outage
EPN failure map
Probability of failure
Road damage map
Probability of damage
Latitude
Longitude

(a)


Restoration Curves
Restoration %
Time (days)
Residential
Commercial
Industrial
Fire station
Police station
Hospital
Water
EPN DT Restoration Dashboard
Day: 6
EPN repair units:
Road repair units:
Restoration bar plots
Building outage map
Probability of outage
EPN failure map
Probability of failure
Road damage map
Probability of damage
Latitude
Longitude

(b)


Restoration Curves
Restoration %
Time (days)
Residential
Commercial
Industrial
Fire station
Police station
Hospital
Water
EPN DT Restoration Dashboard
Day: 16
EPN repair units:
Road repair units:
Restoration bar plots
Building outage map
Probability of outage
EPN failure map
Probability of failure
Road damage map
Probability of damage
Latitude
Longitude

(c)

Figure 5: DT dashboard for: (a) Day 0 (immediately after the hurricane), (b) Day 6, and (c) Day 16 (end of EPN repair and restoration)

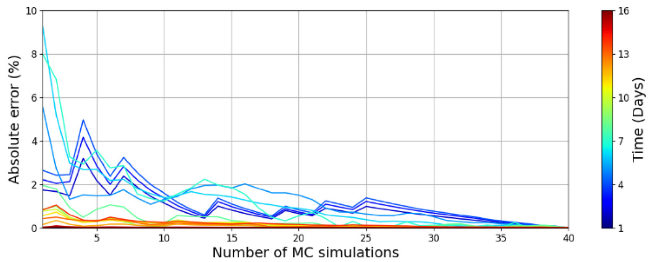


Figure 6: Convergence of the MCS cumulative mean for the benchmark case

4.4.2. Comparison studies

In Figure 7 (a), a comparison is made between the restoration of the benchmark case described above and the actual restoration of Galveston Island following Hurricane Ike, as retrieved from historical records [29]. The almost linear shape of the actual restoration plot, when compared to the S-shaped curve of the simulation plot, suggests that a more efficient restoration could have been attained if a more informed prioritization of elements for repair had been followed, as proposed in this paper. Figure 7 (b) compares the restoration curves of synthetic hurricanes based on Hurricane Ike of various return periods; T=50, 100, and 500 years. The return period events were determined by water level exceedance probabilities at Stewart Beach, near the eastern end of Galveston Island [56]. The results of the hurricane models were obtained from [57, 86]. The time to restoration of the 500-year return period hurricane is significantly larger than the other hurricanes, which shows the considerable effect of the hazard intensity on the restoration process. Figure 7 (c) shows the impact of resource allocation on the restoration process. As anticipated, an increase in the number of repair crew units results in an acceleration of the restoration rate. This graphical representation serves as a tool for evaluating the incremental advantages of adding resources. The transition from 5 to 8 repair units yields significantly more benefit compared to increasing the numbers from 8 to 10 units.

Figure 8 displays the restoration plots for residential, commercial, and industrial customers for different prioritization strategies. In Figure 8 (a), the benchmark case is shown where equal weights are assigned to all customers, resulting in similar restoration plots with small variations influenced by spatial distributions. In contrast, Figure 8 (b) reveals the restoration plots when prioritization is centered around residential customers. In this scenario, the residential restoration plot is shifted slightly to the right, with a more noticeable effect on the delay of restoration for commercial and industrial plots. Then, in Figure 8 (c), the restoration plots are shown when prioritization factors are determined by the expected monetary loss per hour of outage, following the ratios of 1:325:1200 for residential, commercial, and industrial customers, respectively [87]. Therefore, in this case, business recovery takes precedence, and rapid restoration is observed for industrial and commercial buildings compared to the benchmark case, while the restoration of residential buildings is slightly delayed.

Figure 9 demonstrates the impact of prioritizing essential facilities for restoration. Figure 9 (a) shows that when not given priority, the restoration of water facilities takes nearly three times the duration. Similarly, in Figure 9 (b), a significant delay in hospital power restoration is seen when considered as regular customers.

These figures include confidence bands showing one standard deviation above and below the average MCS restoration plots. It is noted that the variability becomes more pronounced when focusing on the restoration of a smaller subset of customers, such as industrial facilities, compared to the total restoration, since the aggregated effect tends to reduce variability in larger systems. This highlights the importance of considering spatial and categorical variability. However, some assumptions made, such as the deterministic hazard model and the use of average repair times, contribute to underestimating the total uncertainty. This motivates a more comprehensive uncertainty quantification in future studies.

