14th International Conference on Structural Safety and Reliability - ICOSSAR'25
1-6 June, 2025 - Los Angeles California, USA
R. Ghanem, E. Johnson, S. Masri and A. Olivier (Eds)

ACCURATE AND EFFICIENT RESILIENCE ASSESSMENT OF COASTAL ELECTRIC POWER DISTRIBUTION NETWORKS

SAEED SOHRABI[1], YOUSEF DARESTANI[2] AND WILLIAM PRINGLE[3]

[1] PhD Candidate, Department of Civil, Environmental, and Geospatial Engineering, Michigan Technological University (Corresponding author)
Houghton, MI, 49931, USA
Email: sohrabi@mtu.edu, ORCID: https://orcid.org/0009-0000-1681-7021

[2]Assistant Professor, Department of Civil, Environmental, and Geospatial Engineering, Michigan Technological University
Houghton, MI, 49931, USA
Email: ydaresta@mtu.edu, ORCID: https://orcid.org/0000-0003-4896-2535

[3] Research Scientist, Environmental Science Division, Argonne National Laboratory
Lemont, IL, 60439, USA
Email: wpringle@anl.gov, ORCID: https://orcid.org/0000-0002-2877-4812

Key words: Resiliency, Artificial Neural Network (ANN), Power Distribution System, Sequential Monte Carlo (SMC) Simulations, Prestressed Concrete (PC) Pole, Wood Pole

Abstract. *Weather events such as storm induced wind, surge, and wave have imposed significant damage to coastal power infrastructure. Although many studies have investigated the performance of coastal infrastructure, there remains a critical gap in computationally efficient probabilistic resilience assessment of coastal distribution systems. This study addresses this issue by first developing a probabilistic wind-surge-wave model, using 10,000 years of synthetic storm dataset. The dataset comprises approximately 3,000 storms. The storms are categorized based on their maximum wind speed. As storm events follow a Poisson Point Process, the time between storm events can be estimated using the exponential distribution. To reduce computational costs, 200 storm samples were selected from the 3,000-storm ensemble such that the CDF of the model remains identical to the original dataset and the storms' spatial distribution is kept uniform. A Sequential Monte Carlo (SMC) simulation was then adopted to simulate storm events over a 70-year period. For the 200-storm ensemble, wind, surge, and wave values are estimated via ADCIRC+SWAN platform. To further decrease the computational costs while ensuring the accuracy of the model, an Artificial Neural Network (ANN) model was trained on failure probabilities estimated by Monte Carlo (MC) simulations, to generate a set of efficient high-fidelity parametrized fragility models for wood and prestressed concrete (PC) poles. To assess the efficiency of the framework, a power distribution* *network, including 5 substations and 3,509 wood poles with classes spanning from 3-5 were identified in Pascagoula, MS, USA, as a case study. Furthermore, 5000 realization of failure survival scenarios were generated to perform a network analysis to determine the number of customers without power. To increase the efficiency of the network analysis, a pre-computed surrogate model is used for fast estimation of power outages and restoration. For resilience enhancement of the network, two different pole replacement strategies including wood replacement strategy and PC replacement strategy were compared. The results showed that the trained ANN model has a near perfect performance with an R^2 score of 0.9999 and RMSE of 0.05%. Resilience estimation of the network for a 70-year period can be estimated within a few minutes. In addition, the superiority of PC replacement strategy over wood replacement strategy in improving the resiliency of the network was shown. This study provides a fast yet efficient framework that can be used in decision making processes to enhance the resiliency of coastal power distribution systems.*

1 INTRODUCTION

Experience has shown that coastal power systems are vulnerable to the combined storm-induced wind, surge, and wave hazards. Due to severe computational costs associated with uncertainties in storms and performance of infrastructure systems, the literature on risk assessment of coastal infrastructure systems is mostly focused on scenario-based storm simulations [1-3]. Although scenario-based simulations provide insights into the performance of the system, they cannot be used effectively for decision making purposes, as they neglect uncertainties associated with storm frequency and severity. Therefore, there is a pressing need for a framework that can efficiently account for uncertainties in estimation of resilience of coastal power distribution systems under the combined impact of wind, surge, and wave hazard.

