Load Prediction Considering Forced Outages

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***Abstract*—This paper introduces a novel probabilistic framework for modeling weather-dependent load availability via an availability factor A, which represents the fraction of load remaining connected under adverse conditions. The method combines outage data with environmental parameters to estimate the probability distribution of A conditioned on weather and geographic context. Using the EAGLE-I dataset for outage records and ASOS weather observations as a use case, we construct a spatiotemporally aligned dataset and train a machine learning model to classify availability into discrete outage severity bins. The resulting model enables the generation of stochastic load scenarios that capture both normal and outage conditions, providing a data-driven basis for probabilistic power flow and resilience studies. The proposed approach serves as a bridge between reliability analysis and load forecasting, allowing utilities and system planners to evaluate potential load reductions due to weather-related events and to integrate these scenarios into operational and planning models. The results for the United States in 2022 show a precision of up to 0.88, indicating robust predictive performance despite strong class imbalance.**

***Index Terms*—load forecast, outage prediction, AI/ML, load scenario generation**

I. Introduction

Forced outages in electric power systems have a significant impact on realized load profiles and complicate the processes of reliability assessment, operational planning, and long-term system design. Such events not only disrupt the supply of electricity to customers but also complicate the planning and real-time operation of transmission and distribution networks. The increasing frequency and severity of weather-related disturbances further highlight the importance of understanding and quantifying the effects of forced outages on system performance.

In recent years, the availability and volume of power grid–relevant data have increased substantially. Among the various factors influencing outage occurrence, environmental and weather conditions remain the primary drivers [1], [2]. Leveraging these datasets enables a more comprehensive analysis of outage behavior and facilitates the development of models that can anticipate or mitigate forced outages in the system. The emergence of artificial intelligence (AI) and machine learning (ML) methods has further enhanced the ability to process large, heterogeneous datasets and uncover complex nonlinear relationships between environmental variables and outage events.

Multiple studies have explored the use of AI/ML techniques for predicting power system outages. Some works focus on extreme weather events and aim to forecast the number of outages within a predefined geographical area [3]–[5] or predict a portion of customers losing power during a specific storm [6]. In contrast, others estimate the probability of outage occurrence in specific regions under severe weather conditions on a daily basis [7], [8]. Extensions of these methods also address the prediction of outage duration and restoration time [9], [10]. Such predictive frameworks are often integrated into decision-support systems that enable utilities to select optimal mitigation measures and resource allocation strategies to minimize the impact of potential outages [11], [12].

A related body of literature addresses generator outages and their effects on power system operation. For example, one study proposed a probabilistic procedure for synthesizing realistic steady-state contingency scenarios using historical generator outage data, applying the approach to simulate storm-induced contingencies on the ACTIVSg2000 synthetic Texas grid [13]. Another work introduced a novel collapse prediction index to assess voltage stability conditions and identify critical lines and generators under various contingency scenarios [14].

However, existing literature primarily concentrates on outage occurrence and duration, while the associated impact on realized load profiles, especially at the transmission level, remains insufficiently addressed. This paper aims to bridge that gap by introducing a novel method for modeling weather-dependent load reductions through a stochastic availability factor framework, providing a quantitative link between outage occurrence and effective load availability.

The contributions of this paper are summarized as follows: (a) Development of a probabilistic framework for modeling load reduction due to forced outages through the availability factor A, representing the fraction of load remaining connected under given weather and environmental conditions; (b) Demonstration of the effectiveness and applicability of the proposed method using real-life open outage and weather datasets.

The rest of this paper is organized as follows. Section II describes the proposed methodology, including the formulation of the availability factor and the associated data requirements.

Section III presents the use case, covering data processing, spatiotemporal correlation, model training, and performance evaluation. Section IV draws the conclusions, and references are given at the end.

II. Methodology

For operational planning and reliability assessments at the transmission level, utilities typically rely on forecasted load profiles, that is, time-series representations of customer demand derived from weather patterns and usage behavior [15], [16]. Numerous forecasting and statistical models have been developed to generate such time-series loads representative of realized consumption [17], [18]. Methodologies for directly incorporating weather and other environmental factors into power system planning tools, including power flow calculations, are presented in [19], [20]. While these methods capture the typical dependence of load on ambient weather conditions, they generally neglect the effects of severe weather events that can lead to partial or total forced outages in the transmission and distribution system. When combined with generation interruptions caused by the same weather phenomena or by the intermittency of renewable resources, these unmodeled effects can significantly alter grid operation and reliability outcomes.