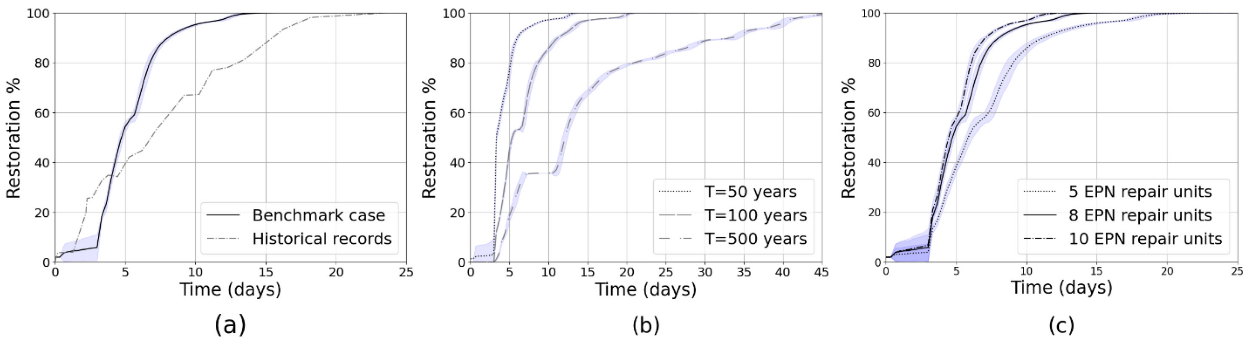


Figure 7: Comparison studies of: (a) the benchmark case restoration against the actual restoration obtained from historical records (b) the restoration plots of various hurricane return periods (c) the effect of allocated resources

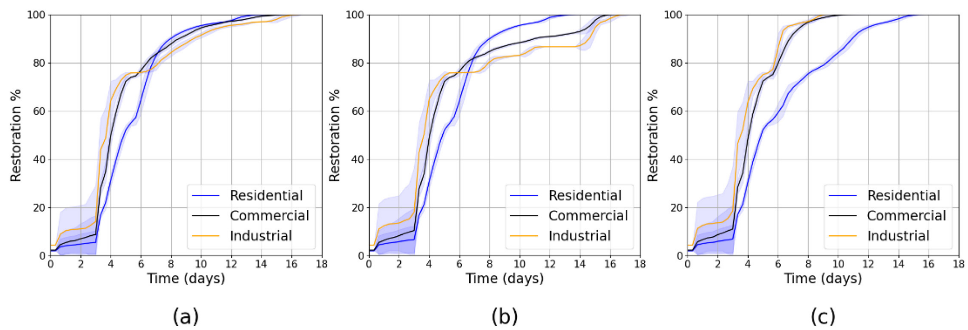


Figure 8: Restoration plots for residential, commercial, and industrial buildings for: (a) equal weights (benchmark case) (b) residential buildings given priority (c) business facilities given priority

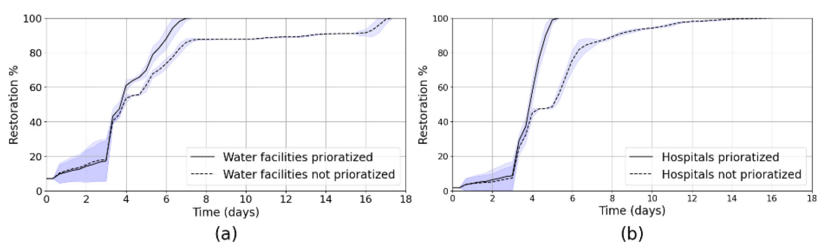


Figure 9: Effect of prioritizing: (a) water facilities (b) hospitals

4.4.3. Updating prior estimations with data evidence via backward propagation

To demonstrate the capability of the DT in updating prior estimates using belief propagation, a case study is considered in which the outage and restoration state of 10 customers have been observed. When data evidence about the outage or restoration status of any customer is obtained, it can be used to update the prior outage probabilities for the entire island. This method influences the estimations for customers connected to the same upstream line as those for whom data has been received, even if there is no direct data available for them. As shown in Figure 10 (a), 5 customers in the middle of the island were observed to have power restored, while another 5 customers in the lower part of the island experienced power outages at the same time. The updated outage map, displayed in Figure 10 (b), shows a significant portion of the island having power restored using only these 10 data points. It is noteworthy that the upper right portion of the island was not significantly updated using the observed data. This is because the observed restored customers receive electricity directly from the mainland substation via an underground electricity cable, as illustrated in Figure 4.

