Response to Reviewer#2

This paper investigated the limitations of existing power outage models, including bounded prediction, out-of-distribution prediction, and physics-aware uncertainties The authors found some of the existing state-of-the-art models may generate unrealistic predictions, and cannot generalize well to extreme events that are not sufficiently represented in the training datasets. The authors discuss some potential ways to address the shortcomings of these models. I have some major comments that authors need to address before publication:

Dear Reviewer,

Thank you for reviewing our manuscript. We are grateful for your comments that have helped to better explain the critical aspects of power outage predictions. Please find detailed responses to your comments.

Comment#1: The problems mentioned by the authors, including limited generalization ability, unbounded predictions, and unreasonable uncertainty variations, are common problem for general machine learning models. Many machine learning community researchers proposed different methods to address these problems. How unique and critical are they for power outage predictions?

Response#1:

We agree with you that paper lacked a discussion on how critical limitations are with the state-of-the-art power outage predictions. We have included a new section 8 as "Discussion" in the manuscript:

"Utilities and government agencies benefit from the power outage predictions ahead of a hurricane as it gives them a chance for effective and efficient pre-disaster planning. However, utilities and governments often have limited resources to deploy for emergency response pre-event and during the event. Jersey Central Power & Light (JCPL), a major utility company in New Jersey, serves 1.1 million consumers. Hurricane Isaias (2020) severely impacted JCPL's power supply, leaving 780,000 consumers without power in New Jersey (Giuliano, 2020). Hurricane Isaias impacted about 8,800 locations, with tree-related damages damaging 700 utility poles, 2,800 cross arms, 600 transformers, and around 80 miles of wire. JCPL mobilized around 1800 crew members to restore services. JCPL restored power for 86% of the consumers in 72 hours (Giuliano, 2020). Robust estimates of spatially distributed outages ahead of a hurricane can assist utilities in asking for crews from other utilities under mutual assistance during disasters ("Enhancing the Resilience of the Nation's Electricity System," 2017).

Erroneous power outage estimates can result in the non-optimal placement of resources, as optimal resource allocation algorithms will use predicted outages (Brown, 2002). Overestimated power outages could result in prioritizing a less affected city, placing more resources on that city than required. Limited mobility during a disaster can lead to prolonged outages, delaying the restoration effects ("Enhancing the Resilience of the Nation's Electricity System," 2017). JCPL predicted 449,312 customers without power ahead of Isaias compared to actual outages of 780,000 (Giuliano, 2020). Limited generalization of the power outage model limits the utilities to arrange the correct number of crews under mutual assistance.

Large manufacturing companies or data centers are covered with business interruption insurance. Power outages from hurricanes can severely impact the operations of these companies. Insurance companies can use simulations on historical disaster data with power outage predictions to decide the insurance premium. Insurance premiums are based on downtime, the time for which power downtime. While calculating downtime is not the scope of this paper, the number of outages is determined to get the downtime (Liu et al., 2007). To determine downtime, insurance companies consider the uncertainty of the disruption, high uncertainty in predictions can lead to high insurance (Johnson, 2001). Thus, more certain estimates can help in a more fair pricing of insurance premiums. Thus, improvements are required to make robust power outage predictions."

Reference:

Brown, R. E. (2002). *Electric Power Distribution Reliability*. http://www.dekker.com

Enhancing the Resilience of the Nation's Electricity System. (2017). In *Enhancing the Resilience of the Nation's Electricity System*. https://doi.org/10.17226/24836

Giuliano, J. (2020). *State of New Jersey New Jersey Board of Public Utilities Review and Assessment of Electric Utility Performance August 4, 2020 Tropical Storm Isaias Weather Event Division of Reliability and Security*.

Johnson, S. G. (2001). *JOURNAL OF INSURANCE COVERAGE Insurance Coverage for Power Outage Losses*.

Liu, H., Davidson, R. A., & Apanasovich, T. v. (2007). Statistical forecasting of electric power restoration times in hurricanes and ice storms. *IEEE Transactions on Power Systems*, *22*(4), 2270–2279. https://doi.org/10.1109/TPWRS.2007.907587

Comment#2: Now there is a variety of more complex power outage prediction models [1], are there any specific reasons for the authors to choose to evaluate traditional machine learning models? These traditional models are known to be less representative.

[1]Xie, Jian, Inalvis Alvarez-Fernandez, and Wei Sun. "A review of machine learning applications in power system resilience." In 2020 IEEE Power & Energy Society General Meeting (PESGM), pp. 1-5. IEEE, 2020.

Response#2:

Thanks for pointing this out. We have included an introduction to more complex power outage prediction models, namely neural networks, kernel methods such as support vector machines, and other tree-ensemble methods, such as AdaBoost, which can model non-linear relationships between input parameters and outages (Xie et al., 2020). However, data availability limits the applicability of these methods at a large scale for power outage predictions from extreme events.

