Power Outage Prediction using Hurricane Forecast

Fatemehalsadat Jafarishiadeh
Department of Electrical and Computer Engineering
University of Utah
Salt Lake City, Utah, USA
fatemeh.jafarishiadeh@utah.edu

Xiao Zhu
Civil And Environmental Engineering
University of Utah
Salt Lake City, Utah, USA
xiao.zhu@utah.edu

Mostafa Sahraei-Ardakani
Department of Electrical and Computer Engineering
University of Utah
Salt Lake City, Utah, USA
mostafa.ardakani@utah.edu

Ge Ou
Department of Civil And Coastal Engineering
University of Florida
Gainesville, Florida, USA
gou@ufl.edu

2022 North American Power Symposium (NAPS) | 978-1-6654-9921-7/22/$31.00 ©2022 IEEE | DOI: 10.1109/NAPS56150.2022.10012152

***Abstract*— Hurricanes are natural weather events that cause recurring and prolonged power outages in the U.S. This paper shows how ensemble weather forecast can be utilized to estimate the extent of temporal and spatial damages that a hurricane can inflict on the power system infrastructure. The line outage estimations, from ensemble members, can be used to compute optimal preventive scheduling for generators, for the duration of the event. The various schedules, can then, be used as alternative plans to choose from, depending on the actual path and wind force of the hurricane, closer to the event. Ensemble forecast for Hurricane Harvey, in the leading days to the landfall, is used to assess the impacts on the 2000 bus synthetic grid (ACTIVSg2000) on the footprint of Texas.**

Keywords—Ensemble forecast, hurricane, efficient emergency response planning, outage prediction, preventive operation, transmission system.

I. Introduction

Severe weather events threaten the security of power systems by impacting various elements simultaneously and causing widespread power outages [1], [2]. The subsequent socioeconomical disturbances are significant for people depending on electricity for various day to day tasks [3]. In the United States alone, natural events are responsible for an annual cost of around $20 billion to $55 billion dollars [4]. Having reliable information about the severity and the location of these events would allow for the rapid recovery of the affected areas, prepare the system operator to come up with contingency plans and if necessary change the operation plan in response to the event [5]. These measures subsequently help restrict the imposed costs to the system and improve the reliability of the grid.

Majority of the recent research on the prediction of occurrence and intensity of outages due to severe natural events benefits from various machine learning techniques [6]–[11]. The key concept in these models is learning from the previous outages and historical weather data and implementing it for the upcoming events. The wind speed, duration of the event, rainfall and lightning strike counts are among features of these models used to learn the number of outages and the failure rate. In [12], the probability of outage happening in a grid cell is predicted, although authors do not provide a specific value for how well the models work. In [3], logistic regression is used for predicting the outage probability of elements in the path of an approaching hurricane. The two factors influencing this probability are the forecasted wind speed and the distance of the element from the center of the storm. The results are promising as the F_1 score calculated is 0.9027, but it should be noted that the weather forecast is assumed exact.

As the predictive system in weather forecast is a non-linear system, the presence of uncertainties in weather variables makes the prediction more challenging [13]. These uncertainties include the initial state, as a small change in the initial state would create significant changes in the trajectory of the weather event [14], [15], and the parameterization of physical phenomena [16], [17]. As such, the accuracy of the forecast drops significantly within one to two days [18]. Taking into account the limitations in accurate prediction of the weather that plays a key role in the complex system of meteorological phenomena and infrastructure is necessary for efficient response from power system operators in face of severe weather events.

Hurricanes are one of the most impactful and recurrent natural event that cause prolonged power outages in the U.S. [19]. The high winds typical of hurricanes can damage the overhead transmission and distribution lines and even lead to collapse of transmission towers. The generation facilities are protected in enclosed spaces and consequently are not susceptible to as much damage as the transmission systems [20]. As the transmission system outages impact larger areas and can restrict the customers' ability to access power even though that area's distribution system has remained intact, the focus of this paper is on predicting transmission system outages.

