# A Novel Digital Twin Framework of Electric Power Infrastructure Systems Subjected to Hurricanes

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**Abstract**

The electric power network (EPN) is one of the most critical infrastructure systems as most lifeline, economic, and social systems depend heavily on it, and any disruption in the network may affect the well-being of modern societies. Being the most vulnerable to natural hazards, the resilience of the EPN has received plenty of attention in recent years, particularly considering the increasing frequency and severity of natural hazards associated with climate instabilities. The data revolution and the recent advances in the fields of artificial intelligence (AI), machine learning (ML), and the Internet of Things (IoT) have prompted researchers to take the next step and expand the available predictive models toward digital twins (DT). However, there is still a lack of an applicable framework for a DT of infrastructure systems in the face of disasters. In this paper, a novel DT framework of the EPN when subjected to hurricanes is proposed that combines physics-based and data-driven models while also employing a dynamic Bayesian network (DBN). The DBN can be updated in near real-time via data sensing to provide a DT that is simple, computationally feasible, scalable, and capable of modeling and estimating the failure and performance states of the various elements of the EPN. The proposed DT framework is applied to Galveston Island's EPN, and the results are validated using historical data, demonstrating that the DT can produce detailed and highly accurate estimations to be used in decision-making for community resilience planning.

**Keywords**: Bayesian network, community resilience, digital twin, electric power network, hurricanes.

**Abbreviations**: AI: artificial intelligence; BN: Bayesian network; CPD: conditional probability distribution; CPS: cyber-physical systems; DBN: dynamic Bayesian network; DT: digital twin;

EPN: electric power network; IoT: internet of things; ML: machine learning; VE: variable elimination.

# 1. Introduction

## *1.1. Motivation and problem statement*

The electric power network (EPN) is one the most important infrastructure systems, supporting many other critical lifelines such as water, transportation, and telecommunication networks, therefore, any disruption in the EPN can have a significant impact on the safety, health, and economic well-being of modern societies. Yet, it is by far the most vulnerable to natural hazards, especially hurricanes. Over the past two decades, hurricanes have resulted in more than $1 trillion of economic losses in the United States (NOAA, 2023), and a significant share of these are direct costs from damage to EPN components as well as indirect costs associated with power outages (Casey et al., 2020). As a result, the EPN's resilience has received a lot of attention in recent years, especially in consideration of the increasing frequency and severity of natural hazards and other disruptive events associated with climate instabilities (Koliou et al., 2020). Therefore, the EPN's reliability and risk mitigation have been extensively studied over the last decade at both the component level (e.g., Shafieezadeh et al., 2013; Salman & Li, 2016; Yuan et al., 2018; Braik et al., 2019; Ma et al., 2020; Darestani, Jeddi, et al., 2021; Ma et al., 2021; Du & Hajjar, 2022) and the system level (e.g., Salman et al., 2015; H. Zhang et al., 2019; Braik et al., 2020; Lee & Ham, 2021; Li et al., 2021; Ma et al., 2022), in addition to its interdependency with other infrastructure systems (e.g., Zimmerman et al., 2017; He & Cha, 2018; Johansen & Tien, 2018; Applegate & Tien, 2019; Zou & Chen, 2019; Lee et al., 2020; He & Cha, 2021). Moreover, many studies have investigated enhancing the resilience of the EPN in the face of extreme weather events by proposing various methods of hardening to the overhead lines, poles, and substations, vegetation management methods, and network redundancy strategies (e.g., Berkeley et al., 2010; Boggess et al., 2014; Hossain et al., 2021; Daeli & Mohagheghi, 2022; Amini et al., 2023).

However, there is still a need to leverage the recent advances in data science and smart technologies and combine them with the available probabilistic modeling methods. This will provide high-fidelity models that can be updated in real-time via intelligent data-sensing to be used in prediction and decision-making. Such a model can be achieved through a digital twin (DT), which integrates the real system with its virtual replica through real-time data transfer. On that account, researchers have been motivated to expand the predictive models toward DT models (Fan et al., 2021), but the proposed methods are still conceptual or focus on a single aspect of the DT, such as data-sensing (e.g., Fan et al., 2020; Ford & Wolf, 2020; Fan et al., 2021; Ham & Kim, 2020; Alibrandi, 2022). Hence, there is still a lack of a practical and applicable framework for a DT of infrastructure systems in the face of natural hazards.

### *1.2. Background on digital twins and their applications in community resilience studies*

The concept of DT is relatively new and was first introduced in 2002 through a product lifecycle management model (Grieves & Vickers, 2017). While different definitions of the DT exist (e.g., Glaessgen & Stargel, 2012; Grieves & Vickers, 2017; Tao et al., 2018; Jiang et al., 2021; Alibrandi, 2022; Dhar et al., 2022), most agree that it integrates the real (physical) system with its virtual replica (high-fidelity model) via real-time data transfer. The concept of DT was immediately adopted in the field of industrial engineering due to its applications in smart manufacturing (Tao et al., 2018). Then, it also gained traction in civil and infrastructure systems engineering, with researchers investigating how to utilize the DT as a step toward smart cities (Cañavera-Herrera et al., 2022).

Recent studies have been proposing frameworks to integrate technologies like smart grids, cyber-physical systems (CPS), the Internet of Things (IoT), big data analytics, and machine learning (ML) to develop EPN DTs (e.g., Zhou et al., 2019; Saad et al., 2020 Darbali-Zamora et al., 2021; Mourtzis et al., 2022). These frameworks have shown promise in enhancing the management and efficiency of EPNs, but their applicability in disaster management faces significant challenges. They heavily rely on continuous real-time data from smart meters and other physical sensors, which can be vulnerable to damage in the aftermath of natural hazards. Moreover, these approaches are built upon an initial state estimation of the EPN's condition, which is continuously updated in real-time using data (Sifat et al., 2022). However, this may not work when there is a widespread destruction of elements within the EPN. In such cases, physics-based methods that consider hazard and structural analysis can offer more reliable estimates (Alibrandi, 2022). Consequently, DT frameworks designed for post-hazard scenarios shift their focus toward obtaining data through alternative means like social sensing and image recognition, which do not rely on physical sensors (Ford & Wolf, 2020; Fan et al., 2021). Since these methods require a large amount of data that is usually not readily available after the disaster, the DT must also incorporate physics-based methods (Alibrandi, 2022).

### *1.3. Background on Bayesian Networks and their applications in digital twins for community resilience planning*

One of the powerful statistical tools that can combine physics-based models, interdependency rules, and updating using evidence data is the Bayesian network (BN). Hence, incorporating the BN within the risk assessment framework allows to account for various epistemic uncertainties in the model, while also providing a systematic method to combine evidence data with the prior physics-based beliefs. This enhances the offline (pre-disaster) predictions and extends the model's capabilities toward online (post-disaster) applications. Therefore, the BN can be extended to a dynamic Bayesian network (DBN) to deal with the change of the states of elements in a dynamic system (Murphy, 2002). Methods incorporating the DBN have recently been proposed as DT models, primarily because the DBN is a simple, intuitive, graphical, scalable, and efficient method that can capture interdependencies between systems, identify critical components, allow for real-time information updates, and most importantly provide probabilistic estimations that can be used in decision-making. For example, Li et al. (2017) proposed a DBN model for the prediction of fatigue crack growth in aircraft wings, and Yu et al. (2021) proposed a DBN model for complex system health monitoring.