Resilience, which describes a system's ability to resist, absorb, and recover from disruptive events, has become a key factor in infrastructure risk assessment [4-7]. Resilience is commonly quantified from time-dependent curves that estimate the post disaster functionality of the system [5, 6, 8]. To determine the functionality curve, first, failure and survival scenarios are generated by estimating the probability of failure for components of the system. The failure probabilities can be estimated by reliability methods such as first order reliability [9, 10] or Monte Carlo simulation [11-16]. First order reliability method is rarely used these days as it does not provide accurate estimates for failure probability. Monte Carlo simulation provides accurate estimates, but it is very time consuming, especially for systems with a large number of components. To remedy this issue, the concept of fragility models has been introduced. The fragility models map the failure probabilities generated by Monte Carlo simulations to simple and easy to use functions. Most fragility models are based on either the CDF of the normal distribution [17] or a logit function estimated by logistic regression [14]. Although such models provide fast estimates, they are not sufficiently accurate.

To address these limitations and to fill in the knowledge gap, this study proposes a computationally efficient (accurate and fast) framework for resilience assessment of coastal power system comprising a large number of components, taking advantage of a novel high fidelity probabilistic storm hazard modeling based on synthetic storms and efficient network performance and recovery models. The probabilistic storm hazard model is integrated with a parametrized fragility model developed using an article neural network (ANN) model for wood and Prestressed concrete (PC) poles to generate failure/survival scenarios. Furthermore, the network analysis is optimized by pre-computing the failed nodes when poles in the system fail.

2 METHODOLOGY

2.1 Probabilistic Wind, Surge, Wave Model

To assess the resilience of coastal power distribution systems under storm-induced wind, surge, and wave, a fully probabilistic storm hazard model is developed based on [16] . Due to the limitation of historical tropical cyclone (TC) data for the Northern Gulf Of Mexico (NGOM), a synthetic storm dataset named STORM was adopted [18]. This dataset comprises 10,000 years of synthetic storm tracks for the North Atlantic Ocean. Within the region of interest, as shown in Fig 1. (a), there are 2,345 synthetic storm tracks with minimum and maximum 10-min sustained wind speeds of 18 and 70 (m/s). The data obtained from STORM dataset was adjusted based on historical storms obtained from the HURDAT2 database [16, 19]. The historical records indicated that the region of interest experienced 45 storms within years 1980 to 2018. Therefore, the return period for synthetic storms was set to 39/45=0.867. Furthermore, a quantile mapping bias correction was employed to adjust the Cumulative Density Function (CDF) of the synthetic dataset based on 10-min sustained wind speed (Fig 2). TC events follow a Poisson point process and therefore the time between consecutive events follows an exponential distribution [20, 21]. Therefore, the time between storm events can be sampled from the following equation:

$$F(t) = 1 - e^{-\frac{t}{T}} \tag{1}$$

where t is the storm arrival time (year); T is the return period of historical dataset assumed 0.866 years $\left(\frac{39\ \text{(years)}}{45\ \text{(number of historical storms)}}\right)$.

For each sampled storm, a synthetic storm can be picked from the 2,345 ensemble of storms in STORM dataset by generating a random number from 0 to 1 and finding a wind speed by inversing the CDF presented in Fig. 2. The storm that is closest to this wind speed will be selected for simulation. The sampled storms are then integrated with the parametrized fragility model developed based on ANN model (more information later in this paper) to perform a Sequential Monte Carlo (SMC) simulation to account for uncertainties associated with the performance of utility poles on annual basis and within a 70- years' service life. This approach also accounts for system aging and cumulative damage over time, which is critical for realistic risk assessment.