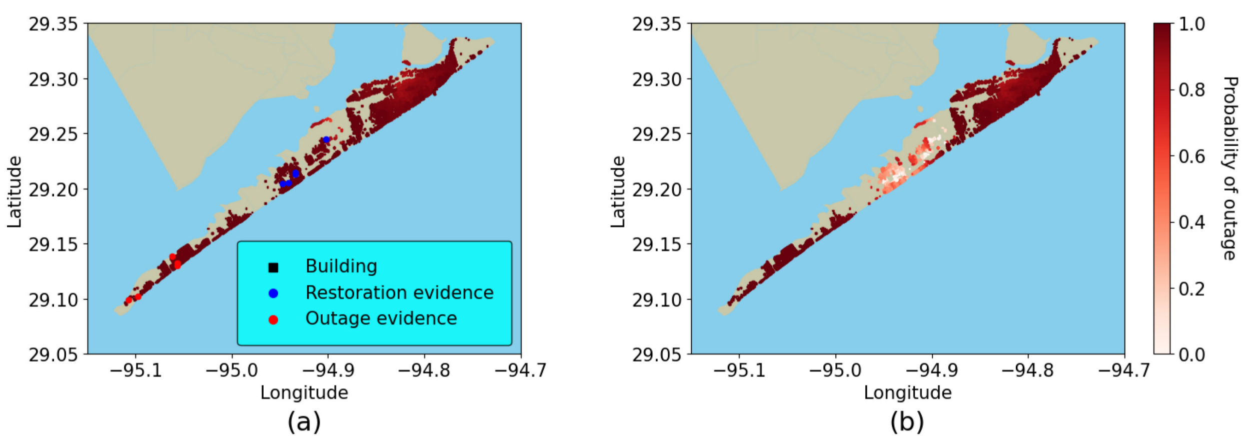


Figure 10: DT outage map for (a) prior estimations (b) posterior estimations using observed data

5. Conclusions and future work

This paper has introduced a novel framework for post-hurricane electric power restoration, leveraging the concept of the DT. As demonstrated in this study, the DT provides dynamic visualizations that offer a holistic evaluation of the EPN performance, while also assessing the condition of the RN and its influence on the mobility of repair units. By employing a DBN that integrates physics-based and data-driven models, the framework expands its capabilities from offline to online learning, enabling real-time updates to continuously enhance the accuracy of the estimations. These capabilities are further extended through simulation and prediction, as showcased by the DES application study. Additionally, the ability to guide and prioritize repair and restoration efforts allows for adaptive decision-making, extending the framework toward a supervisory and control DT.

Despite the promising results, the proposed framework still has limitations in its current form. The case studies rely on scenarios of single hazards rather than comprehensive hazard analysis. Moreover, several assumptions regarding restoration times are treated as deterministic average values rather than probabilistic random variables, potentially underestimating the uncertainty in the results. Additionally, the RN is modeled as a graph network and does not incorporate traffic and flow analysis, nor does it account for debris that might disrupt traffic. Finally, the cascading effect of power outages on the RN is not considered. The water network is only considered by including main water facilities, such as water pumps, instead of modeling a comprehensive water network.

Future research can focus on the RN by conducting comprehensive traffic and flow analyses that account for evacuation, return, the impact of debris, and other important factors that might affect the mobility of repair units. Furthermore, there is a need for a more comprehensive hazard analysis considering the stochastic nature of hurricane loads. Additionally, there exists potential for in-depth analysis of the restoration of the water network and its impact on community functionality and resilience. Future research can also explore the synergy between the disaster management DT of the EPN and the normal operation DT. By integrating these two, where power flow is based on connectivity during disasters and on DC flow analysis during normal operations, researchers can combine the concepts of smart and resilient infrastructure systems.