There are limited options at the operating stage to minimize the consequences of simultaneous element outages in the system. In [21], it is explained that employing microgrid technology enabled the residents of a tower in Greenwich Village, NY to maintain access to power and other utilities for the duration of one week outage caused by Hurricane Sandy. The other viable option that can be employed to benefit people across-the-board is the preventive unit commitment (UC) scheduling with the goal of minimizing load shedding and total cost [22]. The challenge that this solution faces is that solving stochastic unit commitment with numerous line outages is computationally burdensome. The solution time required might not be compatible with the available time. The number of scenarios studied can be reduced to overcome this difficulty, but there is a chance that the hurricane would not follow any of the more probable scenarios. To overcome this possibility, we allow for the inaccurate weather forecast by generating 20 models with different initial time stamps and each an ensemble model of 20 forecasting models. The difficulty in employing an effective

This research is funded by the National Science Foundation through grants 2004658 and 2121875.

978-1-6654-9921-7/22/$31.00 ©2022 IEEE

Authorized licensed use limited to: University of Florida. Downloaded on July 01,2023 at 15:44:00 UTC from IEEE Xplore. Restrictions apply.

response to natural events like hurricane is the limited time available when the path and severity of the event has been solidified. By employing the more probable forecasting analyses and solving the preventive UC for those weather data, we generate various UC schedules in place which can be readily modified or employed at time of the event.

The rest of this paper is organized as follows: the model used for forecasting hurricane is introduced in section II. The impact of hurricane on failure rate of transmission system components is described in section III. The preventive UC is explained in section IV. The case study is presented and discussed in section V. Section VI concludes the paper.

II. Forecasting Hurricane Events

To forecast weather events like hurricanes, meteorologists use the Weather Research and Forecasting (WRF), an atmospheric model, that is widely used in numerical weather prediction (NWP) at governmental centers and also by private companies [23], [24]. The atmospheric modeling has intrinsic errors due to the initial conditions, boundary and surface conditions, numerical approximations, and parameterization of physical processes that is generally divided into initial condition error and modeling error.

Ensemble prediction attempts to compensate the imperfect data and methods available by providing parallel forecasts while introducing perturbations in the initial conditions. Combining forecast produces superior forecasts than the best individual forecaster [25]. What is more, ensemble forecast provides reliability estimation of the forecast [26]. Each model in ensemble modeling samples the uncertainty space of modeling process. As a result, the impact of each uncertainty introduced can be tracked in the forecast uncertainty. The initial conditions are adjusted by adding dynamic perturbation to them using the breeding growing singular or Lyapunov vector perturbations [27]. The lead time also impacts the model performance for forecasting and adds variation on the trajectory.

In this paper, the wind speed and angle of hurricane are predicted with different initial conditions, which are the changes in the start date for performing prediction and also the added perturbations to each initial data. Thus, the trajectory of each prediction and the starting points are varied. The forecasted data is then applied to the infrastructure of power system to investigate the impact of the predicted hurricane on the transmission system components.

III. Impact of Hurricane on Failure Rate of Transmission System Components

The failure rate of power system components specially the transmission lines is vastly impacted by their environment. The longer transmission lines span over larger areas that might experience different weather conditions. These lines can be modeled as series connected segments of the original line, with each segment being located in different weather region. The failure rate of the line is calculated as a function of failure rate of each segment. The failure rate of each segment is derived from the failure stress factor for that weather condition [28], [29]. The failure probability and the weather conditions causing the failures are linked through the fragility curves [5], [30]. Wind speed and wind direction are used for hurricane event studied in this paper.

The wind speed and angle of the forecasted hurricane differ depending on the time and regional characteristics of the transmission component's location. Given the maximum wind speed and wind angle forecasted, the trajectory of hurricane is outlined. Based on the standard distance of transmission towers, the number of towers in a transmission line is estimated. The latitude and longitude of each tower is recorded.

The failure probability of each transmission tower and consequently the transmission line is a function of the wind speed, the finite-element model of transmission tower and the physical attributes of the wind and terrain. The location of transmission towers in relation to the center of hurricane at each time stamp (determined by the wind intensity), is acknowledged by implementing the change in the wind speed [31]. Also, the dynamic wind loading which is comprised of steady and fluctuating wind is implemented to better model the wind [32]. The fragility curve is developed by conducting fragility analysis using the model described in [22], [32]. Fragility curves indicate the likelihood of failure. Based on the limit state defined, the component is considered as damaged if its failure likelihood exceeds the limit.