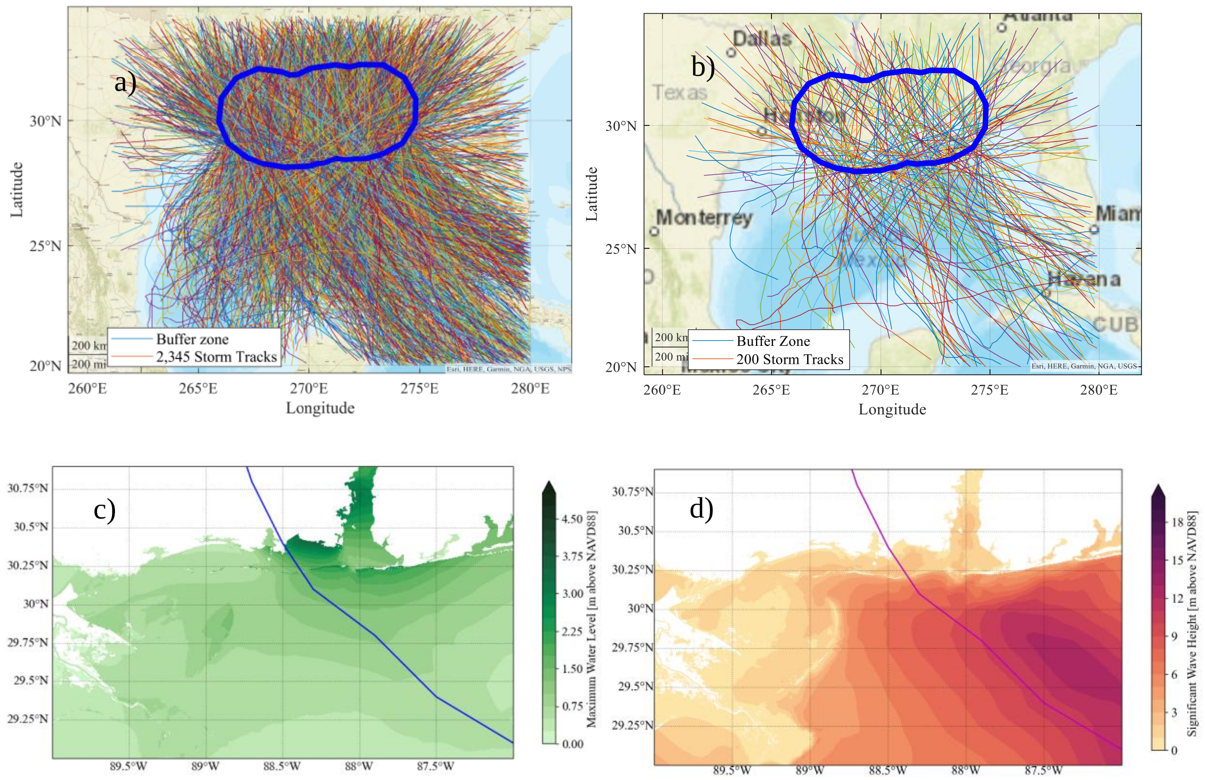

Figure 1. a) 2,345 TC tracks; b) 200 down sampled TC tracks; c) maximum Surge height Storm NO 18; d) Significant wave height Storm NO 18

2.1.1 Storm Down Sampling

Each of the storm tracks contains storm's specifications, including maximum wind speed, maximum pressure, longitude, and latitude of the landfall. To be able to determine maximum wind speed, maximum surge height, and significant wave height induced by each storm track, ADvanced CIRCulation and Simulating Waves Nearshore (ADCIRC+SWAN) hydrodynamic models need to be used [22, 23]. However, ADCIRC+SWAN can be computationally expensive and time-consuming. Therefore, it is not possible to use all the 2,345-storm track through ADCIRC+SWAN. To address this limitation, this study employed the Maximum Dissimilarity Approach (MDA) to select a subset of storm tracks which are representative of the whole dataset. Firstly, for each storm track in the dataset, four features were used for downsampling: (1) maximum wind speed, (2) maximum pressure, (3) the latitude of closest time step to the shore, (4) the longitude of closest time step to the shore. Secondly, each feature normalized in the range of [0,1]. Thirdly, a set of weights were assigned to each feature to differentiate their importance. Finally, the Manhattan distance between any two storm tracks in the dataset were estimated as follows:

$$d(j,k) = \sum_{i=1}^{n} w_i \left| X_{j,i} - X_{k,i} \right| \tag{2}$$

Where j and k are any two storm tracks in the dataset; i is the number of features in each storm track; w is the weight assigned to each feature; X is feature vector. This algorithm starts with selecting a random initial track with the maximum wind speed in range [59,61] (m/s) and sequentially selecting the next storm track in a way that the minimum distance between the selected one and previous tracks are maximized. In this study, 200 storm tracks were selected Fig 1. (b), and the maximum surge and wave estimated using ADCIRC+SWAN, as shown in Fig 1. (c), and Fig 1. (d), respectively.