To account for this uncertainty, we define the nominal complex load at each instance t as $S(t)$:

$$S(t) = P(t) + jQ(t), \tag{1}$$

where $P(t)$ and $Q(t)$ are the active and reactive power components, respectively. We then introduce an adjusted stochastic load S^*:

$$S^*(t) = A \cdot S(t), \tag{2}$$

where $A \in [0, 1]$ is an availability factor modeled as a random variable. The factor A represents the fraction of the nominal load that remains available under prevailing conditions and depends on a set of weather and environmental parameters that may reduce demand from its forecasted level.

A. Availability Factor

The distribution of the availability factor A can be represented in several ways. One approach is to directly model A as a continuous random variable defined on the interval $[0, 1]$. Alternatively, A can be represented through a set of discrete ranges or bins, each corresponding to a distinct level of system availability or outage severity. For instance, the bins may be associated with conditions such as no outage, mild outage, moderate outage, or severe outage.

The second approach is computationally more efficient and provides a practical trade-off between the number and width of bins and the desired level of confidence in the representation. The first approach, by contrast, requires uniform accuracy across the entire domain of A, which can be computationally demanding. As the number of bins increases and their width decreases, the discrete representation asymptotically approaches the continuous one, that is,

$$\lim_{N\to\infty} \text{Bin-based model} = \text{Continuous model}.$$

To formally define the availability bins, we introduce a partition of the unit interval $[0, 1]$ into N disjoint subintervals, or bins, denoted as

$$\mathcal{B}_k = [a_{k-1}, a_k), \quad k = 1, 2, \ldots, N, \tag{3}$$

where

$$0 = a_0 < a_1 < a_2 < \ldots < a_N = 1.$$

Each bin $\mathcal{B}_k$ corresponds to a specific level of system availability or outage severity, where smaller values of A represent higher outage impact. For example, suppose 30% of the nominal load is unavailable due to an outage. In that case, the corresponding availability factor is $A = 0.7$, meaning that only 70% of the projected load remains connected to the system under those conditions.

The probability that the availability factor A falls within bin $\mathcal{B}_k$ is defined as

$$\pi_k(\Omega) = \Pr\{A \in \mathcal{B}_k \mid \Omega\}, \tag{4}$$

where Ω represents the set of weather and environmental parameters affecting system performance. The probabilities satisfy the constraint below:

$$\sum_{k=1}^{N} \pi_k(\Omega) = 1, \qquad \pi_k(\Omega) \in [0, 1]. \tag{5}$$

Within each bin $\mathcal{B}_k$, the conditional distribution of A can be specified by a density function $f_k(a \mid \Omega)$ defined over $\mathcal{B}_k$. The overall conditional density of the availability factor can then be expressed as a mixture:

$$f(a \mid \Omega) = \sum_{k=1}^{N} \pi_k(\Omega) f_k(a \mid \Omega)\, \mathbf{1}_{\mathcal{B}_k}(a), \tag{6}$$

where $\mathbf{1}_{\mathcal{B}_k}(a)$ is the indicator function equal to one if $a \in \mathcal{B}_k$ and zero otherwise.

In the limiting case where $N \to \infty$ and each bin width $(a_k - a_{k-1}) \to 0$, the mixture representation converges to a continuous probability density function of A over $[0, 1]$.

B. Data Requirements

Accurate modeling of the availability factor A requires relevant and high-quality data. Two primary categories of data are necessary.

The first category is outage data for each bus or aggregated network region. This dataset should describe the amount of load subject to forced outages at a given time and location. Outage data may be provided in aggregated or disaggregated form. Aggregated data representing the total unavailable load within a region or time interval can be advantageous for privacy and data security. Disaggregated outage records, on the other hand, allow a more detailed representation of outage propagation and local variability.

Strictly speaking, the availability factor A alone may not be sufficient for complete modeling, since both outage and restoration processes influence the realized load. For example, if during one hour 1 MW of load experiences an outage, and in the following hour half of that load is restored while 2 MW of new load becomes unavailable, then the availability factor framework can be extended to represent this dynamic restoration behavior. Such extensions would require modeling practices that account for utility restoration procedures, crew availability, and the occurrence of concurrent outages.

