Effect of Lightning Features on Predicting Outages Related to Thunderstorms in Distribution Grids

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Abstract

Power outages in the distribution grid profoundly impact everyday human activity and economic welfare, as numerous infrastructures rely on uninterrupted power for sustained operation. Over the past decade, there has been a significant focus on using machine learning (ML) to predict outage state of risk (SoR) in both research and applications. One of the main causes of outages is weather conditions causing equipment failure due to wear and tear, as well as lightning strikes, in this paper. Therefore, we analyzed the consequences of selecting various weather-related ML model features on the outage SoR. We first show the outage SoR prediction results with and without considering lightning features, and then rank the SoR prediction performance based on various other weather features.

Keywords: Machine Learning, State of Risk, Outage Prediction, Lightning, Weather

1. Introduction

Outages in distribution systems may disrupt the power flow to the consumer for an extended period, resulting in compromised quality of life and adverse economic impacts (Watson et al., 2022). Therefore, predicting outages is vital to implementing mitigation measures that can reduce these impacts.

Outage SoR prediction models use various features, ranging from the characteristics of the power system constituents to environmental factors of the area where the system resides, to determine when and where the outage is most likely to occur (Baembitov & Kezunovic, 2023). The statistics show that on average the factors contributing to over 75% of outages in the USA are equipment wear and tear combined with weather and vegetation impacts (*Electric Disturbance Events (OE-417) Annual Summaries*, 2002). Significant work in the past has gone into determining the best features to be used for the ML models aimed at the outage SoR prediction (Omran & El Houby, 2020; Watson et al., 2022; YANG, 2021). Previous studies have primarily focused on environmental weather causes, including lightning and vegetation.

Numerous publications describe ML/AI applications for outage predictions, incorporating historical equipment failure alongside weather, vegetation, and soil data. The optimized output from Decision Trees, Gradient-Boosted Trees, Random Forest, Ensemble Regression, and Bayesian Additive Regression were used to predict outages due to storm events (Cerrai et al., 2019). Different regression models were applied to understand the impact of extreme weather on power infrastructure, enhancing outage predictions by selecting relevant features using random forests (Watson et al., 2022). Decision tree-based machine learning algorithms were used to predict the outages caused by storm events after classifying them according to their severity (Yang et al., 2020). A multi-constrained outage model was simplified into two single-objective subproblems using collaborative neural networks for outage prediction while overcoming the limited data availability of weather events and outages (Onaolapo et al., 2023). However, these works have used weather parameters that are statistically aggregated over the entire period of the event and based their analysis on the number of affected customers rather than the outage SoR. Additionally, the parameters of lightning strikes were not accounted for.

Among the various environmental factors, lightning strikes are recognized as a major cause of outages and blackouts in power systems (Haes Alhelou et al., 2019; Ren et al., 2021). Previous research includes outage rate model based on the number of lightning arresters, number of lightning strikes, and the line density in an area (Miyazaki & Okabe, 2010). Weighted logistic regression was used to map the number of thunderstorm events at a particular area under study to the number of outages that might occur based on the number of thunderstorm events (Doostan & Chowdhury, 2020). Comparison of weather parameters and lightning characteristics have not been included in these studies. A framework was developed for obtaining the probability of lightning-induced failures considering the design criteria, asset condition, and atmospheric status at the time of lightning strikes but without considering the quantities defining the lightning events (Souto et al., 2023). A Bayesian network was trained to predict the outage risk for overhead railway contact lines using a spatiotemporal fragility model and a probabilistic lightning model that accounts for the inherent uncertainties of lightning (Wang et al., 2023). Outage prediction probability obtained from a General Regression Neural Network (GRNN) was compared with other variants of neural networks trained on the number of and distance to lightning strikes, average intensity, and peak current data from the utility (Xie et al., 2019). Although they use several parameters that define the lightning phenomena, the atmospheric parameters are ignored. Also, they don't analyze the contribution of lightning features toward a better outage SoR prediction accuracy or their comparison with other weather features.

Our contribution, elaborated in the next section, is a sensitivity study of the impacts of different lightning features on outage prediction outcomes, which may guide researchers when selecting their data, features, and algorithms in future work.

The rest of the paper is organized as follows. Section 2 provides the problem definition and contribution. Section 3 discussed data preparation steps. Section 4 provides insights into the incorporation of lightning-based features and their importance. Section 5 draws conclusions. References are given at the end.

2. Problem Definition and Contribution

Outages in the power systems pose a threat to secure operation of the grid. The outages lead to both monetary and non-monetary detrimental effects on both: the customers and the utility performance (Schmidthaler & Reichl, 2016; Shuai et al., 2018). Operators of the grid would benefit from the ability to anticipate the outages in separate parts of the system, allowing them to prepare and mitigate the effects (Baembitov & Kezunovic, 2023; Khoshjahan et al., 2023).

A variety of spatial and temporal resolutions can be used in outage predictions. The current study takes 6-hour horizons for the temporal resolution and clusters of approximate size 20 by 20 miles for the spatial resolution. The selection of optimal time windows and cluster size depends on who is using the predictions. Predictions can be used by utilities and customers. Utilities have several time horizons of interest depending on the mitigation action that can be taken. Operations are interested in shorter intervals of several hours, whereas asset management prefers intervals of days. On the customer side, even the shortest intervals of one-hour ahead predictions can be valuable as mitigation actions can be performed in a shorter time.