The advantages of the BN have attracted researchers to utilize it in community resilience in the face of natural hazards, but still, none of the proposed frameworks have extended the BN toward a DT at the community level. For example, Kameshwar et al. (2019) proposed a general framework using a BN for community resilience considering infrastructure interdependencies and incorporating multi-hazards, and Dong et al. (2020) used a BN to model the interdependence between the road network and the stormwater drainage system during floods.

Methods based on BNs and DBNs have been proposed for power outage prediction or to model the EPN and its interdependencies with other systems, but there are no studies available related to extending such models toward a DT. Mensah and Dueñas-Osorio (2014) proposed a general framework for electric power outage prediction during hurricanes using a BN and applied it to a case study that only considered the substations as nodes. The potential of extending the BN toward a hybrid physics-based and data-driven method through Bayesian updating of the network was not explored in that study. More recently, Johansen and Tien (2018), Applegate and Tien (2019), and Lee et al. (2020) used BNs and DBNs to model the interdependency between the power network and other infrastructure systems (mainly the water network). These frameworks were targeted toward the seismic hazard and considered the substations to be the vulnerable components within the power system. Therefore, the proposed frameworks cannot be directly applied to EPNs subjected to wind loads where the distribution and transmission lines are the most vulnerable components. Moreover, the DBN in these studies was used to model the interdependencies between systems and not to update the BN. Applegate and Tien (2019) mentioned that the BN can be updated using evidence data, however, no application study was presented on how this evidence can be obtained in real-time or how to extend the method toward a full hybrid physics-based and data-driven DT.

### *1.4. Data sensing*

The BN framework proposed in this paper allows for the use of data evidence obtained through any data-sensing method to dynamically update the physical (failure or survival) or performance (power outage or restoration) states of any element within the EPN. Traditional methods to obtain outage, restoration, and damage data include calls from customers, utility sensors, and feedback from repair crews. Calls from customers are still by far the main source of power outage data (Meier et al., 2019). However, handling all customer calls after disasters and widespread outages is both expensive and inefficient. Thus, faster methods are needed to help speed up the restoration. While utility companies use methods to detect power outages such as smart meters connected to customers and supervisory control and data acquisition (SCADA) systems connected to substations, the signals of the smart meters will not reach if the network suffers widespread destruction after hurricanes, and the SCADA by itself doesn’t provide sufficient detailed information since the distribution lines are not covered (Meier et al., 2019; Román et al., 2019). Hence, these are still secondary sources and aren’t sufficient to provide real-time outage data necessary to direct restoration efforts following disasters. Feedback from investigations and repair crews is a reliable source for damage and restoration data following site inspections and repairs, but it may also be slow and inefficient and should be accompanied and guided by other data-sensing methods.

Recently, smart sensing methods such as social sensing and image processing have been getting traction and showing potential. Many researchers have investigated the scrapping and analyzing of social media comments (such as tweets) during disasters (e.g., Huang & Xiao, 2015; C. Zhang et al., 2019; Fan et al., 2020; Heglund et al., 2021). Moreover, with the development of artificial intelligence (AI) image recognition and processing models, researchers have proposed methods to identify post-disaster damage via satellite images and aerial photos. For example, Hosseini et al. (2020) proposed a convolutional neural network damage classification model to detect failed poles after hurricanes using unmanned aerial vehicles, and Montoya-Rincon et al. (2022) proposed a ML model to predict outages using satellite night images based on the difference between nightlight radiances before and after the hurricane. In addition to the above, many proposed smart methods can contribute to receiving real-time outage and restoration data. For example, Meier et al. (2019) proposed the use of data from connected thermostats to detect power outages.

### *1.5. Scope*

In this paper, a novel DT framework of the EPN when subjected to hurricane hazards is proposed. The key objective is to develop a DT that can be used in decision-making to turn the predictive models from being passive to active and impacting the real system. Due to the lack of a unified and clear definition of the DT when dealing with cities and infrastructure systems, this paper also proposes a definition of the DT at the community level to be a high-fidelity model of single or multiple infrastructure systems that considers both the physical characteristics and the interdependency rules and can be updated in near real-time to assist with decision-making. The proposed framework combines physics-based and data-driven models while it also employs a DBN that can be updated in near real-time via data-sensing. Therefore, from a Bayesian modeling perspective, the initial estimates based on hazard and fragility analysis represent the prior physics-based belief. After that, the BN is updated using evidence data to follow the real system. With continuous real-time updating, the DBN turns into a high-fidelity hybrid (physics-based and data-driven) model of the real system, and hence the term DT is used in the proposed framework.

This framework provides a DT that is simple, computationally feasible, scalable, and capable of modeling and estimating the damage and performance states of the various elements of the EPN, beginning with the substations and progressing through the transmission lines and distribution lines to finally reach the customers, while also capturing detailed spatial variations and taking into account the different land uses. Hence, it can offer two major capabilities: offline learning and online learning. In preplanning and preparedness for natural hazards, the DT model can be used for offline learning to simulate various hazard scenarios and estimate the system's performance. This can test the efficacy of restoration plans and guide maintenance as well as hardening strategies. Additionally, the DT model can be used in online learning for adaptive decision-making and to direct post-disaster restoration efforts and repair crews by identifying the most critical nodes within the system. By using evidence and feedback from repair crews and other investigation reports, as well as the data from various real-time sensing methods, the DT model has the capability to be updated, and thus strategies and plans can be redirected based on the actual current situation.

The proposed framework is described in detail in this paper starting from data analysis and then proceeding to show how to integrate physics-based hazard and fragility analysis and data-driven DBN in a hybrid DT model that considers all subsystems and components of the EPN and can be updated in near real-time to be used in decision-making. Then, the proposed DT framework is applied using the Galveston testbed subjected to Hurricane Ike hazard and the results are validated using historical records.

## 2. Description of the proposed DT framework

A flowchart of the proposed DT framework is presented in Figure 1, while details are discussed in the following sections.