The second category of required data corresponds to environmental and weather-related factors. Historical weather datasets provide the most common source for this information. Still, the framework can be expanded to include additional contextual variables, such as utility maintenance logs, vegetation management and tree-trimming schedules, aerial and satellite imagery, or other geospatial indicators of risk. These complementary datasets can improve estimation of weather-dependent outage probabilities in both temporal and spatial dimensions [21], [22].

All of the aforementioned datasets must then be spatiotemporally correlated and aligned to form a unified dataset suitable for developing a model for the estimation of the availability factor A [8], [12]. This process typically involves temporal synchronization of weather and outage observations to a common resolution, such as hourly or sub-hourly intervals, and spatial alignment of data sources to a consistent geographical reference, for example, bus coordinates or feeder service areas. Interpolation and spatial averaging techniques may be employed to match weather grid data with electrical network nodes, while time-series resampling ensures consistency across different data reporting intervals. Such spatiotemporal integration enables the construction of a coherent dataset that links environmental conditions to observed outage behavior.

III. Use Case

A. Data Processing

As detailed power system data is defined as Critical Energy/Electric Infrastructure Information (CEII), publicly accessible outage data that directly reflects load reductions at the substation level is not available. To address the gap, the analysis in this study utilizes the EAGLE-I outage dataset [23] that provides aggregated outage reports across U.S. counties, including temporal information on the number of customers affected by power interruptions. To complement these records, the dataset was augmented with estimates of the total number of customers in each county, obtained from [24]. Given the number of reported outages per county, denoted as n_{out}, and the total number of customers n_{total}, the availability factor was calculated as:

$$A = 1 - \frac{n_{\text{out}}}{n_{\text{total}}}. \tag{7}$$

Although this formulation is based on county-level aggregates rather than substation-level measurements, it remains representative of the proposed method and serves as a proof of concept for weather-dependent availability factor estimation.

We use the year 2022 for our analysis. A total of 94,853 events were registered in the EAGLE-I dataset for that year. To select relevant records, the data were filtered by event type description, retaining only the outages associated with weather-related causes.

Based on the event-type descriptions for each outage in the EAGLE-I dataset, only weather-related outages were retained, yielding 67,757 events. The EAGLE-I dataset was then merged with the MCC dataset, which provides estimates of the total number of customers in each county. Using the reported mean number of affected customers for each event as n_{out}, the availability factor was calculated according to (7).

To ensure consistency, events for which the computed availability factor A was less than zero (i.e., where the reported mean number of affected customers exceeded the estimated total number of customers) were discarded. After this filtering, 67,388 valid weather-related outage records remained across the United States. The distribution of the resulting availability factor values is shown in Fig. 1.

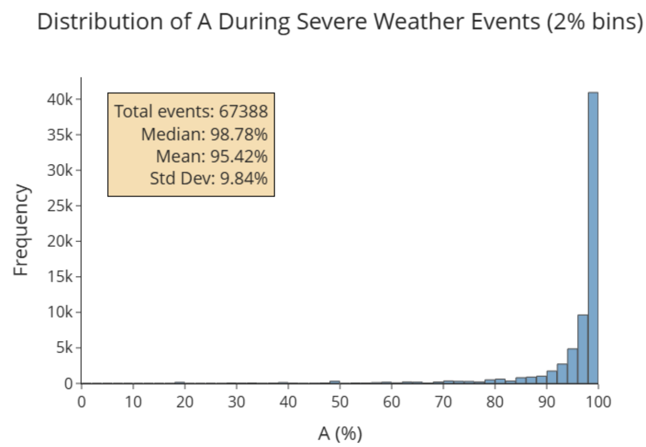

Fig. 1. Distribution of the availability factor A across weather-related outage events in 2022.

To ensure the dataset is representative of each geographic region, events associated with counties (FIPS codes) that have fewer than 15 reported outages during the year were ignored. After this filtering step, 61,136 weather-related outage records remained in the dataset.