IV. Optimal Power System Operation

The day-ahead security-constrained unit commitment (SCUC) is employed to provide preventive optimal operation to minimize load shedding and the total operation cost in the predicted hurricane conditions. The load shedding and over generation are heavily penalized to limit these options to only when there is no other viable option. The mathematical formulation of this problem for each weather prediction is a deterministic mixed-integer linear programming problem. This model is based on DC power flow as used by the power system operators in North America [33]. The linear sensitivity factors are used for the network constraints: thermal power flow limit of lines.

The time and failure probability of transmission system components is used to generate contingency scenarios for the day of hurricane event. By defining a probability threshold for outage classification, lines are assigned working and failed status. Consequently, the network topology is impacted which might result in island formation in the system. As the linear sensitivity factors are topology dependent for each island a new power transfer distribution factor is produced. The line outages that do not change the topology of the power systems are addressed by employing flow cancelation method. Flow canceling transaction are power injection and withdrawal from two pseudo-buses close to the from and to buses of the failed line so that the failed line flow would appear zero to the rest of the system [34]. The framework used for solving the preventive SCUC is shown in Fig. 1.

The total number of variables and constraints required for SCUC for large scale networks, makes it computationally complicated and time consuming to solve. To reduce the solution time, an iterative approach has been employed in which, for the first iteration, none of the lines thermal limit is taken into consideration. The solution of this stage is then used to calculate

Authorized licensed use limited to: University of Florida. Downloaded on July 01,2023 at 15:44:00 UTC from IEEE Xplore. Restrictions apply.

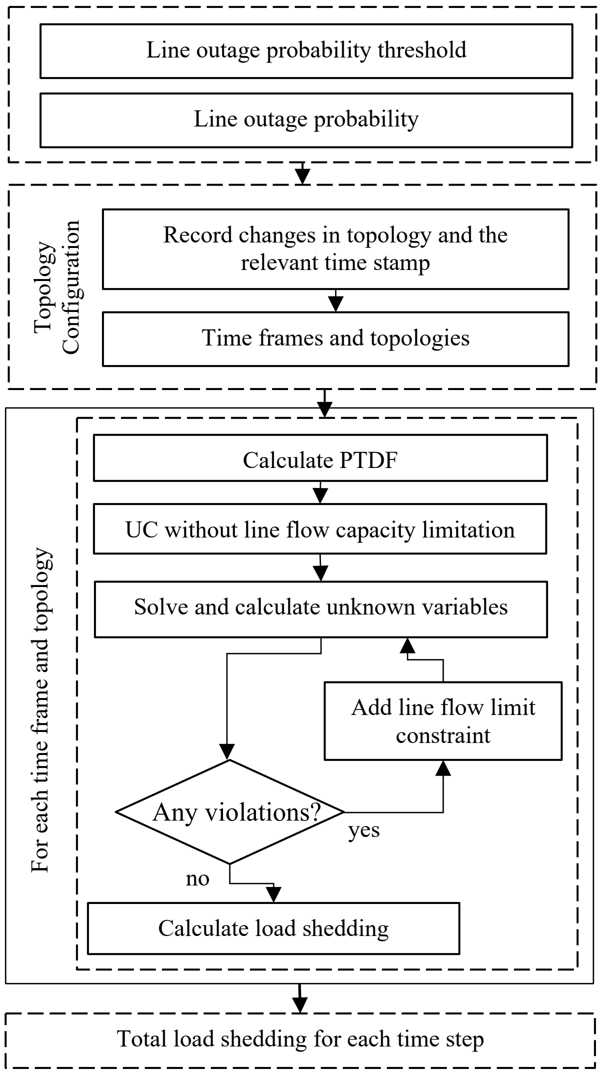


Fig. 1. Preventive SCUC framework.

the line flows. If the flow if any of the transmission lines exceeds its limit, those lines are added to the original problem and the problem is solved again. This process is repeated until no lines' thermal limit is violated [35], [36].

V. Case Study

The implications of implementing this method on the weather data of Hurricane Harvey are presented in this section. The Hurricane weather data of 25th through 27th of August 2017 are forecasted using 20 sets of varying lead times from August 21st to 25th in 6 hours intervals as shown in Table I. For each of these starting dates, 20 models with added dynamic initial perturbations are used to forecast the wind speed and angle for 132 geographical locations scattered over Texas.