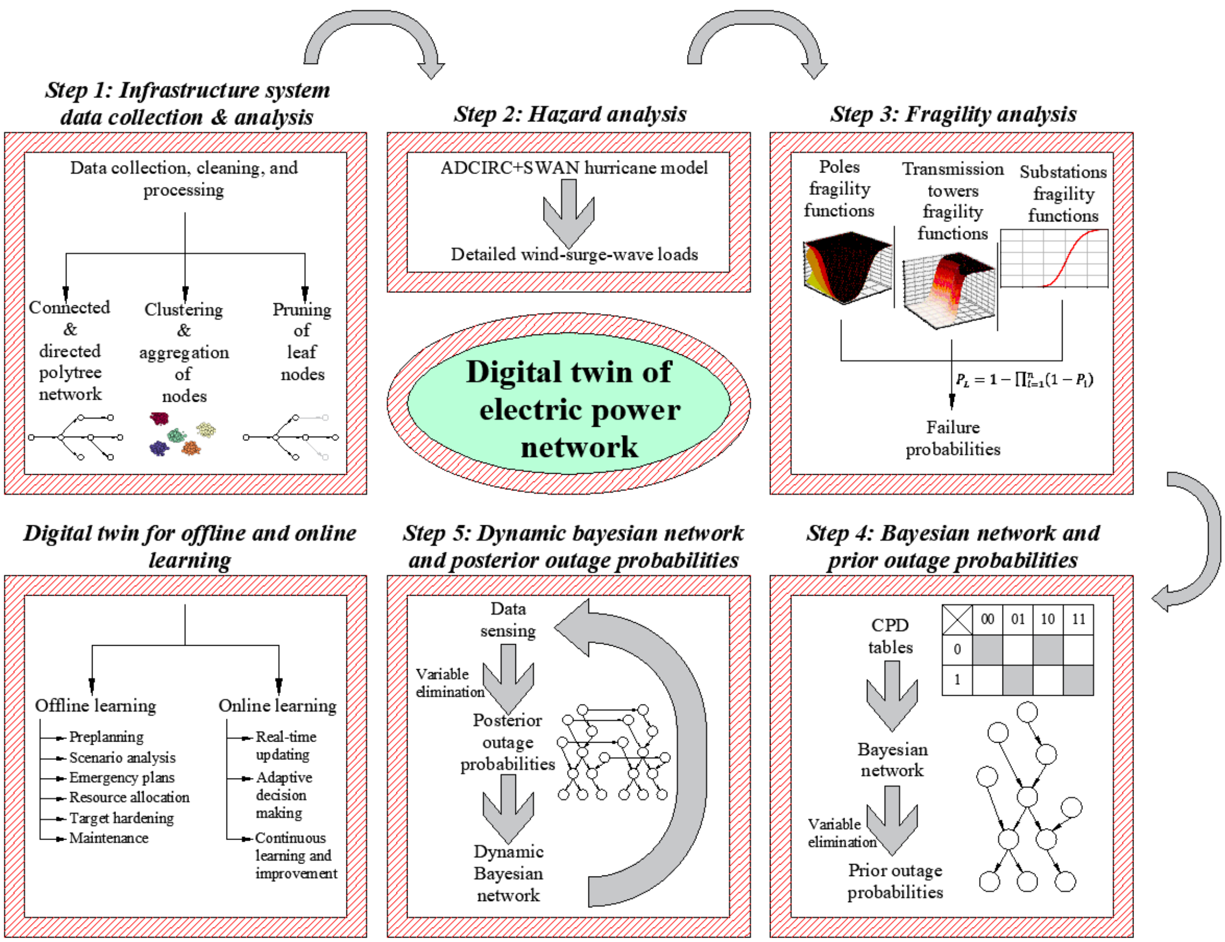



Figure 1: Flowchart showing key steps of the proposed digital twin framework of electric power networks.

### *2.1. Infrastructure system data collection & analysis*

A typical EPN consists of power generating plants, substations, power transmission systems, power distribution systems, and customers (Short, 2014; Hossain et al., 2019). Power plants are rarely affected by hurricanes and therefore are excluded from the proposed DT model. To achieve a high-fidelity model of the EPN, the proposed DT incorporates data on the location and properties of all major elements and their connectivity. This data is typically controlled by utility companies, and access may be restricted due to confidentiality concerns. To overcome data restrictions and facilitate research on community resilience, testbeds provide an environment where researchers can access relevant data, and develop and test their methodologies (Amin Enderami et al., 2022).

This data is cleaned and processed into a usable form, i.e., a directed graph of the network starting from the substations and ending with the customers (receiving service), that can be directly used in the BN. Moreover, a polytree, which is a network where there is only one path between any two nodes (Darwiche, 2009), is incorporated into the model since it allows for the use of the exact BN inference methods with computational time linearly proportional to the size of the data (Murphy, 2001). As the vast majority of the power networks in the U.S. are radial or at least operated radially, a network with no loops can be usually achieved (Short, 2014). However, in the case of the existence of a few loops in the system, it is recommended to break them using the shortest path (Magzhan & Jani, 2013) between the first and last nodes in the cycle. Hence, the proposed EPN model consists of a connected and directed network with no loops.

Based on what is recommended in the literature, the elements are aggregated and clustered into super-nodes that preserve the connectivity and interdependence within the network while reducing its size hence resulting in a computationally cheaper and more scalable method (Applegate & Tien, 2019). The transmission towers and distribution poles are aggregated into transmission lines and distribution lines, respectively in this model. Moreover, buildings can be clustered spatially and categorically into clusters. The Density-based spatial clustering of applications with noise (DBSCAN), which is a popular ML algorithm for spatial clustering based on the maximum distance between any two elements in the cluster (Khan et al., 2014), is used in the proposed DT resulting in clusters of similarly typed buildings that are spatially close and presumed to share a common feeder for electricity. The clustering of buildings may result in some distribution line nodes at the end of the network that are not connected to any cluster. These nodes can be pruned to reduce the size of the network without having a mathematical impact (Darwiche, 2009). In summary, the BN of the proposed model (described in the following sections) consists of substation nodes, transmission line nodes, distribution line nodes, and building cluster nodes.

### *2.2. Hazard analysis*

When studying a community prone to hurricane hazards, a detailed hazard model that captures the spatial variation in wind speed and direction as well as the accompanying wave and surge is needed. The coupling of the Advanced Circulation (ADCIRC) and Simulating Waves Nearshore (SWAN) models (Dietrich et al., 2011) allows for such highly detailed simulation. In the ADCIRC+SWAN model, the shallow-water equations are solved via the ADCIRC model that passes wind velocities and water levels to the SWAN model to simulate short-crested wind-generated waves. Eventually, the simulation will provide spatial variations of wind speed and direction, wave speed, direction, and height, surge height, and highest flood depth over the coastal area (Dietrich et al., 2012; Masoomi et al., 2019). Such a hazard model is incorporated into the proposed DT to perform the hazard analysis and generate the hazard loads on the infrastructure systems and components considered.

A comprehensive risk assessment requires the generation of stochastic hurricane scenarios and subsequent load simulations to quantify hazard load uncertainties (e.g., Wang et al., 2018). This can be performed for different return periods, enabling the assessment of varying levels of hazards and the associated risks (Darestani, Webb, et al., 2021). However, for the application study in this paper (as detailed in Section 3), we relied on the results of a single hindcast simulation of Hurricane

Ike (Darestani, Webb, et al., 2021). While this simulation provides highly detailed estimations of the maximum wind, wave, and surge loads for every location on Galveston Island, it is important to acknowledge that this study does not account for the uncertainties inherent in the hazard analysis, nor does it consider a range of hurricane return period scenarios.