Moreover, the proposed framework can be utilized to analyze restoration efforts focusing on socially vulnerable communities. The simulation analysis offered can further evolve through the application of agent-based modeling, taking into consideration various social systems in conjunction with critical infrastructure systems, ultimately developing a full community DT. Since the proposed DT framework utilizes data to update prior estimates, future research could focus on innovative data collection and analysis approaches to enhance the efficiency of the restoration process. Therefore, this paper establishes the groundwork for a paradigm shift in disaster recovery strategies through more efficient, adaptable, and data-informed methods that enhance post-hurricane electric power restoration, ultimately contributing to more resilient communities.

Relevance to resilience

This paper presents a framework for post-hurricane electric power restoration using a DT approach, focusing on the restoration of the EPN and RN. By prioritizing repairs and optimizing resource allocation, the framework enhances infrastructure resilience, ensuring efficient restoration of essential services crucial for maintaining community functionality and well-being after a disaster. Through adaptive decision-making and data-driven methodologies, the framework contributes to building more resilient communities and enabling real-time updates based on accurate information. Overall, the study underscores the importance of leveraging DT technology to enhance post-disaster recovery efforts, ultimately contributing to community resilience.

Declaration of competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

Financial support for this work was provided by the US National Science Foundation (NSF) under Award Number 2052930. This financial support is gratefully acknowledged. Any opinions, findings, conclusions, and recommendations presented in this paper are those of the authors and do not necessarily reflect the views of NSF.

References

[1] Koliou M, van de Lindt JW, McAllister TP, Ellingwood BR, Dillard M, Cutler H. State of the research in community resilience: Progress and challenges. Sustainable and resilient infrastructure. 2020;5:131-51.

[2] Ford DN, Wolf CM. Smart cities with digital twin systems for disaster management. Journal of management in engineering. 2020;36:04020027.

[3] Moore HE, Bates FL, Layman MV, Parenton VJ. BEFORE THE WIND. A STUDY OF THE RESPONSE TO HURRICANE CARLA. NATIONAL ACADEMY OF SCIENCES-NATIONAL RESEARCH COUNCIL WASHINGTON DC; 1963.

[4] Arab A, Khodaei A, Han Z, Khator SK. Proactive recovery of electric power assets for resiliency enhancement. Ieee Access. 2015;3:99-109.

[5] Helbing D, Ammoser H, Kühnert C. Disasters as extreme events and the importance of network interactions for disaster response management. Extreme events in nature and society. 2006:319-48.

[6] Miller LM, Antonio RJ, Bonanno A. Hazards of neoliberalism: Delayed electric power restoration after Hurricane Ike 1. The British journal of sociology. 2011;62:504-22.

[7] Castillo A. Risk analysis and management in power outage and restoration: A literature survey. Electric Power Systems Research. 2014;107:9-15.

[8] Shafieezadeh A, Onyewuchi UP, Begovic MM, DesRoches R. Age-dependent fragility models of utility wood poles in power distribution networks against extreme wind hazards. IEEE Transactions on Power Delivery. 2013;29:131-9.

[9] Boggess J, Becker G, Mitchell M. Storm & flood hardening of electrical substations. 2014 IEEE PES T&D Conference and Exposition: IEEE; 2014. p. 1-5.

[10] Salman AM, Li Y, Stewart MG. Evaluating system reliability and targeted hardening strategies of power distribution systems subjected to hurricanes. Reliability Engineering & System Safety. 2015;144:319-33.

[11] Yuan H, Zhang W, Zhu J, Bagtzoglou AC. Resilience assessment of overhead power distribution systems under strong winds for hardening prioritization. ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering. 2018;4:04018037.

[12] Braik AM, Salman AM, Li Y. Risk-based reliability and cost analysis of utility poles subjected to tornado hazard. Journal of Aerospace Engineering. 2019;32:04019040.

[13] Braik AM, Salman AM, Li Y. Reliability-based assessment and cost analysis of power distribution systems at risk of Tornado hazard. ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering. 2020;6:04020014.

[14] Darestani YM, Jeddi AB, Shafieezadeh A. Hurricane Fragility Assessment of Power Transmission Towers for a New Set of Performance-Based Limit States. Engineering for Extremes: Decision-Making in an Uncertain World: Springer; 2021. p. 167-88.

[15] Li Y, Salman AM, Braik A, Bjarnadóttir S, Salarieh B. Risk-Based Management of Electric Power Distribution Systems Subjected to Hurricane and Tornado Hazards. Engineering for Extremes: Decision-Making in an Uncertain World: Springer; 2021. p. 143-66.