B. Spatiotemporal Correlation

To enable spatial analysis, each outage record was associated with its corresponding geographic location. This was achieved by matching the county-level Federal Information Processing Standards (FIPS) codes reported in the EAGLE-I dataset to their respective geographic coordinates obtained from [25]. The resulting dataset thus includes latitude and longitude information for each outage event, enabling subsequent spatiotemporal correlation with weather and environmental parameters. The outcome of the FIPS-to-coordinate matching process is illustrated in Fig. 2.

To incorporate environmental parameters, we utilize the Automated Surface Observing Systems (ASOS) dataset [26]. First, the ASOS station metadata are loaded and filtered to include only stations located within the United States, using

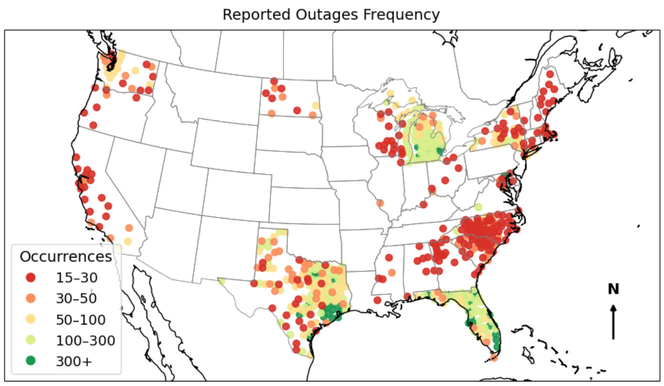

Fig. 2. Spatial distribution of weather-related outages after FIPS-to-coordinate matching.

latitude and longitude constraints of $18° \leq \text{lat} \leq 72°$ and $-179° \leq \text{lon} \leq -65°$. Stations were further filtered to ensure data availability beyond the year 2020.

To associate each outage record with its nearest weather observation, the FIPS-based county coordinates were spatially matched to the closest ASOS weather station using a k-dimensional tree (KDTree) algorithm [27]. This approach efficiently identifies the nearest station in Euclidean distance, enabling the extraction of weather variables corresponding to each outage event.

We then aggregate the start time of each outage to the nearest top-of-the-hour timestamp using the ceiling operation, ensuring temporal alignment with hourly weather observations. To provide a complete temporal representation, the dataset is augmented with records corresponding to normal operating conditions for each unique FIPS code over the entire year. This results in a highly imbalanced dataset, with timestamps corresponding to outage events comprising approximately 1.2% of the total number of records. Such an imbalance is expected, as the power grid operates under normal conditions for the vast majority of the time.

We load the hourly weather data for each matched ASOS station for the entire year. To maintain computational tractability, the weather parameters of air temperature, wind speed, wind gust, and pressure altimeter (in inches of mercury) are selected. The problem of optimal feature selection lies outside the scope of this paper and is left for future research. The selected parameters have been demonstrated to be among the most influential predictors of weather-related outages in related studies [8], [21].

The weather dataset is subsequently cleaned and preprocessed. Missing wind gust values (84%) in the dataset are replaced with the corresponding wind speed values for the same observation period to ensure consistency across all stations. We then merge the weather parameters with the outage records by matching each event to its corresponding ASOS station and applying a temporal tolerance of one hour. For each outage, the weather parameters are taken from the closest available observation to the center of the hour, corresponding to a timestamp 30 minutes before the top of the hour, since the outage may occur at any point within that hour. This approach ensures that each outage record is associated with the most representative local weather conditions preceding the event.

The result of the described spatiotemporal correlation process is a unified dataset containing both normal operating conditions and outage events, with the availability factor A computed for each unique FIPS code and each hour of the year. This integrated spatiotemporal dataset provides the foundation for training a machine learning model that is aimed at estimating the availability factor A under varying weather and environmental conditions across the U.S.

C. Model Training and Evaluation

For this experiment, the number of availability bins was set to $N = 4$, with bin edges defined as $[0, 80, 90, 100]$. The bins represent four levels of outage severity: severe, moderate, mild, and no outage. The no-outage condition, corresponding to $A = 100$, is treated as a distinct bin to clearly separate normal operating states from outage-affected conditions. The resulting class distribution is heavily imbalanced, with the no-outage category dominating the dataset, which reflects the expected operating behavior of the power system under typical conditions.

Each record in the dataset is assigned a categorical label corresponding to its bin based on the calculated availability factor A, resulting in an ordered categorical target variable.