Power Outage Models by (Liu et al., 2007; Han et al., 2009; Guikema et al., 2014; McRoberts et al., 2018; Shashaani et al., 2018) provide outage predictions at a coarser level compared to predictions at component. However, these models are mostly based on open-source, publicly available data and can be generalized at a larger scale to the coastal cities in the United States. Hurricane-caused outages are mostly at the transmission level, which is responsible for city-wide outages (Brown, 2002; poweroutage.us/faq, last accessed: 13 January 2023) rather than the customer meter level. So, predicting city-wide outages can still guide utilities to arrange for crews and emergency backup power ahead of a storm. We have also included this discussion (in blue below) in the introduction section after Line 76:

Previously, researchers have used more complex power outage prediction models, namely neural networks, kernel methods such as support vector machines, and other tree-ensemble methods, such as AdaBoost, which can model non-linear relationships between input parameters and outages (Xie et al., 2020). (Kankanala et al., 2014) employed AdaBoost to predict weather-related power outages. (Kankanala et al., 2014) trained a separate model for each city for daily use, and they did not cover extreme weather outages. (Eskandarpour & Khodaei, 2018 and Eskandarpour et al., 2018) used power grid component-level data with support vector machines. (Rudin et al., 2012) ranked the power grid components (feeder failures, cables, joints, terminators, and transformers) based on their vulnerability to extreme weather events. (Haseltine & Eman, 2017) used a neural network to predict the failure of the power grid components for pre-storm. Such models will require specialized high-resolution power grid component-level data for each city which is not accessible given the data protocols of utility companies. (Sun et al., 2016) used Twitter (https://twitter.com; last accessed: 13 January 2023) data to predict real-time outages. (Jaech et al., 2018) used repair logs data employing Natural Processing with a Recurrent Neural Network to predict real-time outage durations. However, tweets (https://twitter.com; last accessed: 13 January 2023) and repair logs are available after the hurricane made an impact on the city. Thus, leveraging repair logs is not possible to predict outages for pre-event planning ahead of a storm. Hence, data availability limits the applicability of these methods at a large scale for power outage predictions from extreme events.

GLM (Liu et al., 2007), GAM (Han et al., 2009), and Random Forest based power outage prediction models (Guikema et al., 2014; McRoberts et al., 2018; Shashaani et al., 2018) provide outage predictions at a coarser level compared to predictions at component. However, these models are mostly based on open-source, publicly available data and can be generalized at a larger scale to the coastal cities in the United States. Hurricane-caused outages are mostly at the transmission level, which is responsible for city-wide outages (Brown, 2002; poweroutage.us/faq, last accessed: 13 January 2023) rather than the customer meter level. So, predicting city-wide outages can still guide utilities to arrange for crews and emergency backup power ahead of a storm. Hence for the scope of this paper, we focus on GLM, GAM, and Random Forest based power outage prediction models.

Reference:

Brown, R. E. (2002). *Electric Power Distribution Reliability*. http://www.dekker.com

Eskandarpour, R., & Khodaei, A. (2018). Leveraging accuracy-uncertainty tradeoff in SVM to achieve highly accurate outage predictions. *IEEE Transactions on Power Systems*, *33*(1), 1139–1141. https://doi.org/10.1109/TPWRS.2017.2759061

Eskandarpour, R., Khodaei, A., Paaso, A., & Abdullah, N. M. (2018). *Artificial Intelligence Assisted Power Grid Hardening in Response to Extreme Weather Events*. https://doi.org/10.48550/arxiv.1810.02866

Guikema, S. D., Nateghi, R., Quiring, S. M., Staid, A., Reilly, A. C., & Gao, M. (2014). Predicting Hurricane Power Outages to Support Storm Response Planning. *IEEE Access*, *2*(September 2015), 1364–1373. https://doi.org/10.1109/ACCESS.2014.2365716

Han, S. R., Guikema, S. D., & Quiring, S. M. (2009). Improving the predictive accuracy of hurricane power outage forecasts using generalized additive models. *Risk Analysis*, *29*(10), 1443–1453. https://doi.org/10.1111/j.1539-6924.2009.01280.x

Haseltine, C., & Eman, E. E. S. (2017). Prediction of power grid failure using neural network learning. *Proceedings - 16th IEEE International Conference on Machine Learning and Applications, ICMLA 2017*, *2017-December*, 505–510. https://doi.org/10.1109/ICMLA.2017.0-111

Jaech, A., Zhang, B., Ostendorf, M., & Kirschen, D. S. (2018). *Real-Time Prediction of the Duration of Distribution System Outages*. http://arxiv.org/abs/1804.01189

