

Resilience Assessment for Distribution Systems during Hurricanes: A Learning-Based Framework

Soroush Vahedi, *Student Member, IEEE*, Junbo Zhao, *Senior Member, IEEE*, Jin Dong, *Member, IEEE*, Bin Wang and Jianming Lian *Senior Member, IEEE*

Abstract—This paper presents a proactive strategy to enhance the resiliency of distribution systems during hurricanes. A granular probabilistic outage prediction model is developed based on a Bayesian Neural network incorporating various weather parameters, electricity infrastructure data as well as environmental factors, such as tree distance and tree orientation. Dealing with imbalanced and sparse power component outage datasets is however a challenging problem in data mining. To address this, the Bias-Variance Tradeoff method is proposed. Using a resilience assessment model, resilience indices are quantized from both the system and component perspectives in the power distribution system, bringing a clear insight into identifying the weak points of the system. The proposed approach can help recognize the system's weak points and serve as a benchmark for distribution system planning. Numerical results on the modified IEEE 123-node test system demonstrate the effectiveness of the proposed framework considering realistic hurricane scenarios.

Index Terms—Bayesian Neural Network, distribution system resiliency, extreme weather, outage prediction, resilience assessment.

I. INTRODUCTION

Due to climate change, there is increasing extreme weather events induced power outages worldwide [1]. Past storms, such as Hurricanes Irene and Sandy, the October 2011 Nor'easter, and Tropical Storm Isaias devastated the northeastern U.S., leaving millions without power and significant economic losses estimated at \$70 billion annually in the U.S. [2]. Enhancing grid resilience by predicting and mitigating high impact low probability (HILP) events is essential [3]. In general, system resilience is determined by three stages: before the event (proactive scheme), degradation, and post-event recovery [4]. This study explores the specific impact of hurricanes on distribution grids, aiming to promote power resilience and economic stability through proactive measures. Predicting future hurricanes' frequency and severity is challenging due to limited historical data [5], [6]. While hurricane wind field models have been developed for various scenarios [7], [8], most existing approaches lack capturing the probabilistic aspects of hurricanes as random phenomena from a planning standpoint [9]. Weather-related failure risk prediction and assessment, a critical part of assessing system resilience [3], can be categorized into the physics-based approach and data-driven approach [10]. Power grid resilience analysis under extreme weather conditions has largely been done based on physics-based fragility functions to describe the probability of component outages [6], [9], [11], [12]. Machine learning and artificial intelligence techniques are becoming more popular in recent years as physics-based methods have become limited in terms of quantifying various parameters and are unavailability [13]. A proactive scheme based on learning

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described in [14] focused on just two windstorm-related factors: wind speed and distance from the center. Consequently, the researchers in [4] used deep neural networks (DNN) to predict line outage occurrence based on electrical and geographic characteristics but failed to take into account uncertainty in their model and variability of weather conditions. As ML techniques are often evaluated on predictive accuracy, imbalanced data is often overlooked, such as power outages, where fewer components are out of service than are in service [15], [16]. To address this issue, a two-stage model using a random forest (RF) was developed in [15], [16]. The studies showed Synthetic Minority Over-Sampling Technique (SMOTE) performed better at dealing with imbalanced data [17]. Due to parameter tuning, SMOTE may still cause overfitting and reduced model generalization.

Multi-phase resilience trapezoid indices, based on the resilience triangle, have been developed to quantify the performance decline and recovery after severe weather events [18]. These indices, however, only evaluate the resilience of the entire system, which makes it necessary to develop a model to identify weak points in the power system during natural disasters. In distribution networks, detecting outages is challenging due to their unobservable nature compared to transmission systems [19]. A planning-oriented framework was introduced in [6] to assess resilience against hurricane disasters and identify vulnerable points, with a particular focus on a transmission system. However, its applicability to other systems is unclear.

This paper proposes a data-driven approach using a Bayesian Neural Network (BNN) to predicate line outages with uncertainties quantified. The BNN is trained using historical data and various factors describing the network's environment and structure. Hurricane scenarios would be generated using a physics-based model (Bette model [7]) and state enumeration method. The trained BNN then evaluates the probability of each line outage for the generated scenarios, the uncertainty and variability of both weather and power system components, resulting in more reliable and robust prediction for HILP events. The method can also handle skewed distributions of imbalanced datasets and the proposed resilience assessment framework can be applied to other natural hazards for assessing their impacts on power systems [12], [20].