A random forest (RF) classifier is employed for model training. This algorithm is computationally efficient, interpretable, and does not require feature scaling [28]. While other classification models could also be applied, the selection of an optimal algorithm and hyperparameter tuning are considered outside the scope of this study and are left for future research.

Model performance is evaluated using a stratified five-fold cross-validation procedure with $k = 5$, ensuring that the class distribution is preserved across folds. Out-of-fold (OOF) predictions are generated and aggregated to assess model generalization. Performance metrics, including precision, recall, and the F1-score, are computed, along with the confusion matrix for the multiclass classification problem. The resulting quantitative metrics are summarized in Table I.

TABLE I
CLASSIFICATION PERFORMANCE METRICS FOR AVAILABILITY FACTOR BINS

Bin Range	Precision	Recall	F1-Score	Support
0–80	0.88	0.80	0.83	2,659
80–90	0.84	0.73	0.78	2,751
90–100	0.86	0.64	0.73	47,867
=100	1.00	1.00	1.00	4,678,103

To better visualize the results, the confusion matrix is shown in Table. II.

D. Performance Evaluation

The obtained metrics indicate satisfactory model performance. Despite the strong dominance of the no-outage class,

TABLE II
CONFUSION MATRIX FOR AVAILABILITY FACTOR CLASSIFICATION

		Predicted			
		0–80	80–90	90–100	=100
Actual	0–80	**2,119**	43	54	443
	80–90	9	**2,003**	149	590
	90–100	55	139	**30,608**	17,065
	=100	235	204	4,875	**4,672,789**

the model is able to effectively distinguish between different levels of outage severity. Most events are correctly classified into the appropriate availability bins, with F1-scores ranging from 0.73 to 0.83 for minority classes, demonstrating that the model captures the underlying patterns in the data.

Several strategies can be applied to further improve performance, including expanding the dataset to increase spatial and temporal diversity, optimizing model hyperparameters, and employing more advanced classification algorithms. It should be noted that there exists an inherent trade-off between spatiotemporal resolution and model accuracy [1]. As the temporal window becomes shorter or the spatial granularity finer, the resulting metrics typically deteriorate due to increased variability and reduced sample size. However, more advanced models, such as attention-based neural networks, can improve performance [29]. Additionally, asymmetric loss functions can be introduced to reflect the specific reliability priorities of individual utilities [12]. Alternative loss formulations, such as quantile or pinball loss, can also be utilized [30].

For instance, if a more conservative estimate of outage severity is desired, the loss function can be adjusted so that optimistic misclassifications (assigning a less severe class) are penalized more heavily than pessimistic ones. This adjustment would lead to a redistribution of classification errors in the confusion matrix, shifting them below the main diagonal and thereby biasing the model toward safer, more conservative predictions.

In general, the goal of the proposed framework is to generate realistic outage scenarios that utilities can use to assess potential load reductions and their operational impacts. Accordingly, the method emphasizes scenario representativeness rather than pointwise predictive accuracy, distinguishing it from traditional outage prediction models designed for real-time mitigation applications [11], [12].

To complete the modeling of load variability, a sampling strategy must be defined for values of the availability factor A within each bin. This strategy may be as simple as assigning the bin-center value, assuming a uniform distribution within the bin, or employing more advanced formulations such as a piecewise exponential distribution that is continuous at bin boundaries and includes a point mass at $A = 100$. Exploration of different sampling strategies and their effects on power flow simulations and system operation is left for future research.

IV. CONCLUSIONS

In this paper, we presented a method for modeling weather-dependent load availability using an availability factor A and demonstrated its applicability through the use of openly available outage and weather datasets. Based on the results of this study, the following conclusions can be drawn:

1) The proposed method enables estimation of the reduction in load due to forced outages as a function of weather and environmental conditions.
2) The accuracy of the model is satisfactory for the analyzed datasets (F1-score up to 0.83 for the minority class) and can be further improved through the use of higher-quality data, additional features, and optimized ML algorithms.
3) The use of discretized availability bins provides flexibility in controlling model complexity and can be adapted to specific utility requirements and levels of confidence.
4) The framework can be employed for generating stochastic load scenarios for reliability and resilience assessments, supporting more informed operational and planning decisions.

For future work, a detailed analysis of restoration processes and modeling practices based on factors such as utility restoration procedures and the occurrence of concurrent outages will be conducted.