Kankanala, P., Das, S., & Pahwa, A. (2014). Adaboost+: An ensemble learning approach for estimating weather-related outages in distribution systems. *IEEE Transactions on Power Systems*, *29*(1), 359–367. https://doi.org/10.1109/TPWRS.2013.2281137

Liu, H., Davidson, R. A., & Apanasovich, T. v. (2007). Statistical forecasting of electric power restoration times in hurricanes and ice storms. *IEEE Transactions on Power Systems*, *22*(4), 2270–2279. https://doi.org/10.1109/TPWRS.2007.907587

McRoberts, D. B., Quiring, S. M., & Guikema, S. D. (2018). Improving Hurricane Power Outage Prediction Models Through the Inclusion of Local Environmental Factors. *Risk Analysis*, *38*(12), 2722–2737. https://doi.org/10.1111/risa.12728

Rudin, C., Waltz, D., Anderson, R., Boulanger, A., Salleb-Aouissi, A., Chow, M., Dutta, H., Gross, P., Huang, B., Ierome, S., Isaac, D. F., Kressner, A., Passonneau, R. J., Radeva, A., & Wu, L. (2012). Machine learning for the New York City power grid. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *34*(2), 328–345. https://doi.org/10.1109/TPAMI.2011.108

Shashaani, S., Guikema, S. D., Zhai, C., Pino, J. v., & Quiring, S. M. (2018). Multi-Stage Prediction for Zero-Inflated Hurricane Induced Power Outages. *IEEE Access*, *6*, 62432–62449. https://doi.org/10.1109/ACCESS.2018.2877078

Sun, H., Wang, Z., Wang, J., Huang, Z., Carrington, N., & Liao, J. (2016). Data-Driven Power Outage Detection by Social Sensors. *IEEE Transactions on Smart Grid*, *7*(5), 2516–2524. https://doi.org/10.1109/TSG.2016.2546181

Xie, J., Alvarez-Fernandez, I., & Sun, W. (2020). A review of machine learning applications in power system resilience. *IEEE Power and Energy Society General Meeting*, *2020-August*. https://doi.org/10.1109/PESGM41954.2020.9282137

Comment#3: It is unclear to me why beta regression should perform well in general cases. I think it also has its own problems such as strict distribution assumption, and does not address the representativeness issues which eventually cause the poor generalization problem. Could you provide any justifications and performance comparison regarding why Beta regression should be used?

Response#3:

Thank you for pointing this out. While beta regression analysis was not the scope of this paper, we wanted to suggest possible candidate methods to overcome the challenges with state-of-the-art power outage prediction models. The authors are currently exploring the possibility of beta regression as a power outage prediction model. Accordingly, we have modified section 9 on "Suggested future research for "comprehensive" outage risk assessments" to point out that Beta distributions are just a suggestion (and we are currently working on that) as follows:

Efforts are still needed to overcome the limitations of state-of-the-art power outage prediction models. In this paper, we suggest the study of Beta GAMs to address them (Ferrari and Cribari-Neto, 2010; Olkin and Liu, 2003). While beta regression analysis was not the scope of this paper, we suggest possible candidate methods to overcome the challenges with state-of-the-art power outage prediction models. The authors are currently exploring the possibility of beta regression as a power outage prediction model. Beta distributions model random variables that take values from 0 to 1. Thus, it can model the fraction of outages in a city. For illustration, we present the possible prediction ranges of outages with wind speed for a Beta distributed fraction of outages (Yee, 2012; Olkin and Liu, 2003; Douma and Weedon, 2019). Similar to Negative Binomial GAM, Beta GAM can account for the high variability of the input variables and can handle the overdispersion in power outage data (Douma and Weedon, 2019).

Beta GAMs can make bounded predictions on the percentage of customers without electricity. Beta GAMs could extrapolate outages for the extreme (low and high) values of winds. Beta predictions always go from their minimum value of 0 to their maximum value of 1. Beta GAMs could predict the outages with low variance at low and high winds closer to the physics of infrastructure failure. Thus, future research could focus on developing such Beta GAMs for outage prediction.

Reference:

Ferrari, S. L. P., & Cribari-Neto, F. (2010). Beta Regression for Modelling Rates and Proportions. *Http://Dx.Doi.Org/10.1080/0266476042000214501*, *31*(7), 799–815. https://doi.org/10.1080/0266476042000214501

Olkin, I., & Liu, R. (2003). A bivariate beta distribution. *Statistics and Probability Letters*, *62*(4), 407–412. https://doi.org/10.1016/S0167-7152(03)00048-8

Yee, T. W. (2012). *Package "VGAM" (Vector generalized linear and additive models)*. http://www.springer.com/series/692

Douma, J. C., & Weedon, J. T. (2019). Analysing continuous proportions in ecology and evolution: A practical introduction to beta and Dirichlet regression. *Methods in Ecology and Evolution*, *10*(9), 1412–1430. https://doi.org/10.1111/2041-210X.13234