[16] Ma L, Khazaali M, Bocchini P. Component-based fragility analysis of transmission towers subjected to hurricane wind load. Engineering Structures. 2021;242:112586.

[17] Daeli A, Mohagheghi S. Power Grid Infrastructural Resilience against Extreme Events. Energies. 2022;16:64.

[18] Du X, Hajjar J. Hurricane fragility analysis of electrical transmission towers. Electrical Transmission and Substation Structures 2022: Innovating for Critical Global Infrastructure: American Society of Civil Engineers Reston, VA; 2022. p. 348-57.

[19] Lu Q, Zhang W. Integrating dynamic Bayesian network and physics-based modeling for risk analysis of a time-dependent power distribution system during hurricanes. Reliability Engineering & System Safety. 2022;220:108290.

[20] Reilly AC, Davidson RA, Nozick LK, Chen T, Guikema SD. Using data envelopment analysis to evaluate the performance of post-hurricane electric power restoration activities. Reliability Engineering & System Safety. 2016;152:197-204.

[21] Mitsova D, Esnard A-M, Sapat A, Lai BS. Socioeconomic vulnerability and electric power restoration timelines in Florida: the case of Hurricane Irma. Natural Hazards. 2018;94:689-709.

[22] Ulak MB, Kocatepe A, Konila Sriram LM, Ozguven EE, Arghandeh R. Assessment of the hurricane-induced power outages from a demographic, socioeconomic, and transportation perspective. Natural hazards. 2018;92:1489-508.

[23] Beck AL, Cha EJ. Probabilistic disaster social impact assessment of infrastructure system nodes. Structure and Infrastructure Engineering. 2022:1-12.

[24] Mensah AF, Dueñas-Osorio L. Efficient resilience assessment framework for electric power systems affected by hurricane events. Journal of Structural Engineering. 2016;142:C4015013.

[25] He X, Cha EJ. Modeling the damage and recovery of interdependent critical infrastructure systems from natural hazards. Reliability engineering & System safety. 2018;177:162-75.

[26] Johansen C, Tien I. Probabilistic multi-scale modeling of interdependencies between critical infrastructure systems for resilience. Sustainable and Resilient Infrastructure. 2018;3:1-15.

[27] Khomami MS, Sepasian MS. Pre-hurricane optimal placement model of repair teams to improve distribution network resilience. Electric Power Systems Research. 2018;165:1-8.

[28] Applegate CJ, Tien I. Framework for probabilistic vulnerability analysis of interdependent infrastructure systems. Journal of Computing in Civil Engineering. 2019;33:04018058.

[29] He X, Cha EJ. DIN II: incorporation of multi-level interdependencies and uncertainties for infrastructure system recovery modeling. Structure and Infrastructure Engineering. 2021;17:1566-81.

[30] Opabola EA, Galasso C. A Probabilistic Framework for Post-Disaster Recovery Modeling of Buildings and Electric Power Networks in Developing Countries. Reliability Engineering & System Safety. 2023:109679.

[31] Han SR, Guikema SD, Quiring SM. Improving the predictive accuracy of hurricane power outage forecasts using generalized additive models. Risk Analysis: An International Journal. 2009;29:1443-53.

[32] Guikema SD, Nateghi R, Quiring SM, Staid A, Reilly AC, Gao M. Predicting hurricane power outages to support storm response planning. Ieee Access. 2014;2:1364-73.

[33] Nateghi R, Guikema S, Quiring SM. Power outage estimation for tropical cyclones: Improved accuracy with simpler models. Risk analysis. 2014;34:1069-78.

[34] Dehghanian P, Zhang B, Dokic T, Kezunovic M. Predictive risk analytics for weather-resilient operation of electric power systems. IEEE Transactions on Sustainable Energy. 2018;10:3-15.

[35] Kabir E, Guikema SD, Quiring SM. Predicting thunderstorm-induced power outages to support utility restoration. IEEE Transactions on Power Systems. 2019;34:4370-81.

[36] Ham Y, Kim J. Participatory sensing and digital twin city: Updating virtual city models for enhanced risk-informed decision-making. Journal of Management in Engineering. 2020;36:04020005.