The weather predictions of the ensemble model for hour 18 of 25th through 27th of August using two different prediction starting date is shown in Fig. 2. The model performed on August 21, has 120 hours of lead time and predicts the hurricane landfall would happen before 6 p.m. on August 25 and by then would

TABLE I. Ensemble Model Structure Used in Weather Forecast and Their Start-Time

Prediction Start Time	Individual Models Constructing Ensemble	Output of Each Individual Model
08/21/2017 – 0:00	Model 1	Speed
		Angle
	⋮	⋮
	Model 20	Speed
		Angle
	⋮	
08/25/2017 – 18:00	Model 1	Speed
		Angle
	⋮	⋮
	Model 20	Speed
		Angle

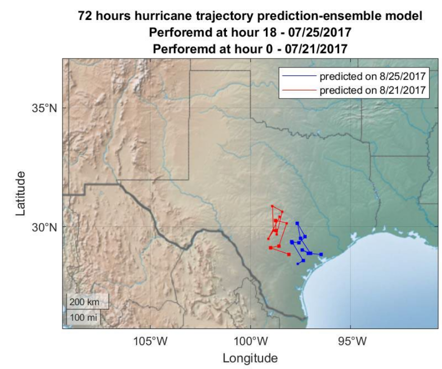


Fig. 2. Predicted hurricane trajectory at 6:00 p.m. of 25th through 27th of August 2017 using ensemble models with prediction performed at 0:00 a.m. of 21st of August and 6:00 p.m. of 25th of August.

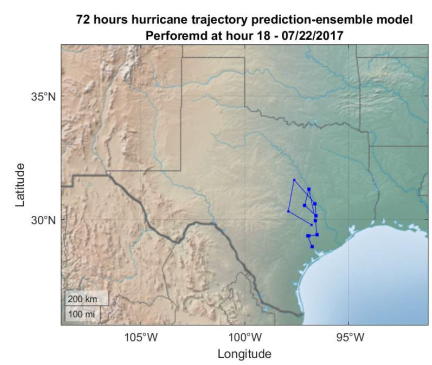


Fig. 3. Predicted hurricane trajectory at 6:00 p.m. of 25th through 27th of August 2017 using ensemble model performed at 6:00 p.m. on 22nd.

move further inland. The prediction performed on August 25, with zero hour start date is concurrent with the time window of interest for hurricane. There is limited leeway for system operator to schedule units efficiently at this stage. We chose prediction model performed on August 22, at hour 18 (Fig. 3) to describe the impacts of weather prediction on power system scheduling and load shedding.

All the towers in this study are assumed to have a generic design, with 55 m length, built from steel and have L-shape cross section. The predicted wind speed changes over height for most

Authorized licensed use limited to: University of Florida. Downloaded on July 01,2023 at 15:44:00 UTC from IEEE Xplore. Restrictions apply.

TABLE II. CHANGE IN THE TOPOLOGY OF POWER TRANSMISSION SYSTEM DURING THE 72 HOURS OF STUDY

Hour	Number of Segments	Buses in Main Segment	Number of 1 Bus Segments
25	3	1998	2
28	9	1983	5
31	18	1972	13
34	26	1936	16
37	33	1913	21
40	34	1906	21
43	37	1903	22
46	39	1901	24

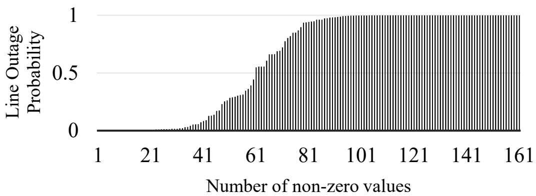


Fig. 4. The values of line outage probabilities based on prediction of hour 18 on 22nd of August 2017.

transmission towers in open terrain, is a function of the constant wind speed at 10 m height. By assuming that the ACTIVSg2000 system is mapped on Texas, the location of transmission lines and towers are specified. Given the wind speed and angle calculated for the location of transmission towers, the probabilities of line outages can be calculated. For the prediction performed on the 22nd of August, the distribution of non-zero line outage probabilities are shown in Fig. 4.

There are more than 3000 lines in this system, we limit the portrayed probabilities to unique non-zero values. Majority of the lines have outage probability of zero. For the remaining lines, depending on when hurricane hits the surrounding area, the lines outage probability will pick up and after the hurricane passed those areas, their probability will drop to zero again.