### *2.3. Fragility analysis*

In this step of the proposed framework, fragility analysis for every element of the model is performed. A fragility function gives the conditional probability of failure given a hazard's intensity measure. Therefore, the probability of physical failure of each element of the model is computed using fragility functions and the loads obtained from the hazard analysis. Hence, the binary physical state (failure or survival) of the EPN elements is computed. The fragility functions used in this study are adopted from the existing literature and described below.

Darestani et al. (2022) have recently proposed a surrogate parametrized fragility function for <u>*wood utility poles*</u> fitted into a logistic regression model that considers various intensity measures and pole properties as its parameters, including wind speed $V_W$ (m/s) (3-s gust), wind direction $\theta_W$ (radians), water velocity $V_F$ (m/s), surge height $H_S$ (m), significant wave height $H_W$ (m), pole height $H_P$ (m), pole age $t_P$ (years), and conductor's effective area $A_C$ (m$^2$). The fragility functions for wood utility poles proposed by Darestani et al. (2022) are incorporated into the DT model. The probability of failure for the utility poles is then computed using Eq. (1), where $\sigma(y)$ is the standard logistic function defined in Eq. (2), and the coefficients $\alpha_0$ to $\alpha_7$ (for pole's rapture limit state and assuming stiff soil) obtained from Darestani et al. (2022) are summarized in Table 1 for classes 3, 4, and 5. Figure 2 (a) shows a multidimensional plot of the fragility function with varying intensity measures for $V_W, V_F, H_S,$ and $H_W$, while fixing the remaining parameters.

$$P(Pole\ failure|V_W, \theta_w, V_F, H_S, H_W, H_P, t_P, A_C) = \sigma\big(\alpha_0 + \alpha_1 V_W + \alpha_2\big(H_p - H_S - H_W\big) + \alpha_3 V_F H_S + \alpha_4 V_W \sin(\theta_W) + \alpha_5 V_W A_C + \alpha_6 max(t_P, 25) + \alpha_7 H_W\big) \quad (1)$$

$$\sigma(y) = (1 + \exp(-y))^{-1} \quad (2)$$

Table 1: Coefficients for wood pole's fragility function (data from Darestani et al. 2022)

| Class | $\alpha_0$ | $\alpha_1$ | $\alpha_2$ | $\alpha_3$ | $\alpha_4$ | $\alpha_5$ | $\alpha_6$ | $\alpha_7$ |
|---|---|---|---|---|---|---|---|---|
| 3 | -7.2476 | 0.02157 | 0.051976 | 0.29907 | 0.027067 | 0.002424 | 0.027865 | 0.51853 |
| 4 | -6.9997 | 0.020323 | 0.042443 | 0.30771 | 0.030009 | 0.00284 | 0.02892 | 0.53529 |
| 5 | -6.798 | 0.021067 | 0.040692 | 0.33019 | 0.033158 | 0.002863 | 0.026811 | 0.56842 |

The fragility function of *transmission towers* used in this study is obtained from Darestani, Jeddi, et al. (2021). More specifically, the extensive damage limit state is adopted to represent the physical failure of the tower. Therefore, the probability of failure for transmission towers subjected to wind speed $V_W$ (m/s) and direction $\theta_W$ relative to conductors is computed using Eq. (3), where the wind load is projected into perpendicular and parallel components. Parameters $\beta_0, \beta_1, \beta_2$, and $\beta_3$ obtained from Darestani, Jeddi, et al. (2021) are equal to -12.1438, 0.2056, -9.5395, and 0.1235 respectively (where $\beta_1$ and $\beta_3$ are scaled to modify the units from (mph) in Darestani, Jeddi, et al. (2021) to (m/s) in this study). Figure 2 (b) shows the fragility surface of transmission towers subjected to wind load.

$$P(Tower\ failure|V_W, \theta_W) = 1 - [1 - \sigma(\beta_0 + \beta_1 V_W \sin(\theta_W))][1 - \sigma(\beta_2 + \beta_3 V_W \cos(\theta_W))] \quad (3)$$

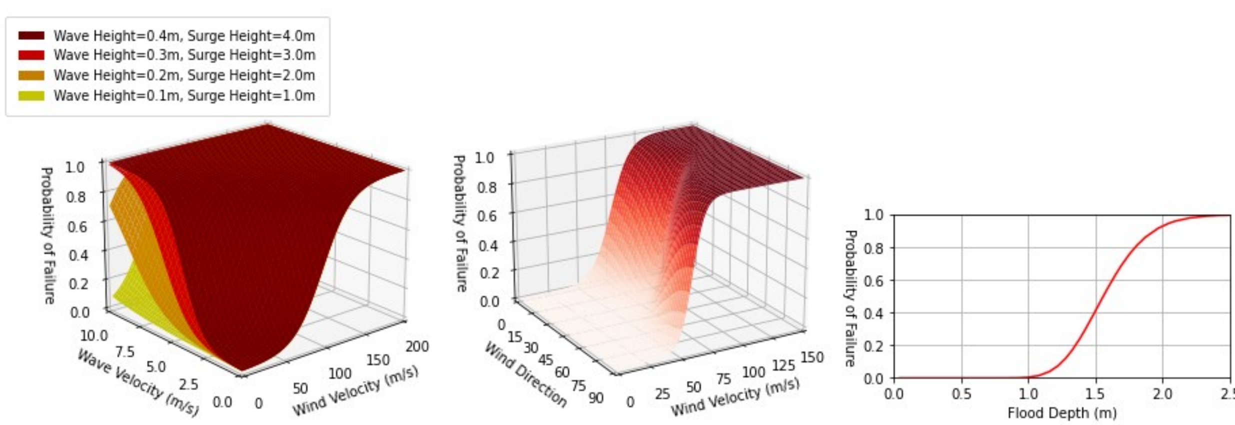
The electrical substations are rarely damaged by wind but are vulnerable to flooding caused by the flood accompanying hurricanes. The fragility curve for *electrical substations* adopted from FEMA (FEMA, 2009) and obtained from Sánchez-Muñoz et al. (2020) is incorporated into the model, where the intensity measure is the flood height $F$ (m). The curve was fitted to a lognormal distribution with parameters $\lambda = 0.443$ and $\zeta = 0.168$. Therefore, the probability of failure of substations can be computed using Eq. (4), where $\Phi(y)$ is the cumulative distribution function of the standard normal distribution. Figure 2 (c) shows the fragility curve for substations subjected to flood.

$$P(substation\ failure|F) = \Phi\big((\ln(F) - \lambda)/\zeta\big) \quad (4)$$

Once the fragility functions for all elements of the DT model are acquired, the probability of damage for a line $P_L$ containing $n$ elements (poles or towers) can be calculated using Eq. (5), where $P_i$ is the probability of failure of the i[th] element within the line.

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

It should be noted that ignoring the effect of adjacent elements might under-estimate the failure probabilities of connected poles and towers, while not considering the statistical correlations might over-estimate the probabilities of failure of lines (Salman et al., 2015; Darestani et al., 2017). However, due to the lack of data on the spatial correlation between adjacent poles and towers and to simplify the model, an assumption of statistical independence between elements within a line $P_L$ is adopted. Furthermore, it's worth noting that in this paper, the parameters of the fragility functions are modeled as point estimates. While previous studies have suggested modeling these parameters as random variables, which would allow for the incorporation of uncertainties and subsequent updating based on data evidence (e.g., Lu & Zhang, 2022), this approach would significantly impact the computational efficiency of the framework required for online learning.