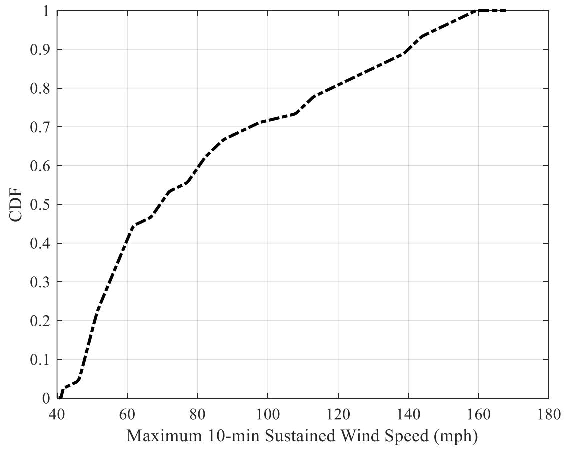

Figure 2. Empirical CDF (ECDF) of STORM dataset as a function of maximum 10-min sustained wind speed. The data is adjusted using Quantile mapping Bias Correction to match historical storms.

3 FRAGILITY MODELS DEVELOPED USING ARTIFICIAL NEURAL NETWORK (ANN)

In this study, two main modes of failure including the pole rupture and foundation failure due to overturning were considered for utility poles. The total probability of failure can then be estimated by combining the probabilities from each mode into De Morgan’s law [16]. Estimating total probability of failure due to combined wind, surge, and wave hazard using MC simulations for a large-scale network can be computationally demanding and time-consuming as the analysis needs to be performed thousands of times. To address this limitation, this study adopts Artificial Neural Network (ANN) to generate a high fidelity and efficient parametrized fragility model for both wood and PC poles. Firstly, 80,000 training data were generated for the input features, using Halton-Quasi random sampling method [24]. The input features consist of storm intensity measures (wind velocity, surge height, significant wave height, and wind direction) and pole specifications (pole height, conductor effective area, and age). Secondly, 80,000 output targets (probabilities of failure) were generated using MC simulations. To train the ANN model, 80% of the samples allocated for cross-fold validation [25, 26], 10% for the validation within ANN, and 10% as test points. ANN was trained for wood pole classes 3,4,5, and PC class F. Table. 1 summarizes the performance metrics of trained ANN, using coefficient of determination (R^2) and Root Mean Squared Error (RMSE) for Class 3 wood and Class F PC pole.

Table 1: Evaluation metrics for trained ANN models for ole Rupture (PR) and Foundation Failure (FF).

Pole Class	PR (RMSE) (%)	PR (R^2)	FF (RMSE) (%)	FF (R^2)
3 (wood)	0.046	0.9999	0.049	0.9999
F(PC)	0.038	0.9999	0.038	0.9999

Moreover, ANN models were evaluated against MC simulations (Fig 3). The constant parameters used in estimating the probability of failure are summarized in Table 2.

Table 2: Constant parameters used for estimating Probabilities of failures in Fig. 2

Parameter	Surge Velocity (mph)	Surge Height (ft)	Angle (degrees)	Conductor Effective Area (ft^2)	Pole Height (ft)	Significant Wave Height (ft)	Soil	Number of Strands
Value	2	5	90	64.58	40	2	Very Stiff	14

As is shown in Fig 3, the ANN predictions demonstrated a very good match with the estimated probability of failure obtained from MC simulations with RMSE of 0.094% and 0.052% for PC pole and wood pole, respectively. Not only does ANN provide a very accurate prediction compared to MC simulations, but also it reduces the computational time significantly.