To determine line outage status, a threshold value is chosen based on which lines with outage probability higher would be considered disconnected from the system. The outage probability of these disconnected lines could be zero for the following hours, but because the damages inflicted on the transmission lines are not repaired until after the event, the lines are considered down for the duration of simulation. The line outages at the last hour of predicted hurricane with two threshold values of 0.05 and 0.95 is shown in Fig. 5 and Fig. 6, respectively. The number of failed lines for thresholds 0.05 and 0.95 are 125 and 78, respectively.

By choosing the prediction of August 22, at hour 18, and with outage probability threshold of 0.05, the first line outage happens on hour 16 on August 25 and the last line outages happen on hour 17 of August 27. The preventive SCUC time frame is set from hour 0 of 25th to hour 0 of 28th to include the duration of the event. During this time, the line outages cause changes in the topology of power system as shown in Table II.

The preventive SCUC for all the segments created is formulated and simulated using Python 3.9 with a CPLEX MILP solver. $7.44 E+8 is calculated as the total cost and the

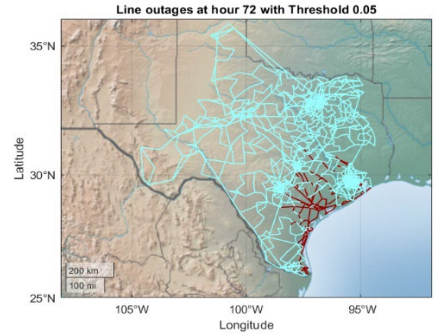


Fig. 5. Line outages in the ACTIVSg2000 power transmission system with probability threshold of 0.05.

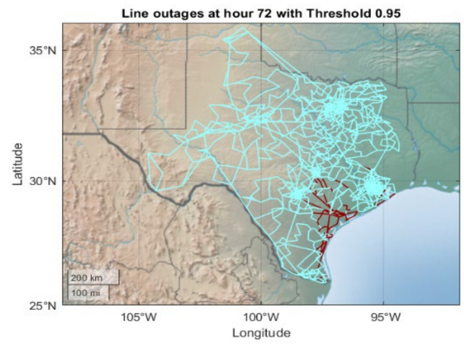
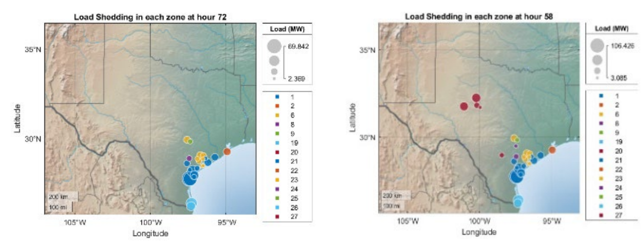


Fig. 6. Line outages in the ACTIVSg2000 power transmission system with probability threshold of 0.95.



(a) (b)

Fig. 7. Total load shedding in various zones at hour 72 (a) and hour 58 (b).

simulation take 2 hours and 28 minutes to find a solution. 138 lines are added through iterative procedure to the constraints to be monitored as their flow exceeded their thermal limit. The high cost is due to the high penalty of load shedding and the inevitable load shedding that happens because of line outages. The total load shedding with probability threshold of 0.05 is 22,980 MW.

The load buses that are disconnected from the main network and do not have generator attached to them will experience load shedding for the duration of event. But due to inadequacy of the generating power available in the main network or reduction in system connectivity and lower power transfer capability, main network also faces load shedding for few hours as shown in Fig. 7. Each of the ensemble weather prediction is similarly used to predict load shedding and schedule generating units to operate the distressed power system optimally. The predicted load shedding for each bus is shown in Fig. 8.

Authorized licensed use limited to: University of Florida. Downloaded on July 01,2023 at 15:44:00 UTC from IEEE Xplore. Restrictions apply.