II. PROPOSED METHOD

The proposed framework as shown in Fig. 1 consists of three main steps. Firstly, a probabilistic hurricane model is developed by parameter recognition and state enumeration (combinatorial method) [6]. Secondly, an outage predictive model (OPM) for the distribution network is built using BNNs based on historical data for predicting line failures during potential hurricanes. Finally, a resilience assessment model is established to quantify system and component resilience, including the impact-increment-based state enumeration (IISE) method for efficient computation [21], [22].

A. Probabilistic hurricane Model

This paper uses the Batts model to simulate real-time wind speed at multiple hurricane locations [6]. The model quantifies hurricane uncertainty by parameter identification and probability distributions.

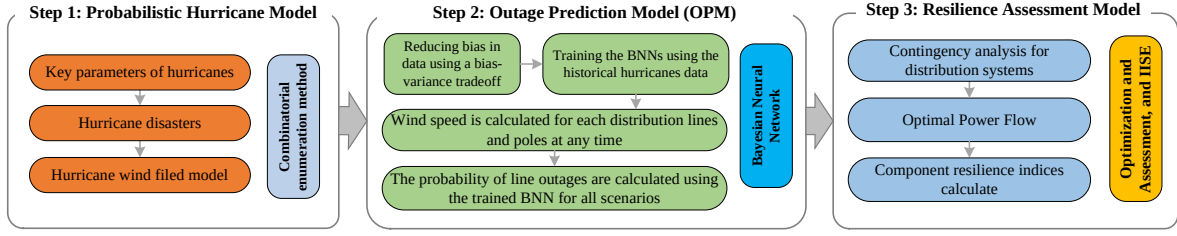


Fig. 1. The proposed probabilistic outage prediction framework for distribution system resilience assessment.

The hurricane attenuation is modeled by reducing pressure differences between the periphery and its center.

$$\Delta H(t) = 0.75\Delta H_0 - 0.508 [1 + \sin(\varphi - \theta)] t, \quad (1)$$

where $\Delta H(t)$ is the central pressure difference at time t (hour), $\Delta H_0(t)$ is the original central pressure difference before the hurricane landing, which are given in mm, θ is the angle between the hurricane motion direction and the due north direction - the clockwise is positive, φ is the angle between coastline and the due north direction. Then, the maximum wind speed is calculated as follows:

$$v_{r_{\max}}(t) = 6.029 \sqrt{0.75\Delta H_0 - 0.508 [1 + \sin(\varphi - \theta)] t} + 0.5v_T, \quad (2)$$

where v_T is the translational speed of a hurricane (m/s). The wind speed of a specific location in the hurricane wind field is given by

$$v_r(t) = \begin{cases} v_{r_{\max}}(t)d(t)/r_{\max}(t), & d(t) \leq r_{\max} \\ v_{r_{\max}}(t)(r_{\max}(t)/d(t))^{0.6}, & d(t) > r_{\max} \end{cases}, \quad (3)$$

where $d(t)$ is the distance between a location and the hurricane center at time t , and $r_{\max}$ is the radius of maximum wind speed, which can be calculated:

$$r_{\max}(t) = \exp(2.63 - 5.086 \times 10^{-5} \Delta H(t)^2 + 0.0395y(t)), \quad (4)$$

where $y(t)$ is the latitude of hurricane center at time t . It should be noted that the ΔH in (4) is given in mb. A hurricane center can be identified at time t by translating latitude and longitude coordinates to rectangular axes:

$$x(t) = x_0 + v_T t \cos \theta, \quad (5)$$

$$y(t) = y_0 + v_T t \sin \theta, \quad (6)$$

The distance between a location and the hurricane center at time t is calculated as follows:

$$d(t) = \sqrt{[x_d - (x_0 + v_T t \sin \theta)]^2 + [y_d - (y_0 + v_T t \cos \theta)]^2}, \quad (7)$$

where x_d and y_d are the longitude and the latitude of d meters from the hurricane center, respectively; x_0 and y_0 are the longitude and the latitude of the hurricane landing sites, respectively. To calculate the duration time of a hurricane, (8) is defined based on the central pressure differences:

$$T = 1.476\Delta H_0 [1 + \sin(\varphi - \theta)], \quad (8)$$

The main key parameters affecting hurricane wind speed are the original pressure difference $\Delta H_0(t)$ (1), translational speed v_T , motion direction θ , and landing site coordinates (x_0, y_0) . Thus, the probability density function of these key parameters can produce potential hurricanes and their likelihoods. Based on the combinatorial enumeration method [10], the occurrence probability of a hurricane w in a specific region can be obtained by (9)

$$P_w = P_r(\Delta H_0, w) P_r(v_T, w) P_r(\theta_w) P_r(x_0, w, y_0, w), \quad (9)$$