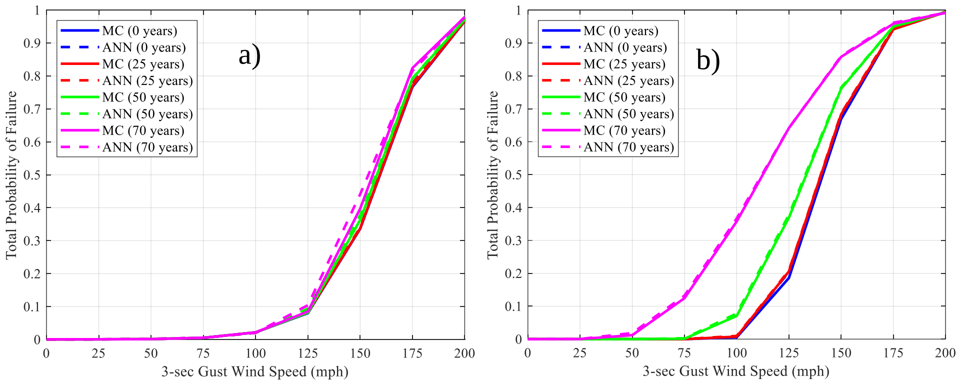

Figure 3. Total probability of failure, comparing ANN against Monte Carlo (MC) simulations: a) PC pole class F; b) Wood pole class 3.

To evaluate the computational run time of ANN against MC simulations, total probability of failure for a power distribution network comprised of 3,509 utility poles, as shown in Fig 4, over a 70-year life span subjected to 200 storms was determined. As is shown in Table 3, ANN is 6,065% faster compared to MC simulations. The results show the superiority of ANN models over traditional MC simulations in terms of being highly accurate and less time-consuming.

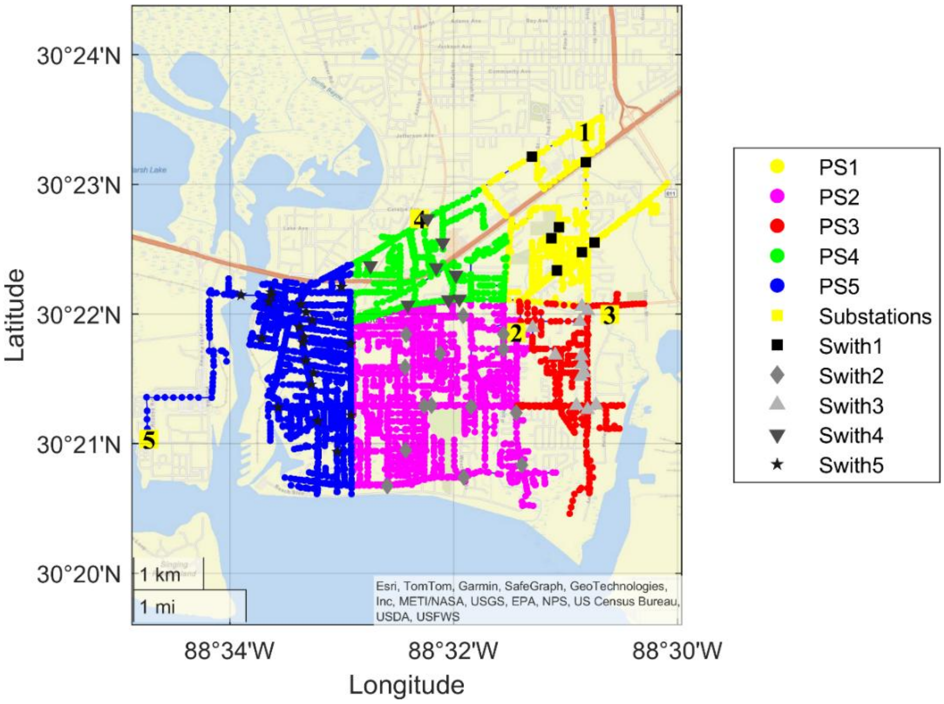

Figure 4. Power distribution system including 3,509 poles assigned to five substations (PS1-PS5) along with corresponding protective switches (switch1-switch5) in Pascagoula, MS, USA

Table 3: Total probability of failure runtime, comparing ANN and MC simulations for 3,509 wood poles.