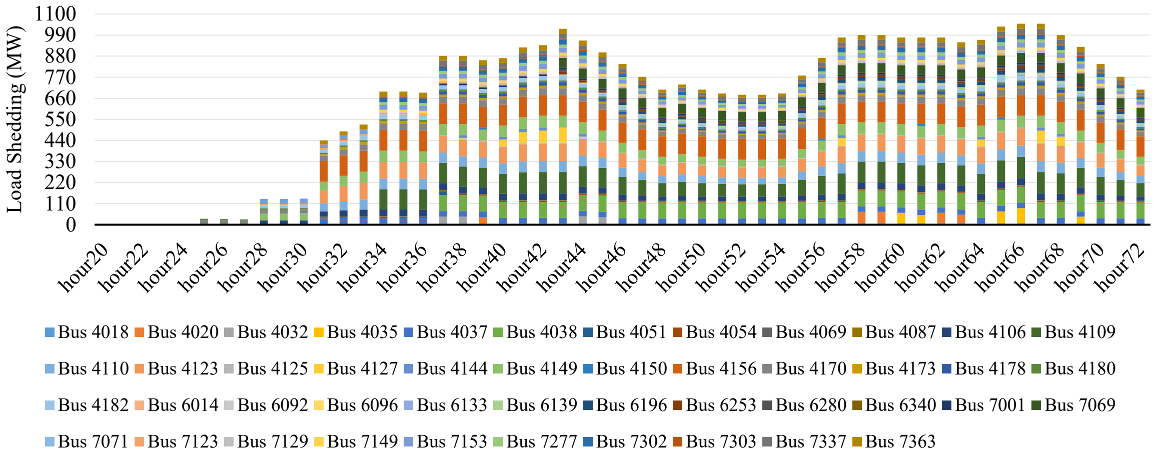


Fig. 8. Hourly load shedding during the hurricane predicted at 6 p.m. 22nd of August at each bus.

I. Conclusion

The devastating impacts that hurricanes can have on the power system infrastructure and subsequently affect people' access to crucial services, can be managed to some extent with thorough emergency response planning. These preprepared responses are made using the weather forecast of leading days to the hurricane event. To improve the accuracy and comprehensiveness of the forecast, ensemble methods are used in this paper. Their impact on the power system infrastructure is estimated and accordingly the line outage probabilities are calculated. Various scenarios are developed, and their corresponding emergency response are planned based-on the line outage probabilities provided. The emergency response can then be improved upon the comparison of more updated weather data and the scenarios available. The proposed method is applied on the ACTIVSg2000 system mapped on Texas, with simulation run time of near 150 minutes. The consecutive changes in the network topology are also predicted that should be studied for maintaining system security.

References

[1] E. Bompard, T. Huang, Y. Wu, and M. Cremenescu, "Classification and trend analysis of threats origins to the security of power systems," Int. J. Electr. Power Energy Syst., vol. 50, pp. 50–64, 2013, doi: https://doi.org/10.1016/j.ijepes.2013.02.008.

[2] F. Yang, P. Watson, M. Koukoula, and E. N. Anagnostou, "Enhancing Weather-Related Power Outage Prediction by Event Severity Classification," IEEE Access, vol. 8, pp. 60029–60042, 2020, doi: 10.1109/ACCESS.2020.2983159.

[3] R. Eskandarpour and A. Khodaei, "Machine Learning Based Power Grid Outage Prediction in Response to Extreme Events," IEEE Trans. Power Syst., vol. 32, no. 4, pp. 3315–3316, Jul. 2017, doi: 10.1109/TPWRS.2016.2631895.

[4] R. J. Campbell, "Weather-related power outages and electric system resiliency," Congr. Res. Serv., Washington, DC, USA, Tech. Rep. R42696, Aug. 2012. [Online]. Available: http://www.fas.org/sgp/crs/misc/R42696.pdf

[5] M. Panteli and P. Mancarella, "Modeling and Evaluating the Resilience of Critical Electrical Power Infrastructure to Extreme Weather Events," IEEE Syst. J., vol. 11, no. 3, pp. 1733–1742, Sep. 2017, doi: 10.1109/JSYST.2015.2389272.

[6] R. Eskandarpour and A. Khodaei, "Leveraging Accuracy-Uncertainty Tradeoff in SVM to Achieve Highly Accurate Outage Predictions," IEEE Trans. Power Syst., vol. 33, no. 1, pp. 1139–1141, Jan. 2018, doi: 10.1109/TPWRS.2017.2759061.

[7] "A Statistical Forecast Model of Weather-Related Damage to a Major Electric Utility in: Journal of Applied Meteorology and Climatology Volume 51 Issue 2 (2011)." https://journals.ametsoc.org/view/journals/apme/51/2/jamc-d-11-09.1.xml (accessed Jul. 02, 2022).

[8] A. I. Sarwat, M. Amini, A. Domijan, A. Damnjanovic, and F. Kaleem, "Weather-based interruption prediction in the smart grid utilizing chronological data," J. Mod. Power Syst. Clean Energy, vol. 4, no. 2, pp. 308–315, Apr. 2016, doi: 10.1007/s40565-015-0120-4.