The probability density function of each key parameter is divided into several equal portions. Within these segments, a group of key parameters are enumerated to create potential hurricanes. For example, given the original pressure difference $\Delta H_0(t)$, its probability density function is divided into c equal portions with C_H interval. Thus, the occurrence probability for the original pressure difference under hurricane w denoted by $\Delta H_{0,w}(t)$ is obtained by

$$P_r(\Delta H_{0,w}) = \int_{\Delta H_{0,w} - C_H/2}^{\Delta H_{0,w} + C_H/2} f(\Delta H_0) d\Delta H_0, \quad (10)$$

Thus, $Pr()$ in (9 and 10) is the probability of each parameter, and c is the length of each portion.

B. Proposed Outage Prediction Model (OPM)

Traditional models, namely regression or decision trees [23], [24], assume noise-free and deterministic observations. Power outage prediction problems may involve measurement errors, missing values, and variability. Bayesian Neural Networks (BNNs) [25] address the uncertainties by modeling the posterior distribution of parameters based on data and prior distributions. This paper establishes BBN for predicting line failures. Firstly, the BBN is trained using historical windstorm data and applied to assess line failure probability for all generated hurricane scenarios.

1) *Bayesian Neural Network*: The method uses probability distributions to represent parameters and estimate uncertainty (refer to Fig. 2). By using the prior distribution to represent the parameters, the average value on models would be calculated during training. This hinders overfitting by providing regularity to the network. Given the features inputs $\mathcal{D} = \{x_i\}_{i=1}^N$ and known line outage probability $\mathcal{D} = \{y_i\}_{j=1}^N$ with unknown parameters ω , the Bayesian formula calculates posterior distribution $p(\omega|\mathcal{D})$:

$$p(\omega|\mathcal{D}) = \frac{p(\mathcal{D}|\omega)p(\omega)}{\int p(\mathcal{D}|\omega)p(\omega)d\omega} \quad (11)$$

where the term $p(\omega)$ refers to the initial distribution of the intended data, while $p(\omega|\mathcal{D})$ is the likelihood function giving prior confidence in the model productive ability. Nonetheless, posterior distribution $p(\omega|\mathcal{D})$ is intractable directly for neural networks. To address this, Bayes by Backprop [26] is used as a variational inference technique for approximating the Bayesian posterior distribution. The method is to simplify approximate distribution $\omega \sim q_\theta(\omega|\mathcal{D})$ with variational parameters θ , which then approaches the underlying true distribution $p(\omega|\mathcal{D})$. The objective aims to minimize the Kullback-Leibler (KL) divergence between p and q , with the optimal objective θ_{opt} .

$$\begin{aligned} \theta_{opt} &= \arg \min_{\theta} \text{KL}[q_\theta(\omega|\mathcal{D})||p(\omega|\mathcal{D})] \\ &= \arg \min_{\theta} \text{KL}[q_\theta(\omega|\mathcal{D})||p(\omega)] - \mathbb{E}_{q(\omega|\theta)}[\log p(\mathcal{D}|\omega)] \\ &\quad + \log p(\mathcal{D}) \end{aligned} \quad (12)$$

where $\text{KL}[q_\theta(\omega|\mathcal{D})]$ denotes the KL divergence between variational posterior and prior. The term $\mathbb{E}_{q(\omega|\theta)}[\log p(\mathcal{D}|\omega)]$ is the degree of fit

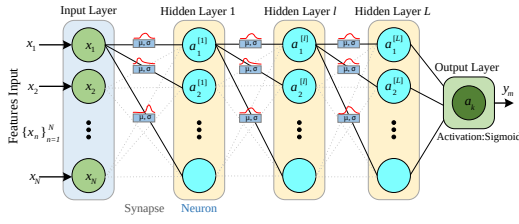


Fig. 2. The structure of Bayesian neural networks.