Algorithm	Run Time (hours)
ANN	7.1
MC Simulations	437.715

4 OPTIMIZED OUTAGE DETERMINATION

A real-world distribution network in Pascagoula, MS, USA, comprising of 3509 poles, five substations, and 61 protective devices, was modeled as a radial graph for resiliency assessment. In addition, an adjacency matrix was constructed, representing the connection of each node to its neighboring nodes. In power network, any pole failure activates protective devices that isolate downstream poles to prevent systemwide outages. To determine the location of outages a graph-based analysis needs to be done to determine what nodes are disconnected from power in the presence of failed nodes. However, applying such process especially in a Sequential Monte Carlo (SMC) simulations that comprise of hundred of thousands of failures is extremely computationally intensive and time consuming. To improve efficiency, outage scenarios were precomputed for individual pole failures and recalled during SMC simulations, significantly reducing runtime, as it is summarized in Table 4. Table 4 represents the runtime comparison of proposed outage determination method against dynamic determination through 1,000 SMC simulations over 70-year life span. The proposed method showed to be 10,753 times faster than the traditional dynamic determination. The results underscore the superiority of proposed surrogate model to reduce computational time for determining coastal power distribution network outage determination.

Table 4: Runtime comparison of precomputed outage method and traditional dynamic determination for 1,000 scenarios

Algorithm	Run Time (hours)
Precomputed outage method	0.116
Dynamic determination through the SMC	1,247.4

5 NETWORK RESILIENCE ASSESMENT

In this study, to estimate the resilience of coastal power distribution networks under storms threat, a Sequential Monte Carlo (SMC) simulation method was employed to capture the occurrence of multiple storm events as well as accounting for updating the pole's age after each failure. To obtain failure/survival status, 5,000 SMC simulations were conducted in which at each sequence a random number between 0 and 1 generated. If the random number is greater than the probability of pole failure obtained from ANN models, the pole survives, otherwise the pole fails. To assign a storm number to each sequence, a random cumulative density function (CDF) between 0 and 1 was generated and corresponding maximum speed were interpolated (Fig. 2). Each maximum wind speed is representative of a storm number. In addition, system quality is determined based on the number of outages and corresponding restoration time. The restoration time for each pole follows a normal distribution with the mean value of 5 hours and standard deviations of 2.5 hours and for conductors it also follows a normal distribution with a mean of 4 hr and standard deviation of 2 hr. [5]. The resiliency of a system is then determined as:

$$R = \frac{1}{t_c}\int_0^{t_c} Q d_t \tag{3}$$

where t_c is maximum time that takes for the network to bounce back to its full functionality after a storm hazard; Q is the system quality which is a function of number of outages and determined as:

$$Q = 1 - \frac{n_o}{n_{total}} \tag{4}$$

where n_o is the number of outages in the system; n_{total} is the total number of customers in the system.

To estimates the resilience of coastal power distribution network using Eq. (3) and Eq. (4), a power distribution network comprised of 3,509 utility poles located in Pascagoula, MS, USA were considered as the case study. Fig 5 illustrates the resilience of network over a 70-year life span comparing two pole replacement strategies, including wood replacement strategy and prestressed Concrete (PC) replacement strategy. In the first strategy, it is assumed that the network is made of wood poles, and any failed poles will be replaced by a new wood pole. However, the second strategy assumes that any failed poles will be replaced by a new PC pole.

The results highlight the superiority of PC replacement strategy over wood replacement strategy in all age intervals. The resilience for PC replacement strategy shows an initial increase in the first three decades, reaching 98.44%. As the system continues to age, the resilience gradually drops to 97.19% in year 70. This trend represents that replacing failed wood poles with new PC pole, leads to enhancing the system resilience by 1.17% and 0.08% in the first thirty and seventy years of life service, respectively. On the other hand, wood replacement strategy shows a steady decline in system resilience, starting with 97.10% resilience and dropping to 94.86% after 70 years. The system resilience difference between the two strategies becomes more dominant as the system ages with PC replacement strategy being 2.33% more resilient at year 70. The results underscore the superiority of PC replacement strategy over traditional wood replacement.

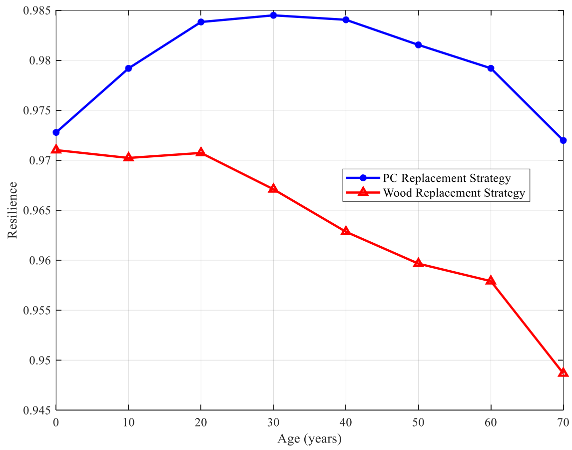

Figure 5. Resilience of Power distribution network over 70-year life span, comparing wood replacement strategy and Prestressed Concrete (PC) replacement strategy