(a) (b) (c)

Figure 2: Fragility functions for (a) Wood poles under various combinations of wind-wave-surge loads; (b) Transmission towers subjected to wind load of various velocities and directions; (c) Substations subjected to various flood depths.

### *2.4. Bayesian network and prior outage probabilities*

A BN is a probabilistic directed acyclic graph representing the causal structure between variables. The random variables are represented by nodes, while the edges between the nodes represent conditional dependencies. The BN can be viewed as a compact representation of the joint probability distribution between the random variables. In general, the full joint probability distribution of a BN with $n$ number of nodes can be written as shown in Eq. (6).

$$P(X_1, X_2, \dots, X_n) = \prod_{i=1}^{n} P\big(X_i | Parents(X_i)\big) \quad (6)$$

For this model, two types of nodes are assigned to each substation, transmission line, and distribution line in the BN. The first node (physical node) represents the physical state of the element (failed or survived) and is equal to the probability of failure discussed in Section 2.3, while the second node (performance node) represents the performance state of the element (outage or functioning) and is governed by both the state of the physical node of the same element and the state of the performance node of the upstream element. This is further explained using Figure 3 which presents a version of a small sample BN. In Figure 3, "F" stands for physical node, while "P" stands for performance node. Therefore, $FS_1$, $FT_1$, $FD_1$, and $FD_2$ are the physical nodes of substation-1, transmission line-1, distribution line-1, and distribution line-2, respectively, while $PS_1$, $PT_1$, $PD_1$, and $PD_2$ are the performance nodes of the above. Moreover, building clusters $C_1$, $C_2$, and $C_3$ are assigned performance nodes representing the state of power outage/restoration.

The edges between nodes represent the conditional dependencies. Hence, conditional probability distribution (CPD) tables are constructed to show the conditional probabilities for each child node given its parent nodes. In this paper, 0 is used to represent failure or outage, while 1 is used for survival or restoration. For a node without parents (such as the physical nodes in the EPN), the

CPD simply includes the physical probability of failure $P_f$ discussed in the previous section and shown in Figure 4 (a). On the other hand, the CPD of the performance node for the most upstream element (such as $PS_1$ in Figure 3) depends only on the physical node of the same element, as shown in Figure 4 (b). Moreover, the CPD of the performance node for the intermediate elements depends on both the physical node of the same element and its parent performance node, as shown in Figure 4 (c), while the CPD of the customer's performance node depends only on its parent performance node, as shown in Figure 4 (d).

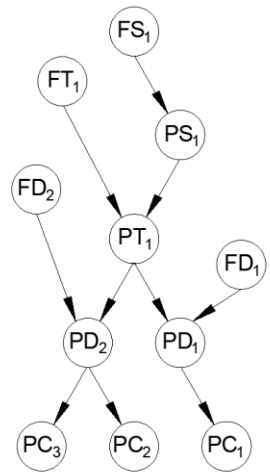



Figure 3: Sample BN.

| | |
|---|---|
| F=0 | $P_f$ |
| F=1 | 1-$P_f$ |

(a)

| | F=0 | F=1 |
|---|---|---|
| P=0 | 1 | 0 |
| P=1 | 0 | 1 |

(b)

| | $P_{parent}$=0 & F=0 | $P_{parent}$=1 & F=0 | $P_{parent}$=0 & F=1 | $P_{parent}$=1 & F=1 |
|---|---|---|---|---|
| P=0 | 1 | 1 | 1 | 0 |
| P=1 | 0 | 0 | 0 | 1 |

(c)

| | $P_{parent}$=0 | $P_{parent}$=1 |
|---|---|---|
| P=0 | 1 | 0 |
| P=1 | 0 | 1 |

(d)

Figure 4: CPD tables for (a) physical node; (b) upstream performance node; (c) intermediate performance node; (d) customer performance node. F= 0 or 1 represent the failure or survival states of the node respectively, P=0 or 1 represents the outage or restoration states of the node respectively, and $P_f$ is the probability of failure of the node

After building the BN, the probability of failure for every node within the network is calculated using forward propagation exact inference algorithms such as the variable elimination (VE) (Darwiche, 2009) algorithm. The VE algorithm is used to efficiently calculate marginal probabilities in the BN by iteratively eliminating variables until the desired variable is the only one left.

A simple example of a BN ($X_1 \rightarrow X_2 \rightarrow X_3 \rightarrow X_4$) can be used to demonstrate the VE algorithm, where $X_1, X_2, X_3$, and $X_4$ are binary random variables having $\mathrm{P}(X_1)$, $\mathrm{P}(X_2|X_1)$, $\mathrm{P}(X_3|X_2)$, and $\mathrm{P}(X_4|X_3)$ as factors representing the conditional probabilities associated with their nodes. These conditional probabilities can be directly obtained from the BN's CPD tables. Hence, the joint probability distribution can be factorized as shown in Eq. (7). If the desired query is to compute $\mathrm{P}(X_4)$, then $X_1$,$X_2$, and $X_3$ need to be eliminated via VE as shown in Eq. (8).

$$P(X_1, X_2, X_3, X_4) = \mathrm{P}(X_4|X_3)\,\mathrm{P}(X_3|X_2)\,\mathrm{P}(X_2|X_1)\,\mathrm{P}(X_1) \tag{7}$$

$$\mathrm{P}(X_4) = \sum_{X_3}\Big[\sum_{X_2}\Big(\sum_{X_1}[\mathrm{P}(X_4|X_3)\,\mathrm{P}(X_3|X_2)\,\mathrm{P}(X_2|X_1)\,\mathrm{P}(X_1)]\Big)\Big] = \sum_{X_3}\Big[\mathrm{P}(X_4|X_3)\sum_{X_2}\Big(\mathrm{P}(X_3|X_2)\sum_{X_1}[\mathrm{P}(X_2|X_1)\,\mathrm{P}(X_1)]\Big)\Big] = \sum_{X_3}\Big[\mathrm{P}(X_4|X_3)\sum_{X_2}[\mathrm{P}(X_3|X_2)\,\mathrm{P}(X_2)]\Big] = \sum_{X_3}[\mathrm{P}(X_4|X_3)\,\mathrm{P}(X_3)] \tag{8}$$

The process described above is generalizable to larger networks consisting of any number of nodes that are not necessarily in a chain. Therefore, the VE algorithm can evaluate the prior outage probabilities for every functional node by systematically computing their marginal probabilities by eliminating their parent nodes through forward propagation (Darwiche, 2009). While, in general, the computational complexity of the VE algorithm is exponentially related to the size of the data, it drops down to being linearly related if the BN is a polytree, as discussed in Section 2.1.