between the weight and the prior. The term $\log p(\mathcal{D})$ can be dropped since it is not dependent on θ . Given the unbiased Monte Carlo gradients, a tractable objective function can be defined as follows:

$$\mathcal{F}(\mathcal{D}, \theta) \approx \sum_{i=1}^n \log q_{\theta}(\omega^{(i)} | \mathcal{D}) - \log p(\omega^{(i)}) - \log p(\mathcal{D} | \omega^{(i)}) \quad (13)$$

where the term $q_{\theta}(\omega^{(i)} | \mathcal{D})$ denotes the variational posterior, which cannot be directly computed. To evaluate the gradients of this term, the reparameterization is used. This assumes that weights ω are obtained by sampling a Gaussian distribution with mean μ and standard deviation σ , where σ is parameterized as the non-negative value $\sigma = \log(1 + e^{\rho})$. The variational posterior parameters θ can be expressed as $\theta = (\mu, \rho)$, while $p(\omega^{(i)})$ is the prior distribution over weight $\omega^{(i)}$ as a univariate Gaussian distribution.

$$p(\omega^{(i)}) = \prod_i \mathcal{N}(\omega_i | 0, \sigma_p^2). \quad (14)$$

The term $p(\mathcal{D} | \omega^{(i)})$ represents the likelihood cost of observation input.

2) *Bias-Variance Tradeoff*: An imbalanced power outage data set can result in high bias due to its imbalanced nature. Thus, this paper has used a uniformly random method to help balance scenarios with probabilities near one and zero by removing data samples with probabilities close to zero. Let's assume the expected prediction error is expressed as follows:

$$EPE = E[(y - \tilde{y})] \quad (15)$$

where y is the true response value, $\tilde{y}$ is the predicted response value and E is the expectation operator. The EPE can be further decomposed into:

$$EPE = Var(\tilde{y}) + [Bias(\tilde{y})]^2 + Var(\epsilon) \quad (16)$$

where $Var(\tilde{y})$ is the variance of the model predictions, $Bias(\tilde{y})$ is the bias of the model predictions and $Var(\epsilon)$ is the variance of the irreducible error. In this way, $Bias(\tilde{y})$ can be reduced by removing samples with low probabilities. Since samples with high probabilities are preserved, $Var(\tilde{y})$ would not be affected much (the variability of model predictions does not change). This means that the model can still capture variability in the data. It can also make predictions not be overly constrained or limited by the removal of biased samples.

C. Resilience Assessment Model

1) *System Resilience Assessment*: The system resilience index R_{sys} is assumed equal to the expected load shedding subjected to the enumerated failure scenarios due to various potential hurricane disasters. To simplify the computational burden and preserve the result accuracy, the IISE method is used. Thus, the system resilience indices are based on considering J orders for failure scenarios in each hurricane.

$$R_{sys} = \sum_{w=1}^W P_w \sum_{j=1}^J \sum_{s \in \Omega_A^j} \left(\prod_{i \in s} p_{w,i} \right) \Delta I_{w,s}, \quad (17)$$

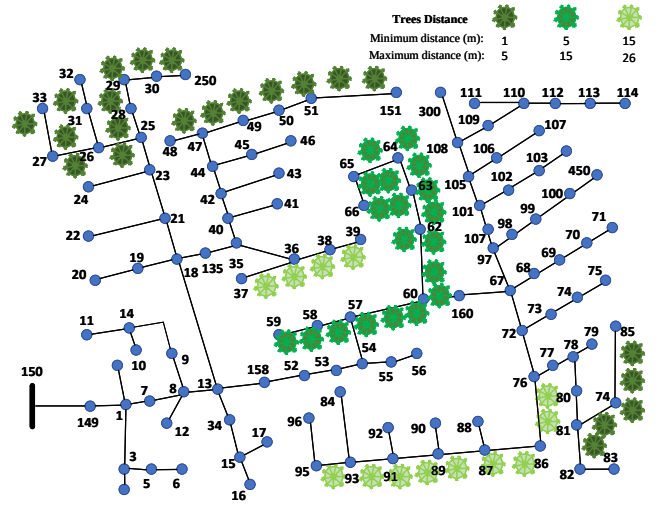


Fig. 3. Topology of the modified IEEE 123-node system.

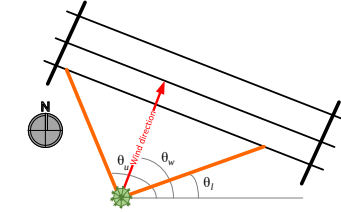


Fig. 4. Risk of the tree falling on the distribution line.

where W is the total number of potential hurricane disasters, the probability of hurricane w is shown by P_w , Ω_A^j is the j order subset of A and failure scenario is represented with s , including various combination of distribution lines failures. The term $p_{w,i}$ is the failure probability of the i^{th} line under specific hurricane w , and the impact-increment of load shedding of the failure scenario s under hurricane w is shown with $\Delta I_{w,s}$. The impact of the distribution line cut is determined by doing a contingency analysis proposed in [27]. To do so, line flows and bus voltages following one or more component failures are calculated and any overloading, voltage violation, isolated bus, or split island are identified.