6 SUMMARY AND CONCLUSION

This study proposed an accurate and computationally efficient method for evaluating the resilience of coastal power distribution network under storm-induced wind, surge, and wave threat. A probabilistic storm hazard model was integrated with trained artificial neural network (ANN) models and a precomputed outage simulation approach to significantly reduce the computational time, while maintaining a high accuracy in estimating the resilience of network.

The ANN model trained for prestressed concrete (PC) and wood utility poles demonstrated near-perfect accuracy with R^2 score of 0.9999, reducing the computational cost of predicting probabilities of failure by over 6,000% compared to Monte Carlo (MC) simulations. In addition, the precomputed outage simulation method, showed to be computationally 10,753 times faster than traditional dynamic approach for estimating a network of 3,509 poles over 70-year life span.

The network resilience assessment was conducted for the case study located in Pascagoula, MS, USA, revealed that the choice of pole replacement strategy affects the system resilience over the life span. PC replacement strategy showed to be constantly outperforming the wood replacement strategy. After 70 years, the resilience of the network improved 2.33%, highlighting the superiority of PC replacement over wood replacement. The results of this study can be used as a strong framework for decision makers for improving the coastal power network resilience under storm hazard

REFERENCES

[1] A. M. Salman and Y. Li, "Age-dependent fragility and life-cycle cost analysis of wood and steel power distribution poles subjected to hurricanes," *Structure and Infrastructure Engineering*, vol. 12, no. 8, pp. 890-903, 2016/08/02 2016, doi: 10.1080/15732479.2015.1053949.

[2] A. M. Salman, Y. Li, and M. G. Stewart, "Evaluating system reliability and targeted hardening strategies of power distribution systems subjected to hurricanes," *Reliability Engineering & System Safety*, vol. 144, pp. 319-333, 2015/12/01/ 2015, doi: https://doi.org/10.1016/j.ress.2015.07.028.

[3] M. Li, J. Wang, and X. Sun, "Scenario-based risk framework selection and assessment model development for natural disasters: a case study of typhoon storm surges," *Natural Hazards*, vol. 80, pp. 2037-2054, 2016.

[4] M. Ouyang and L. Dueñas-Osorio, "Time-dependent resilience assessment and improvement of urban infrastructure systems," *Chaos: An Interdisciplinary Journal of Nonlinear Science*, vol. 22, no. 3, 2012.

[5] Y. M. Darestani, K. Sanny, A. Shafieezadeh, and E. Fereshtehnejad, "Life cycle resilience quantification and enhancement of power distribution systems: A risk-based approach," *Structural Safety*, vol. 90, p. 102075, 2021.

[6] M. Bruneau *et al.*, "A framework to quantitatively assess and enhance the seismic resilience of communities," *Earthquake spectra*, vol. 19, no. 4, pp. 733-752, 2003.

[7] R. Suresh, P. Akbari, and C. A. MacKenzie, "A value-focused thinking approach to measure community resilience," *arXiv preprint arXiv:2408.00901*, 2024.

[8] M. Panteli, P. Mancarella, D. N. Trakas, E. Kyriakides, and N. D. Hatziargyriou, "Metrics and quantification of operational and infrastructure resilience in power systems," *IEEE Transactions on Power Systems*, vol. 32, no. 6, pp. 4732-4742, 2017.

[9] Y. Hu, J. Ji, Z. Sun, and D. Dias, "First order reliability-based design optimization of 3D pile-reinforced slopes with Pareto optimality," *Computers and Geotechnics*, vol. 162, p. 105635, 2023.

[10] A. Tabandeh, G. Jia, and P. Gardoni, "A review and assessment of importance sampling methods for reliability analysis," *Structural Safety*, vol. 97, p. 102216, 2022.

[11] S. Yaghmaei-Sabegh, E. Shokrgozar-Yatimdar, and P. Shoaeifar, "Temporal clustering PSHA based on smoothing: a case study in the New Madrid seismic zone of the central USA," *Journal of Seismology*, pp. 1-17, 2022.