### *2.5. Dynamic Bayesian network and posterior outage probabilities*

The prior probabilities of the BN can be updated when new data (evidence) becomes available. The proposed DT is designed to be updatable using various sources of evidence, whether it is observed physical failure of substations, transmission towers, or utility poles, or being a detected outage/restoration of any substation, line, or building within the network.

The VE algorithm discussed earlier is again used to perform forward and/or backward propagation to compute the posterior marginals, where the joint probability distribution is conditioned over the evidence (Darwiche, 2009). The BN must be updated in real-time since the evidence data comes in separate batches, and because the outage and restoration states change over time, and therefore should only be used at the time it had been received.

The iterative updating of the BN is performed in the proposed model using a DBN, where the updated failure probabilities of physical nodes become the initial probabilities of failures of the next BN. As shown in Figure 5, if evidence is received that customer $C_3$ is out of power, then the probabilities of the entire BN at time $t_0$ ($BN_0$) are updated using the VE algorithm. Hence, knowing the real-time state of a few nodes within the system can enhance our estimations for all nodes that share common parent (upstream) nodes with them. Then, the updated physical node probabilities are passed to the BN at the time step $t_1$ ($BN_1$). Again, if evidence is received that the distribution line $D_2$ is out of power while customer $C_1$ got its power restored, then the failure probabilities of physical nodes of $BN_1$ are updated and then passed to the next BN at the time step $t_2$ (BN2). Likewise, the DBN is updated for every time step $t_m$.

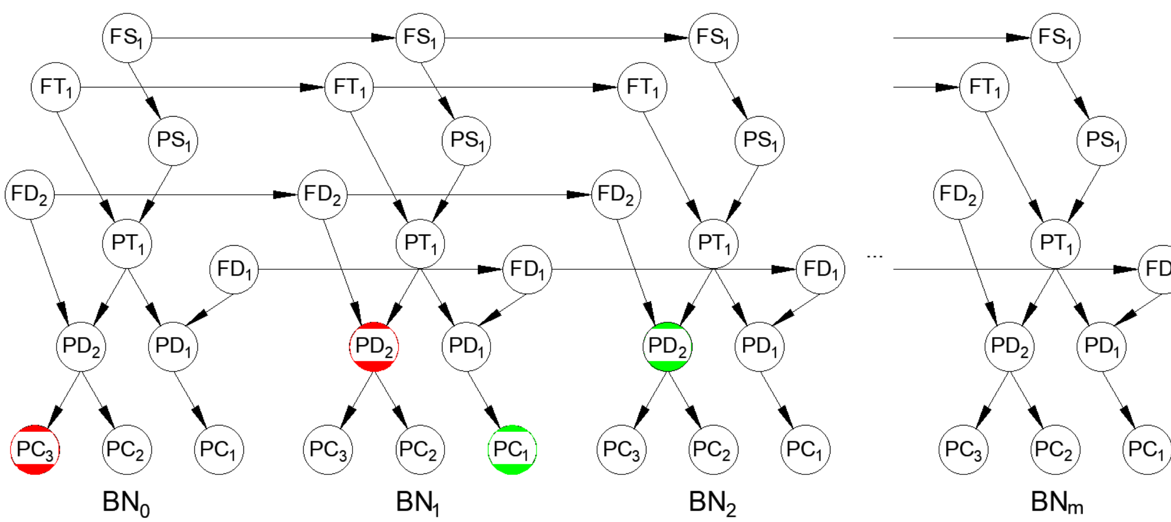



Figure 5: Sample DBN.

## 3. Application case study

### *3.1. Application of DT model on Galveston Island testbed*

The application of the proposed DT framework is demonstrated via an application case study for the Galveston Island testbed subjected to Hurricane Ike hazard loads. An extensive literature review on the Galveston testbed and other testbeds used in community resilience research is summarized in Amin Enderami et al. (2022). Detailed data of Galveston's EPN (locations, properties, and connectivity of substations, transmission towers, and utility poles) and building inventories (locations and properties) in addition to Ike's simulation data were obtained from Darestani and Padgett (2022) and Incore (2023).

The data was cleaned and processed as discussed in section 2.1 to ensure a connected, directed, and polytree network starting from the substation located on the mainland before Galveston's bridge and continuing through transmission towers, intermediate substations, and distribution poles. Except for a submarine power cable that connects the mainland to Galveston Island, all lines are assumed to be overhead. Moreover, the distribution lines consist of 3 wires of a 0.0183m diameter (Salman et al., 2015), and the substations are assumed to lay on an elevated foundation pad 0.7m tall, above which they will be vulnerable to flooding.

The cleaned EPN dataset consists of 13,207 utility poles, 52 transmission towers, and 9 substations, in addition to 24,756, 2,681, and 357 residential, commercial, and industrial building inventories, respectively. These buildings were clustered using the DBSCAN algorithm into 2,102, 1,108, and 248 residential, commercial, and industrial clusters, respectively. In order to balance between computational efficiency (larger clusters) and model accuracy (smaller clusters), a 40m maximum distance for clustering was selected. Moreover, the EPN poles and towers were aggregated into lines, and the end lines (leaf nodes) not connected to building clusters were pruned. In summary at the DT model, the EPN consists of 2,718 distribution lines, 1 transmission line, and

9 substations. The EPN of Galveston Island is shown in Figure 6, and the building inventory map before and after clustering is shown in Figure 7 (a) and Figure 7 (b), respectively.

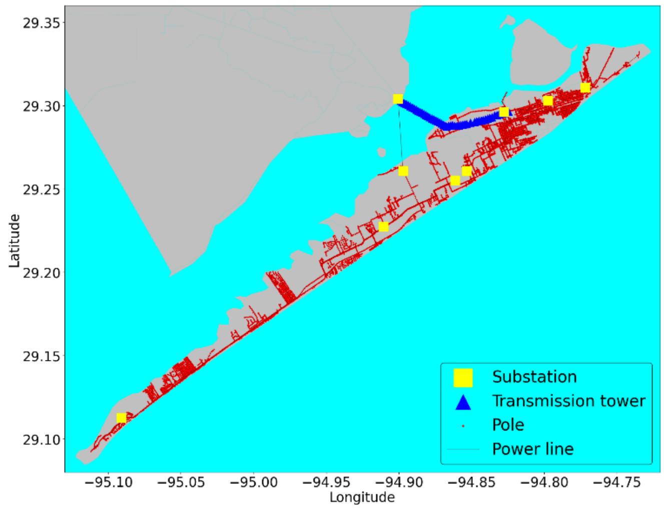


Figure 6: Graphic view of Galveston Island's EPN incorporated in the DT model.