[37] Fan C, Zhang C, Yahja A, Mostafavi A. Disaster City Digital Twin: A vision for integrating artificial and human intelligence for disaster management. International Journal of Information Management. 2021;56:102049.

[38] Alibrandi U. Risk-informed digital twin of buildings and infrastructures for sustainable and resilient urban communities. ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering. 2022;8:04022032.

[39] Deng T, Zhang K, Shen Z-JM. A systematic review of a digital twin city: A new pattern of urban governance toward smart cities. Journal of Management Science and Engineering. 2021;6:125-34.

[40] Qi Q, Tao F, Hu T, Anwer N, Liu A, Wei Y et al. Enabling technologies and tools for digital twin. Journal of Manufacturing Systems. 2021;58:3-21.

[41] Zhou M, Yan J, Feng D. Digital twin framework and its application to power grid online analysis. CSEE Journal of Power and Energy Systems. 2019;5:391-8.

[42] Saad A, Faddel S, Mohammed O. IoT-based digital twin for energy cyber-physical systems: design and implementation. Energies. 2020;13:4762.

[43] Darbali-Zamora R, Johnson J, Summers A, Jones CB, Hansen C, Showalter C. State estimation-based distributed energy resource optimization for distribution voltage regulation in telemetry-sparse environments using a real-time digital twin. Energies. 2021;14:774.

[44] Mourtzis D, Angelopoulos J, Panopoulos N. Development of a PSS for smart grid energy distribution optimization based on digital twin. Procedia CIRP. 2022;107:1138-43.

[45] Braik AM, Koliou M. A novel digital twin framework of electric power infrastructure systems subjected to hurricanes. International Journal of Disaster Risk Reduction. 2023:104020.

[46] De Albuquerque JP, Herfort B, Brenning A, Zipf A. A geographic approach for combining social media and authoritative data towards identifying useful information for disaster management. International journal of geographical information science. 2015;29:667-89.

[47] Chen Y, Han D. Water quality monitoring in smart city: A pilot project. Automation in Construction. 2018;89:307-16.

[48] Ragini JR, Anand PR, Bhaskar V. Big data analytics for disaster response and recovery through sentiment analysis. International Journal of Information Management. 2018;42:13-24.

[49] Fan C, Jiang Y, Mostafavi A. Social sensing in disaster city digital twin: Integrated textual–visual–geo framework for situational awareness during built environment disruptions. Journal of Management in Engineering. 2020;36:04020002.

[50] Azad S, Ghandehari M. A study on the association of socioeconomic and physical cofactors contributing to power restoration after hurricane Maria. IEEE Access. 2021;9:98654-64.

[51] Wang H, Fang Y-P, Zio E. Resilience-oriented optimal post-disruption reconfiguration for coupled traffic-power systems. Reliability Engineering & System Safety. 2022;222:108408.

[52] Shuai H, Li F, She B, Wang X, Zhao J. Post-storm repair crew dispatch for distribution grid restoration using stochastic Monte Carlo tree search and deep neural networks. International Journal of Electrical Power & Energy Systems. 2023;144:108477.

[53] Kritzinger W, Karner M, Traar G, Henjes J, Sihn W. Digital Twin in manufacturing: A categorical literature review and classification. Ifac-PapersOnline. 2018;51:1016-22.

[54] Wagg D, Worden K, Barthorpe R, Gardner P. Digital twins: state-of-the-art and future directions for modeling and simulation in engineering dynamics applications. ASCE-ASME J Risk and Uncert in Engrg Sys Part B Mech Engrg. 2020;6.

[55] Wang Y, Mao X, Jiang W. Long-term hazard analysis of destructive storm surges using the ADCIRC-SWAN model: A case study of Bohai Sea, China. International journal of applied earth observation and geoinformation. 2018;73:52-62.

[56] Darestani YM, Webb B, Padgett JE, Pennison G, Fereshtehnejad E. Fragility analysis of coastal roadways and performance assessment of coastal transportation systems subjected to storm hazards. Journal of Performance of Constructed Facilities. 2021;35:04021088.

[57] Incore. Galveston Testbed. 2023.

[58] Darestani Y, Padgett J, Shafieezadeh A. Parametrized Wind–Surge–Wave Fragility Functions for Wood Utility Poles. Journal of Structural Engineering. 2022;148:04022057.