2) *Component Resilience Assessment*: The component resilience index is to detect the vulnerable lines that may cause severe load shedding after their cut by the hurricane. The component resilience indices based on the IISE method are calculated via (19) [10]

$$R_m = \sum_{w=1}^W P_w \sum_{j=1}^J \left[p_{w,m} \sum_{\substack{s_m \in \Omega_A^j \\ m \in s_m}} \left(\prod_{i \in s_m} p_{w,i} \right) \Delta I_{w,s_m} \right] \quad (19)$$

where $p_{w,m}$ is the cumulative failure probability of the m^{th} distribution line under hurricane w . The term s_m represents a failure scenario denoted by a set of corresponding failed distribution lines, including the m^{th} distribution line.

III. CASE STUDY

The practicality and effectiveness of the proposed framework are tested on the modified IEEE 123-node distribution system [28]. Originally, there were 122 overhead radial distribution lines [29]. The system is transformed into a balanced system as per [30] (Fig. 3). The blue circle shows the distribution nodes with their associated

number. Only distribution line damages are taken into account, with distribution poles assumed to stand every 38 meters along the lines. As per [31], it is possible to estimate the positions of all line segments and towers. According to [10], Guangdong province's coastal areas are often affected by hurricanes. The modified IEEE 123-bus distribution system is attached to the geographical map of Guangdong province. The simulation time interval is set to 10 minutes.

A. BNN Model Training and Validation

The effectiveness of the proposed OPM-based BNN is tested with a group of crucial lines on each branch, considering different physical and environmental factors. To include geographical features in the OPM, different distance classes from high trees and different positions of trees relative to the lines (tree azimuth class) are considered for this study, see Fig. 3. In general, five selected features are used for OPM: average distance from a tall tree, tree azimuth class, the average distance between line and hurricane, and the average speed and central pressure of a hurricane. To highlight the importance of the tree azimuth class, Fig. 4 illustrates that if the wind direction falls within the range $[\theta_l, \theta_u]$, a tree is deemed to have the potential to fall on the line, and is classified as a risk tree. The BNN model with four hidden layers is used here for OPM. Due to the lack of historical data, 1500 scenarios are synthesized by using physical models proposed in [6] and [9]. A distance coefficient has been incorporated into the physical models to account for the impact of varying distances from trees on line outages. Using this coefficient, the design wind speed of each line and pole in the physical model is decreased deceptively as the distance from the tree decreases (the probability of line outage is proportional to the design wind speed in the physical models). After applying a bias-variance tradeoff to the generated data, the OPM-based BNN is implemented; while 80% of the data is utilized for training the BNN, the remaining is applied for validation testing. According to Fig. 5, the trained BNN demonstrates effective prediction performance with a 99.7% confidence interval. According to this figure, univariate marginal distributions of the predicted and real probability for line outages show bias-variance tradeoff has successfully reduced bias in data while maintaining variance in data.

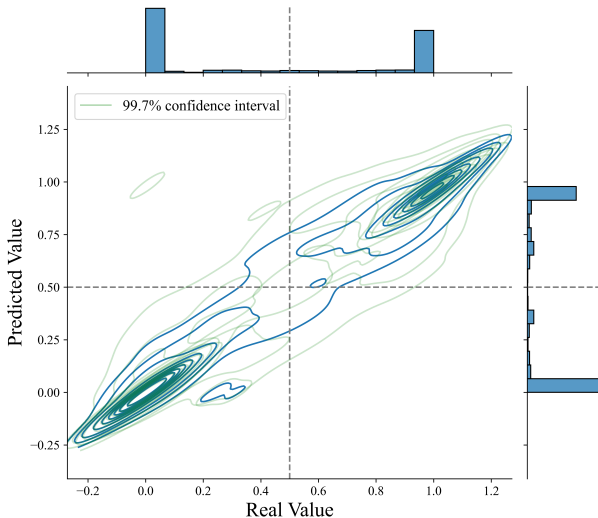


Fig. 5. The predicted value for test data vs real value.