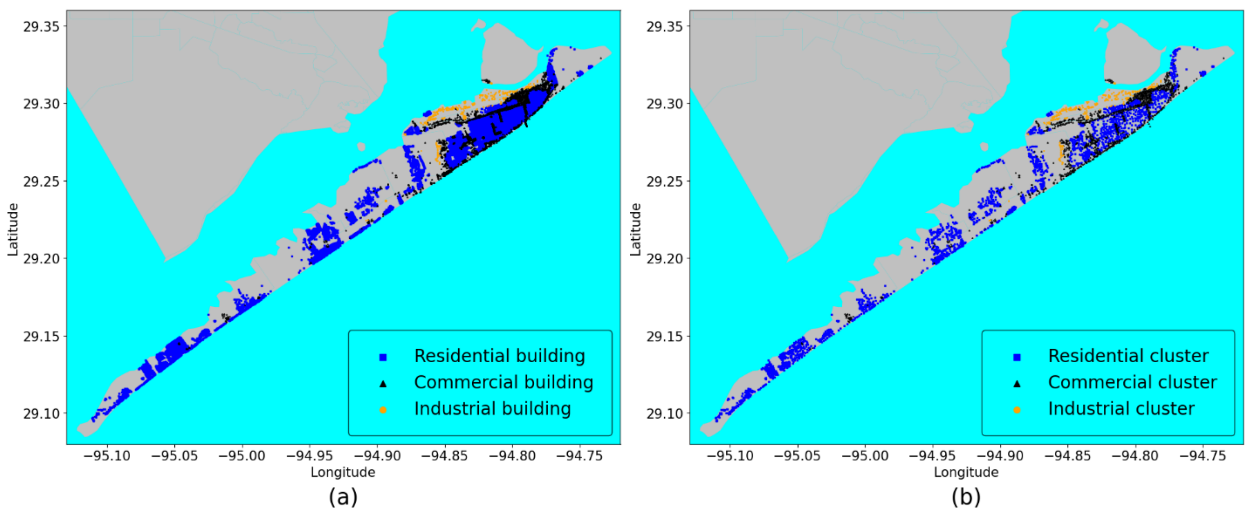


Figure 7: Building inventory map: (a) before clustering; (b) after clustering.

Fragility functions were used to estimate the failure probabilities shown in Figure 8. To get more insight on the estimations, the expected number of failures for each category (substations, tower, or poles) was calculated by summing the probabilities of failures for elements within the category by assuming that they follow independent Bernoulli distributions (Wang, 1993). The transmission towers are the least affected, with 0 expected failed towers, while the utility poles suffered considerable damage with 211 expected failed poles. Moreover, the substations are highly vulnerable to large flood depths with 4 substations experiencing flooding.

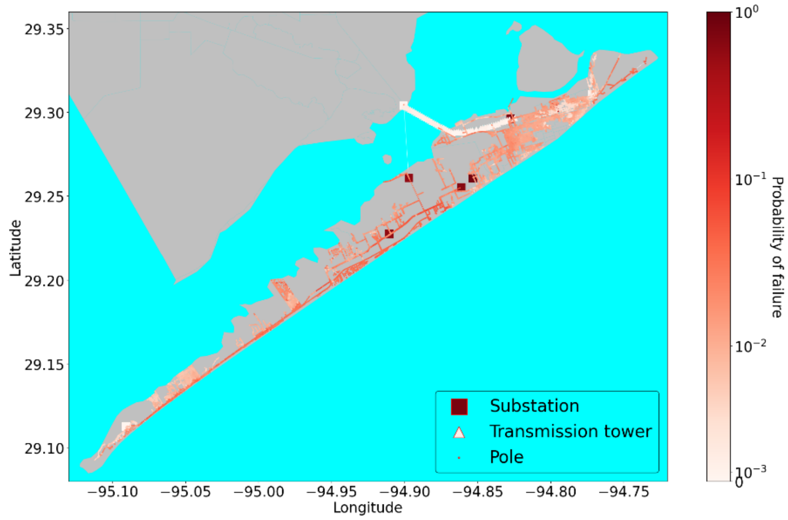



Figure 8: Estimated probability of failure to EPN's elements.

In the next step of the proposed framework, the BN was built using the 8,914 EPN and customer nodes, and the VE forward propagation was used to estimate the outage probabilities for customers, as shown in Figure 9 (a). The model estimated an almost complete power outage for the entire island, with 96.3% of the customer's electricity estimated to be wiped out. Building-type specific estimations can be made to allow decision-makers to give different weights to different land uses, with estimated outages of 96.4%, 96.0%, and 94.2% for residential, commercial, and industrial buildings, respectively. Moreover, since the priority of repair is usually given to the substations, decision-makers might be interested in the outage conditions immediately after the substations are repaired. This can be estimated by updating the BN using the repair evidence. We performed this scenario (all substations are repaired) and the results are shown in Figure 9 (b). After updating the physical state of all substations to "repaired", the model's estimations show that electricity was restored to customers in some areas on the island. However, the model still estimates a large blackout due to failed poles.

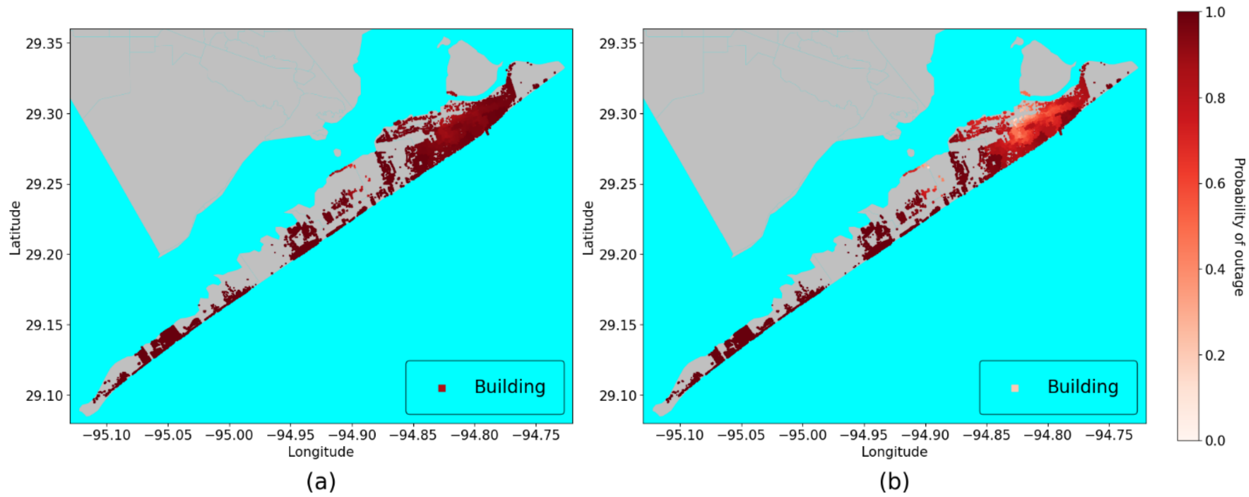



Figure 9: DT outage map for: (a) prior estimations (b) posterior estimations after repair of substations.