[59] Sánchez-Muñoz D, Domínguez-García JL, Martínez-Gomariz E, Russo B, Stevens J, Pardo M. Electrical grid risk assessment against flooding in Barcelona and Bristol cities. Sustainability. 2020;12:1527.

[60] Brown RE. Electric power distribution reliability: CRC press; 2017.

[61] Khakzad N, Khan F, Amyotte P. Safety analysis in process facilities: Comparison of fault tree and Bayesian network approaches. Reliability Engineering & System Safety. 2011;96:925-32.

[62] Darwiche A. Modeling and reasoning with Bayesian networks: Cambridge university press; 2009.

[63] Ertugay K, Argyroudis S, Düzgün HŞ. Accessibility modeling in earthquake case considering road closure probabilities: A case study of health and shelter service accessibility in Thessaloniki, Greece. International journal of disaster risk reduction. 2016;17:49-66.

[64] Wilson RJ. Introduction to Graph Theory uPDF eBook: Pearson Higher Ed; 2015.

[65] Zou Q, Chen S. Enhancing resilience of interdependent traffic-electric power system. Reliability Engineering & System Safety. 2019;191:106557.

[66] Zou Q, Chen S. Resilience modeling of interdependent traffic-electric power system subject to hurricanes. Journal of Infrastructure Systems. 2020;26:04019034.

[67] Feng K, Lin N. Modeling and analyzing the traffic flow during evacuation in Hurricane Irma (2017). Transportation research part D: transport and environment. 2022;110:103412.

[68] Aghababaei M, Koliou M. An agent-based modeling approach for community resilience assessment accounting for system interdependencies: Application on education system. Engineering Structures. 2022;255:113889.

[69] Aghababaei M, Koliou M. Community resilience assessment via agent-based modeling approach. Computer-Aided Civil and Infrastructure Engineering. 2023;38:920-39.

[70] Han X, Koliou M. Investigation of effects of hazard geometry and mitigation strategies on community resilience under tornado hazards using an Agent-based modeling approach. Resilient Cities and Structures. 2024;3:1-19.

[71] CenterPointEnergy. How we restore power after storms. 2013.

[72] Ouyang M, Dueñas-Osorio L. Multi-dimensional hurricane resilience assessment of electric power systems. Structural Safety. 2014;48:15-24.

[73] CarolinaCountry. How power is restored after a storm. 2016.

[74] EEI E. Restoring Power After a Storm: A Step-by-Step Process. 2023.

[75] Murphy K. The bayes net toolbox for matlab. Computing science and statistics. 2001;33:1024-34.

[76] Rose A, Benavides J, Chang SE, Szczesniak P, Lim D. The regional economic impact of an earthquake: Direct and indirect effects of electricity lifeline disruptions. Journal of Regional Science. 1997;37:437-58.

[77] Sydnor S, Niehm L, Lee Y, Marshall M, Schrank H. Analysis of post-disaster damage and disruptive impacts on the operating status of small businesses after Hurricane Katrina. Natural Hazards. 2017;85:1637-63.

[78] Liu H, Tatano H, Samaddar S. Analysis of post-disaster business recovery: Differences in industrial sectors and impacts of production inputs. International Journal of Disaster Risk Reduction. 2023;87:103577.

[79] Darestani Y, Padgett J. Galveston Island (TX) Electric Power Network Data. 2022.

[80] SPDCPB. Spatial Data Collection and Products Branch. TIGER/Line Shapefile, 2021, County, Galveston County, TX, All Roads. 2022.

[81] GalvestonGIS. City of Galveston's GIS Data Download Site. 2023.

[82] Robinson S. Simulation: the practice of model development and use: Bloomsbury Publishing; 2014.

[83] Fan X, Zhang X, Wang X, Yu X. A deep reinforcement learning model for resilient road network recovery under earthquake or flooding hazards. Journal of Infrastructure Preservation and Resilience. 2023;4:8.

[84] Wang YH. On the number of successes in independent trials. Statistica Sinica. 1993:295-312.

[85] Ouyang M, Dueñas-Osorio L, Min X. A three-stage resilience analysis framework for urban infrastructure systems. Structural Safety. 2012;36:23-31.

[86] Incore. Hurricane Ike's hindcast data. 2023b.

[87] LaCommare KH, Eto JH. Cost of power interruptions to electricity consumers in the United States (US). Energy. 2006;31:1845-55.