[9] J. He, D. W. Wanik, B. M. Hartman, E. N. Anagnostou, M. Astitha, and M. E. B. Frediani, "Nonparametric Tree-Based Predictive Modeling of Storm Outages on an Electric Distribution Network," Risk Anal. Off. Publ. Soc. Risk Anal., vol. 37, no. 3, pp. 441–458, Mar. 2017, doi: 10.1111/risa.12652.

[10] Y. Kor, M. Z. Reformat, and P. Musilek, "Predicting Weather-related Power Outages in Distribution Grid," in 2020 IEEE Power & Energy Society General Meeting (PESGM), Aug. 2020, pp. 1–5. doi: 10.1109/PESGM41954.2020.9281829.

[11] A. K. Onaolapo, R. Pillay Carpanen, D. G. Dorrell, and E. E. Ojo, "Event-Driven Power Outage Prediction using Collaborative Neural Networks," IEEE Trans. Ind. Inform., pp. 1–1, 2022, doi: 10.1109/TII.2022.3178695.

[12] D. W. Wanik, J. R. Parent, E. N. Anagnostou, and B. M. Hartman, "Using vegetation management and LiDAR-derived tree height data to improve outage predictions for electric utilities," Electr. Power Syst. Res., vol. 146, pp. 236–245, May 2017, doi: 10.1016/j.epsr.2017.01.039.

[13] D. Cerrai et al., "Predicting Storm Outages Through New Representations of Weather and Vegetation," IEEE Access, vol. 7, pp. 29639–29654, 2019, doi: 10.1109/ACCESS.2019.2902558.

[14] E. N. Lorenz, "Deterministic Nonperiodic Flow," J. Atmospheric Sci., vol. 20, no. 2, pp. 130–141, Mar. 1963, doi: 10.1175/1520-0469(1963)020<0130:DNF>2.0.CO;2.

[15] R. H. Langland, M. A. Shapiro, and R. Gelaro, "Initial Condition Sensitivity and Error Growth in Forecasts of the 25 January 2000 East Coast Snowstorm," Mon. Weather Rev., vol. 130, no. 4, pp. 957–974, Apr. 2002, doi: 10.1175/1520-0493(2002)130<0957:ICSAEG>2.0.CO;2.

[16] G. A. Grell, "Semi-prognostic tests of cumulus parameterization schemes in the middle latitudes," Ph.D., University of Miami, United States -- Florida. Accessed: Jul. 03, 2022. [Online]. Available:

Authorized licensed use limited to: University of Florida. Downloaded on July 01,2023 at 15:44:00 UTC from IEEE Xplore. Restrictions apply.

https://www.proquest.com/docview/303596482/abstract/A73979C6E86143F3PQ/1

[17] M. E. B. Frediani, J. P. Hacker, E. N. Anagnostou, and T. Hopson, "Evaluation of PBL Parameterizations for Modeling Surface Wind Speed during Storms in the Northeast United States," Weather Forecast., vol. 31, no. 5, pp. 1511–1528, Oct. 2016, doi: 10.1175/WAF-D-15-0139.1.

[18] M. S. Jones, B. A. Colle, and J. S. Tongue, "Evaluation of a Mesoscale Short-Range Ensemble Forecast System over the Northeast United States," Weather Forecast., vol. 22, no. 1, pp. 36–55, Feb. 2007, doi: 10.1175/WAF973.1.

[19] "Economic Benefits of Increasing Electric Grid Resilience to Weather Outages," Energy.gov. https://www.energy.gov/downloads/economic-benefits-increasing-electric-grid-resilience-weather-outages (accessed Jul. 03, 2022).

[20] P. Hoffman, W. Bryan, and A. Lippert, "Comparing the Impacts of the 2005 and 2008 Hurricanes on U.S. Energy Infrastructure," US Dep. Energy, 2009.

[21] R. Panora, J. E. Gehret, M. M. Furse, and R. H. Lasseter, "Real-World Performance of a CERTS Microgrid in Manhattan," IEEE Trans. Sustain. Energy, vol. 5, no. 4, pp. 1356–1360, Oct. 2014, doi: 10.1109/TSTE.2014.2301953.