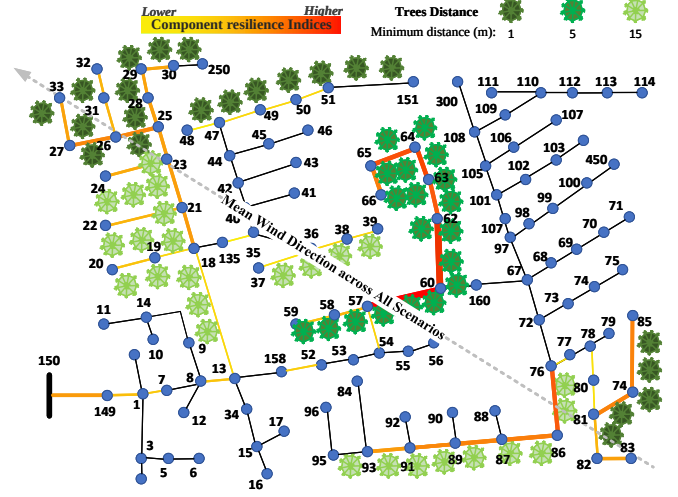


Fig. 6. The system resiliency under potential Hurricane scenarios.

B. Resilience Assessment under Potential Hurricane Scenarios

Considering historical data on hurricanes, the probability density function of each key parameter in the given region is calculated. The combinatorial enumeration is then applied to determine the probability of various hurricane disasters arising from the probabilistic hurricane model. The more potential hurricanes of about 4,000 are produced, for which the probability of line outages is subsequently calculated using the trained OPM-based BNN. The resilience indices are then calculated and the results are shown in Fig. 6 and Table. I. The system and component resilience indices are calculated with the default order of the enumerated failure scenario set to 3 for this system under all possible hurricane scenarios. During the calculation process of the system resilience index, the probability of occurrence of each hurricane scenario, the cumulative failure probability of each distribution corridor, and the impact increment of each failure scenario were calculated regarding the component resilience indices explained in subsection II-C. The 50 corridors with higher component resilience indices (R_m) are selected and shown by different colors based on their resilience indices in Fig. 6. The darker the color line is, the more fragile the corridor is. Across all scenarios, the average central pressure difference is 82 hPa, average the translational speed is 33.37 km/h, and the average motion direction is west-northwest (as shown with a gray dashed line in this figure). Results shown in 6 reveal that proximity to tall trees significantly affects the vulnerability of power lines to the hurricane. It is noteworthy that lines situated closer to these tall trees were more susceptible to wind-induced failures, which raises concerns about the potential for wind-induced failures in severe weather events. Moreover, the power distribution components' resilience was greatly influenced by the tree azimuth class, which represents the angular direction of trees relative to power lines. Notably, power lines located between nodes 48 to 50 exhibited different fragility than those in the north, east, and east-northeast areas relative to the trees. It is evident from this that the positioning of power lines as compared to trees' orientation has a significant effect on their ability to stand up to hurricane-force winds.

Table. I shows the system resiliency index (first row) and the component resilience index only for the five most vulnerable lines (from the second to the sixth row). Accordingly, it is deducible that lines between 57 to 64 are more vulnerable to hurricane disasters. The results can further provide a reference for enhancement strategies to increase the system's resilience to hurricanes.

Resiliency Indices	Result (MWh)
R_{sys}	0.4256
$RL_{Bus_{57} \text{ to } Bus_{60}}$	0.0567
$RL_{Bus_{60} \text{ to } Bus_{62}}$	0.0341
$RL_{Bus_{63} \text{ to } Bus_{64}}$	0.033
$RL_{Bus_{64} \text{ to } Bus_{65}}$	0.0288
$RL_{Bus_{62} \text{ to } Bus_{63}}$	0.0221

TABLE I
OBTAINED RESILIENCE INDICES UNDER ORIGINAL HURRICANE.

IV. CONCLUSION

This paper proposes a learning-based resilience assessment framework for power distribution systems. Compared to traditional OPM, which assumes noise-free and deterministic observations, OPM is developed based on BNN to address uncertainties caused by measurement errors, missing values, and intrinsic variability in power outage prediction. Using historical data and factors that describe the network's environment and structure, the trained BNN displays effective prediction performance with a 99.7% confidence interval. The predicted and actual probability distributions for line outages illustrate a successful bias-variance tradeoff, reducing bias in the data while preserving variance. The OPM-based BNN predicts the probability of distribution line failure for each scenario. Based on component resilience assessment, results indicate that tall trees significantly impact power line vulnerability. Additionally, the tree azimuth class plays a crucial role in power distribution component resilience. By using the proposed method, resilient expansion or upgrade of the distribution system can be accomplished efficiently and effectively. The future work will be on testing the proposed method for actual distribution systems.

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