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REFERENCES

[1] R. Baembitov, A. Karmacharya, M. Kezunovic, D. Saranovic, and Z. Obradovic, "Interpretability of the ml-based state of risk predictions for the electric grid forced outages," *IFAC-PapersOnLine*, vol. 59, no. 9, pp. 181–186, 2025, 1st IFAC Workshop on Smart Energy System for efficient and sustainable smart grids and smart cities - SENSYS 2025. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2405896325007232

[2] U.S. Department of Energy, "Electric disturbance events (OE–417) annual summaries," [Online]. Available: https://www.oe.netl.doe.gov/OE417_annual_summary.aspx, 2002–2021.

[3] P. L. Watson, D. Cerrai, M. Koukoula, D. W. Wanik, and E. Anagnostou, "Weather-related power outage model with a growing domain: structure, performance, and generalisability," *The Journal of Engineering*, vol. 2020, no. 10, pp. 817–826, 2020. [Online]. Available: https://ietresearch.onlinelibrary.wiley.com/doi/abs/10.1049/joe.2019.1274

[4] P. L. Watson, A. Spaulding, M. Koukoula, and E. Anagnostou, "Improved quantitative prediction of power outages caused by extreme weather events," *Weather and Climate Extremes*, vol. 37, p. 100487, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2212094722000664

[5] P. L. Watson, M. Koukoula, and E. Anagnostou, "Influence of the characteristics of weather information in a thunderstorm-related power outage prediction system," *Forecasting*, vol. 3, no. 3, pp. 541–560, 2021. [Online]. Available: https://www.mdpi.com/2571-9394/3/3/34

[6] J. Liu, Z. Zhang, Y. Cheng, J. Lee, S. Paal, and D. Li, "A wide-and-deep-based time sequence model for predicting power outages caused by extreme winter storms," *Proceedings of the ICA*, vol. 7, p. 6, 2025. [Online]. Available: https://ica-proc.copernicus.org/articles/7/6/2025/

[7] R. Baembitov, M. Kezunovic, D. Saranovic, and Z. Obradovic, "Sensitivity analysis of machine learning algorithms for outage risk prediction," in *Proc. 57th Hawaii International Conference on System Sciences (HICSS-57)*, Honolulu, Hawaii, 2024.

[8] R. Baembitov, M. Kezunovic, K. A. Brewster, and Z. Obradovic, "Incorporating wind modeling into electric grid outage risk prediction and mitigation solution," *IEEE Access*, vol. 11, pp. 4373–4380, 2023.

[9] R. Aljurbua, R. Baembitov, C. Petridis, D. Saranovic, M. Kezunovic, and Z. Obradovic, "Spatiotemporal multiplex network model for predicting forced outage severity in distribution grids," in *Proc. Engineering Applications of Neural Networks (EANN)*. Cham: Springer Nature Switzerland, 2025, pp. 165–178.

[10] H. Hou, C. Liu, R. Wei, H. He, L. Wang, and W. Li, "Outage duration prediction under typhoon disaster with stacking ensemble learning," *Reliability Engineering & System Safety*, vol. 237, p. 109398, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0951832023003125

[11] T. Dokic and M. Kezunovic, "Predictive risk management for dynamic tree trimming scheduling for distribution networks," *IEEE Transactions on Smart Grid*, vol. 10, no. 5, pp. 4776–4785, 2018. [Online]. Available: https://ieeexplore.ieee.org/document/8453895

[12] R. Baembitov and M. Kezunovic, "State of risk prediction for management and mitigation of vegetation and weather caused outages in distribution networks," *IEEE Access*, pp. 1–1, 2023.

[13] B. Austgen, M. Garcia, B. Pierre, J. Hasenbein, and E. Kutanoglu, "Winter storm scenario generation for power grids based on historical generator outages," in *Proc. IEEE/PES Transmission and Distribution Conference and Exposition (T&D)*, 2022, pp. 1–5.

[14] S. Mokred, Y. Wang, and T. Chen, "A novel collapse prediction index for voltage stability analysis and contingency ranking in power systems," *Protection and Control of Modern Power Systems*, vol. 8, no. 1, pp. 1–27, 2023.