[22] M. Sahraei-Ardakani and G. Ou, "Day-ahead preventive scheduling of power systems during natuaral hazards via stochastic optimization," in 2017 IEEE Power & Energy Society General Meeting, Jul. 2017, pp. 1–1. doi: 10.1109/PESGM.2017.8274453.

[23] J. G. Powers et al., "The Weather Research and Forecasting Model: Overview, System Efforts, and Future Directions," Bull. Am. Meteorol. Soc., vol. 98, no. 8, pp. 1717–1737, Aug. 2017, doi: 10.1175/BAMS-D-15-00308.1.

[24] C. Skamarock et al., "A Description of the Advanced Research WRF Version 3," 2008, doi: 10.5065/D68S4MVH.

[25] F. Sanders, "On Subjective Probability Forecasting," J. Appl. Meteorol. Climatol., vol. 2, no. 2, pp. 191–201, Apr. 1963, doi: 10.1175/1520-0450(1963)002<0191:OSPF>2.0.CO;2.

[26] E. Kalnay, "Atmospheric Modeling, Data Assimilation and Predictability," Higher Education from Cambridge University Press, Nov. 06, 2002. https://www.cambridge.org/highereducation/books/atmospheric-modeling-data-assimilation-and-predictability/C5FD207439132836E85027754CE9BC1A (accessed Jul. 06, 2022).

[27] T. T. Warner, Numerical Weather and Climate Prediction. Cambridge: Cambridge University Press, 2010. doi: 10.1017/CBO9780511763243.

[28] M. R. Bhuiyan and R. N. Allan, "Inclusion of weather effects in composite system reliability evaluation using sequential simulation," IEE Proc. - Gener. Transm. Distrib., vol. 141, no. 6, pp. 575–584, Nov. 1994, doi: 10.1049/ip-gtd:19941573.

[29] Y. Liu and C. Singh, "A Methodology for Evaluation of Hurricane Impact on Composite Power System Reliability," IEEE Trans. Power Syst., vol. 26, no. 1, pp. 145–152, Feb. 2011, doi: 10.1109/TPWRS.2010.2050219.

[30] G. C. Marano, R. Greco, and M. Mezzina, "Stochastic approach for analytical fragility curves," KSCE J. Civ. Eng., vol. 12, no. 5, pp. 305–312, Sep. 2008, doi: 10.1007/s12205-008-0305-8.

[31] S. P. Batke, M. Jocque, and D. L. Kelly, "Modelling Hurricane Exposure and Wind Speed on a Mesoclimate Scale: A Case Study from Cusuco NP, Honduras," PLOS ONE, vol. 9, no. 3, p. e91306, Mar. 2014, doi: 10.1371/journal.pone.0091306.

[32] Y. Sang, J. Xue, M. Sahraei-Ardakani, and G. Ou, "An Integrated Preventive Operation Framework for Power Systems During Hurricanes," IEEE Syst. J., vol. PP, Oct. 2019, doi: 10.1109/JSYST.2019.2947672.

[33] B. Stott, J. Jardim, and O. Alsac, "DC Power Flow Revisited," IEEE Trans. Power Syst., vol. 24, no. 3, pp. 1290–1300, Aug. 2009, doi: 10.1109/TPWRS.2009.2021235.

[34] P. A. Ruiz, E. Goldis, A. M. Rudkevich, M. C. Caramanis, C. R. Philbrick, and J. M. Foster, "Security-Constrained Transmission Topology Control MILP Formulation Using Sensitivity Factors," IEEE Trans. Power Syst., vol. 32, no. 2, pp. 1597–1605, Mar. 2017, doi: 10.1109/TPWRS.2016.2577689.

[35] F. Mohammadi and M. Sahraei-Ardakani, "Tractable Stochastic Unit Commitment for Large Systems During Predictable Hazards," IEEE Access, vol. 8, pp. 115078–115088, 2020, doi: 10.1109/ACCESS.2020.3004391.

[36] F. Mohammadi and M. Sahraei-Ardakani, "Multidimensional Scenario Selection for Power Systems with Stochastic Failures," IEEE Trans. Power Syst., vol. 35, no. 6, pp. 4528–4538, Nov. 2020, doi: 10.1109/TPWRS.2020.2990877.

Authorized licensed use limited to: University of Florida. Downloaded on July 01,2023 at 15:44:00 UTC from IEEE Xplore. Restrictions apply.