[12] B. K. Low and C. W. Boon, "Probability-based design of reinforced rock slopes using coupled FORM and Monte Carlo methods," *Rock Mechanics and Rock Engineering*, vol. 57, no. 2, pp. 1195-1217, 2024.
[13] M. Kia, A. Amini, M. Bayat, and P. Ziehl, "Probabilistic seismic demand analysis of structures using reliability approaches," *Journal of Earthquake and Tsunami*, vol. 15, no. 03, p. 2150011, 2021.
[14] Y. Darestani, J. Padgett, and A. Shafieezadeh, "Parametrized Wind-Surge-Wave Fragility Functions for Wood Utility Poles," (in English), *Journal of Structural Engineering*, vol. 148, no. 6, p. 04022057, Jun 1 2022, doi: Artn 04022057
10.1061/(Asce)St.1943-541x.0003319.
[15] A. Naseri, A. MirzaGoltabar Roshan, H. Pahlavan, and G. Ghodrati Amiri, "Numerical analysis and vulnerability assessment of horizontally curved multiframe RC box-girder and CFRP retrofitting of existing bridges," *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering*, vol. 8, no. 3, p. 04022031, 2022.
[16] S. Sohrabi, Y. Darestani, W. J. Pringle, D. M. Dowden, and P. Dehghanian, "Life Cycle Cost Analysis of Prestressed Concrete Poles Subjected to Wind, Surges, and Waves," *Journal of Structural Engineering*, vol. 151, no. 7, p. 04025069, 2025, doi: doi:10.1061/JSENDH.STENG-13840.
[17] Y. Mohammadi Darestani and A. Shafieezadeh, "Multi-dimensional wind fragility functions for wood utility poles," *Engineering Structures*, vol. 183, pp. 937-948, 2019/03/15/ 2019, doi: https://doi.org/10.1016/j.engstruct.2019.01.048.
[18] N. Bloemendaal, I. D. Haigh, H. de Moel, S. Muis, R. J. Haarsma, and J. C. Aerts, "Generation of a global synthetic tropical cyclone hazard dataset using STORM," *Scientific data*, vol. 7, no. 1, p. 40, 2020.
[19] NOAA. *HURDAT2 Dataset*, doi: https://www.nhc.noaa.gov/data/.
[20] P. Vickery, P. Skerlj, and L. Twisdale, "Simulation of hurricane risk in the US using empirical track model," *Journal of structural engineering*, vol. 126, no. 10, pp. 1222-1237, 2000.
[21] S. N. Chiu, D. Stoyan, W. S. Kendall, and J. Mecke, *Stochastic geometry and its applications*. John Wiley & Sons, 2013.
[22] W. J. Pringle, D. Wirasaet, K. J. Roberts, and J. J. Westerink, "Global storm tide modeling with ADCIRC v55: unstructured mesh design and performance," *Geoscientific Model Development Discussions*, vol. 2020, pp. 1-30, 2020.
[23] W. J. Pringle, J. Wang, K. J. Roberts, and V. R. Kotamarthi, "Projected changes to cool-season storm tides in the 21st century along the northeastern United States coast," *Earth's Future*, vol. 9, no. 7, p. e2020EF001940, 2021.
[24] L. Kocis and W. J. Whiten, "Computational investigations of low-discrepancy sequences," *ACM Trans. Math. Softw.*, vol. 23, no. 2, pp. 266–294, 1997, doi: 10.1145/264029.264064.
[25] M. Mohammadagha, M. Najafi, V. Kaushal, and A. M. A. Jibreen, "Machine Learning Models for Reinforced Concrete Pipes Condition Prediction: The State-of-the-Art Using

Artificial Neural Networks and Multiple Linear Regression in a Wisconsin Case Study," *arXiv preprint arXiv:2502.00363*, 2025.

[26] S. Mazloom, A. Rabbani, H. Rahami, and N. Sa'adati, "A Two-Stage Damage Localization and Quantification Method in Trusses Using Optimization Methods and Artificial Neural Network by Modal Features," *Iranian Journal of Science and Technology, Transactions of Civil Engineering*, pp. 1-18, 2024.