[15] D. Wallison, U. Habiba, F. Safdarian, and T. J. Overbye, "Autoregressive and neural network models for weather-informed load forecasts," in *2023 IEEE Kansas Power and Energy Conference (KPEC)*, Manhattan, KS, USA, 2023, pp. 1–5.

[16] H. Li, J. H. Yeo, A. L. Bornsheuer, and T. J. Overbye, "The creation and validation of load time series for synthetic electric power systems," *IEEE Transactions on Power Systems*, vol. 36, no. 2, pp. 961–969, 2021.

[17] C. Kuster, Y. Rezgui, and M. Mourshed, "Electrical load forecasting models: A critical systematic review," *Sustainable Cities and Society*, vol. 35, pp. 257–270, 2017. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2210670717305899

[18] S. Ali, S. Bogarra, M. N. Riaz, P. P. Phyo, D. Flynn, and A. Taha, "From time-series to hybrid models: Advancements in short-term load forecasting embracing smart grid paradigm," *Applied Sciences*, vol. 14, no. 11, p. 4442, 2024. [Online]. Available: https://www.mdpi.com/2076-3417/14/11/4442

[19] T. J. Overbye, F. Safdarian, W. Trinh, Z. Mao, J. Snodgrass, and J. Yeo, "An approach for the direct inclusion of weather information in the power flow," in *Proc. 56th Hawaii International Conference on System Sciences (HICSS-56)*, Maui, Hawaii, 2023.

[20] F. Safdarian, J. Cook, K. Zhgun, T. Overbye, and J. Snodgrass, "Power flow modeling of the impacts of weather and other resiliency hazards with a focus on transmission planning," in *58th Hawaii International Conference on System Sciences (HICSS-58)*, Waikoloa, HI, 2025.

[21] R. Baembitov, A. M. Karmacharya, M. Kezunovic, D. Saranovic, and Z. Obradovic, "Effect of lightning features on predicting outages related to thunderstorms in distribution grids," in *Proc. 58th Hawaii International Conference on System Sciences (HICSS-58)*, Waikoloa, HI, 2025.

[22] J. P. Montoya-Rincon, S. Azad, R. Pokhrel, M. Ghandehari, M. P. Jensen, and J. E. Gonzalez, "On the use of satellite nightlights for power outages prediction," *IEEE Access*, vol. 10, pp. 16 729–16 739, 2022.

[23] B. She, V. Adetola, and J. Y. Yun, "Event-correlated outage dataset in america," Open Energy Data Initiative (OEDI), Pacific Northwest National Laboratory, https://data.openei.org/submissions/6458, 2024, accessed: 2025-11-06. [Online]. Available: https://data.openei.org/submissions/6458

[24] C. Brelsford *et al.*, "The Environment for Analysis of Geo-Located Energy Information's Recorded Electricity Outages 2014-2024," 11 2023. [Online]. Available: https://figshare.com/articles/dataset/The_Environment_for_Analysis_of_Geo-Located_Energy_Information_s_Recorded_Electricity_Outages_2014-2022/24237376

[25] J. Byster, "FIPS latitude and longitude mapping dataset (fips_map.json)," [Online]. Available: https://github.com/josh-byster/fips_lat_long, 2023.

[26] Iowa Environmental Mesonet, "ASOS surface observation dataset," [Online]. Available: https://mesonet.agron.iastate.edu/request/download.phtml, 2025.

[27] J. L. Bentley, "Multidimensional binary search trees used for associative searching," *Commun. ACM*, vol. 18, no. 9, p. 509–517, Sep. 1975. [Online]. Available: https://doi.org/10.1145/361002.361007

[28] L. Breiman, "Random forests," *Machine Learning*, vol. 45, no. 1, pp. 5–32, 2001. [Online]. Available: https://link.springer.com/article/10.1023/A:1010933404324

[29] D. Saranovic, Z. Obradovic, R. Baembitov, and M. Kezunovic, "Granular spatio-temporal grid-based machine learning for forced outage prediction in electrical networks," in *Proc. 59th Hawaii International Conference on System Sciences (HICSS-59)*, Maui, Hawaii, 2026.

[30] Y. Chung, W. Neiswanger, I. Char, and J. Schneider, "Beyond pinball loss: Quantile methods for calibrated uncertainty quantification," *arXiv preprint arXiv:2011.09588*, 2020. [Online]. Available: https://arxiv.org/abs/2011.09588