#### *3.1.1. Validation of the case study results using historical data*

As per the historical records, Hurricane Ike destroyed 10,300 utility poles, 238 transmission towers, and 383 substations, causing 3.9 million customers in nine states in the United States to lose power (Hoffman et al., 2009). However, the majority of the damaged transmission towers were reported to be in Louisiana and east Texas, while transmission towers in the Greater Houston area performed well with no major damage (Prochazka, 2009). Outages were primarily caused by damage to distribution lines and substations, with 8,500 utility poles in the Greater Houston area requiring replacement following the hurricane (Mckinley, 2008; Prochazka, 2009). Furthermore, four substations on Galveston Island were flooded, with three being restored within three days and the fourth requiring complete replacement (Prochazka, 2009). The day after the hurricane, two of the major power supplying companies in the Greater Houston area reported that 99% of their customers were without power and that the electricity in the Galveston Island and Bolivar Peninsula had been completely wiped out (Reuters, 2008; Hoffman et al., 2009).

The DT model's results, as presented in Figure 9 (a) and discussed in the previous section, are consistent with the historical data, as the model estimated a nearly complete power outage for most of the island. Furthermore, the model estimated considerable failure to utility poles and substations, while transmission towers had low failure probabilities. The validation of the model's results against the historical records is summarized in Table 2.

Table 2: Validation of the DT model estimations with historical data

| | **Historical records** (Mckinley, 2008; Reuters, 2008; Hoffman et al., 2009; Prochazka, 2009) | **DT model estimations** |
|---|---|---|
| **Power outage** | 99% of customers lost electricity in the Greater Houston Region | 96.3% of customers lost electricity in Galveston |
| **Flooded substations** | 4 in Galveston | 4 in Galveston |
| **Damaged towers** | 0 in Galveston | 0 in Galveston |
| **Damaged poles** | Considerable damage to utility poles (~8500) in the Greater Houston Region | 211 in Galveston |

### *3.2. Case study using Twitter data and dynamic Bayesian network*

The DBN method discussed in section 2.5 can be used to update the BN using evidence data. Scrapping tweets as old as Hurricane Ike is difficult because of Twitter's policies that make it harder to scrape tweets the older they get. This and the fact that Twitter was still a new social media platform at that time and geotagging was not as common as it is today makes it almost impossible to scrape tweets from the time of Ike's occurrence to be applied in this study. In order to evaluate the capability of the proposed framework to be updated with real-time data, tweets were instead scraped for winter storm Uri which resulted in a power outage in Texas and particularly Galveston Island in 2021 (King et al., 2021). Tweet scrapping was performed using the SNSCRAPE Python library (JustAnotherArchivist, 2021). The tweets were filtered to only include geotagged tweets between February 13$^{th}$ and 20$^{th}$ (2021) that include the keywords "power", "outage", and "electricity" with the geotagged locations being on Galveston Island. We obtained 65 tweets and manually classified them into "outage", "restoration", and "neutral" tweets. After the classification, the data includes 36 outage tweets and 19 restoration tweets, each of which was assigned to the nearest residential building, and then used as evidence to update the DBN. While the use of Uri's data doesn't have historical accuracy as it comes from a different storm, it still can demonstrate how the BN can be updated and follow the data obtained from the actual system in real-time. Therefore, when evidence data is obtained for the outage/restoration state of any customer, this information can be used to update the prior outage probabilities for the entire island, affecting the estimations for customers who share a common upstream line with those for whom evidence have been received, even if we haven't directly obtained data for them. This is shown in Figure 10 (b), where the posterior outage probabilities show the restoration of power to large areas of the island driven by only 19 restoration tweets.

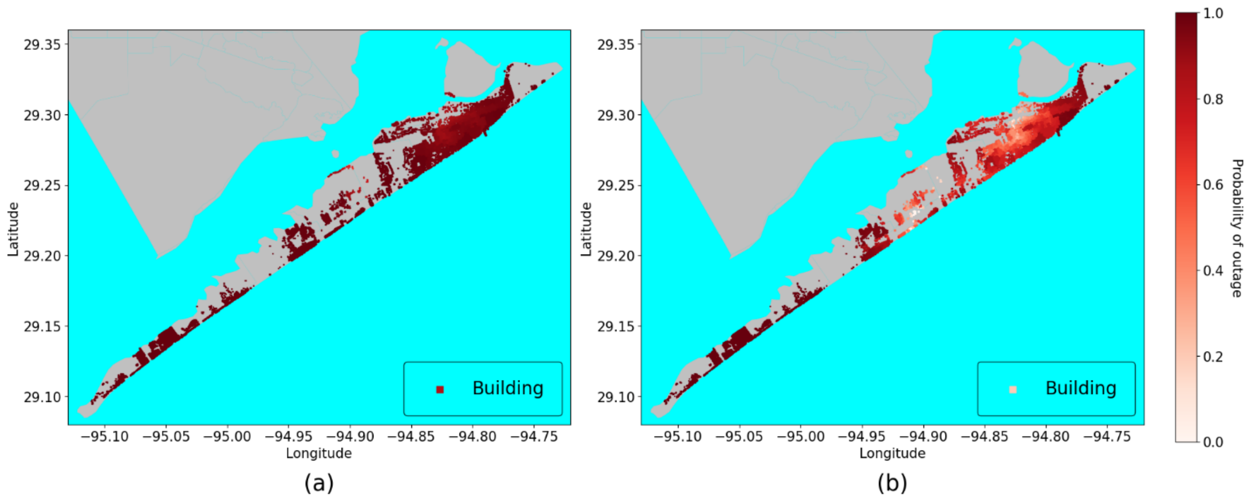



Figure 10: DT outage map for (a) prior estimations (b) posterior estimations using Twitter data (related to winter storm Uri).

### *3.3. Discussion on the computational efficiency of the proposed DT framework*

The Python programming language is used to code all the analysis in this study on a desktop computer with 64 GB RAM, (3.7) GHz CPU, and Intel Xeon E3 processor. The BN was highly efficient in modeling thousands of nodes, with approximately 75 seconds of run time for the forward propagation algorithm. Moreover, the total run time for the iterative updating of the DBN using Twitter's data was around 16 minutes.

## 4. Conclusions and future work

This paper introduces a simple and practical DT framework of the EPN when subjected to hurricanes. First, the foundations of the concept of the DT at the community level are clearly established, and the DT is presented as a tool for prediction and decision-making, thus making it applicable and giving it a clear and well-defined purpose. Then, the proposed framework is discussed in detail starting from data analysis and ending with the use of the DT for offline and online learning. After that, the DT is applied to the Galveston testbed using Ike's simulated hurricane as an application case study, and it is demonstrated that the proposed method is capable of efficiently modeling a large network with tens of thousands of EPN elements and buildings. Finally, the results are validated using historical outage and failure data and are shown to provide detailed and highly accurate estimations.

The proposed DT is designed to be scalable and able to extend to model other infrastructure systems and ultimately model the community as a system of systems. Moreover, it can pave the way for future DT frameworks. Therefore, future research can expand the current work to model the interdependencies between the EPN and other critical infrastructure systems such as water, transportation, and telecommunication networks. The proposed framework can also be extended to a life cycle and periodic maintenance DT of the EPN and other infrastructure systems. Future research can target post-disaster management and how the proposed DT can be used to guide and redirect restoration plans. Thus, this paper lays the groundwork for future research on community and infrastructure digital twins, which is a crucial step toward achieving smart and resilient city planning.

## 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.

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