Since the outages are mainly caused by the weather, it's important to understand the components of severe weather that cause the outages. One such cause is lightning strikes. This paper focuses on the sensitivity analysis of predictive models to lightning data. As was shown in the previous section, the current literature falls short of analyzing this phenomenon.

Therefore, our contribution lies in evaluating the effect of including lightning features as ML model inputs on the accuracy of outage SoR prediction. We train and test an ML model on data with and without features showing their effect on model performance. Additionally, we rank the input features in order of importance for the algorithm's performance when predicting outage SoR. This study focuses on SoR for outages due to severe weather rather than extreme and catastrophic events.

3. Data Preparation

3.1 Clustering feeders in GIS

The first step of the approach is to split the service territory into several geographical sections for which the SoR predictions would be made.

In an actual utility system used for this study, over 281 thousand feeders were first matched to their substations of origin (86 unique substations). Next, substations with feeders were clustered into 7 non-overlapping clusters. The segmentation was performed manually in ArcGIS to keep clusters comparable in size, not overlapping and compact. The area of the entire service territory is approximately 100x100 miles. The number of clusters was selected empirically to accommodate the geographical characteristics of the terrain and relevant parts of the service territory. Due to data privacy concerns, we cannot present the full map of the service area. Instead, Fig. 1 shows relative cluster locations and their size acquired by using the Minimum Bounding Geometry tool in ArcGIS Pro set to a convex hull.

The resulting 7 clusters become the prediction entities for the study. Outage SoR levels would correspond to the clusters' locations. The clustering method depends on the application and can be performed in different ways. One might consider geographical locations, underlying terrestrial characteristics, surface elevation, operational districts of a utility and other characteristics that can be used to break down the service territory into several sections.

Several ways to cluster a service territory are discussed in (Watson et al., 2020). This paper addresses the influence of considering additional data and does not explore the variations in the clustering methodology.

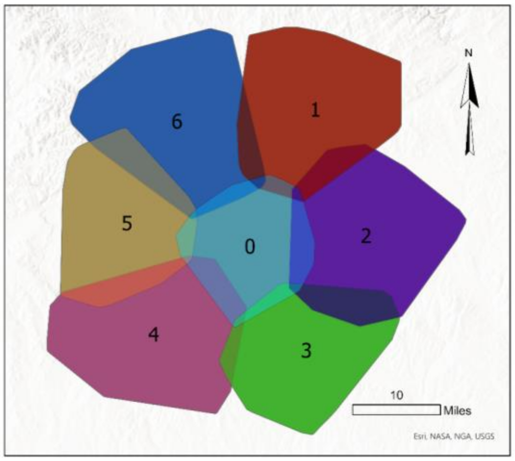

Figure 1. Convex hull of per-cluster feeder locations

3.2 Spatiotemporal correlation and preprocessing of outages

Our study uses 5 years of historical outage data from January 2018 to December 2022 from a utility in Texas. The provided outage logs contained power interruption information down to a meter, so there have been over 9 million rows in the original dataset. Information contained outage occurrence and restoration times, feeder ID, and cause codes. We cleaned and preprocessed the data, discarding the rows with missing data. The missing data was a relatively small part of the dataset, resulting in less than 1% rows discarded.

To correlate outages, one needs to determine the spatial and temporal references. Spatially, the location of the 7 clusters was used as reference intervals. In the temporal dimension, we created evenly spaced timestamps (6-hour) and used the intervals in between as reference intervals. The correlation process matches an outage to a specific location in space and a specific temporal bin. It can be thought of as putting an outage to a spatiotemporal cube.

A single spatiotemporal cube would contain several outage occurrences with different durations and causes. To aggregate them into a single row, we averaged the durations of outages and registered each of the cause codes in a separate column. In such manner the cube is described by average outage duration and a set of cause codes. Since the focus of this study is on lighting caused outages, we have only selected the outages that had “thunderstorms” and “lightning” as causes discarding the rest. After aggregation, there was a total of 3589 examples with outages out of 51128 total examples, which constitutes around 7%.

3.3 Weather data preprocessing

To exclude the noise from weather forecasts on the analysis of feature importance, we use the actual weather during the outages.

The ASOS dataset (*Automated Surface Observing Systems*, 2016) serves as a basis for weather feature extraction. We used only the following numerical data: pressure, dew point temperature, wind gust speed, precipitation levels, relative humidity, wind speed and direction, and temperature.

Weather was correlated to clusters in each of the 6-hour intervals. We used minimum, maximum, and mean functions to describe a weather parameter within a temporal window. Then, to correlate weather to clusters, we selected the closest weather stations to clusters and calculated the mean of temporal means, minimum of temporal minimums, and maximum of temporal maximums. The procedure is described in detail at (Baembitov et al., 2024). These statistics are often used in modeling spatiotemporal data (Elnekave et al., 2007; Li et al., 2010). The outcome of this step is the correlated weather parameters to cluster locations in each of the temporal periods. The total number of weather features is 168: for each of the 8 parameters (temperature, pressure, etc.), we calculate 3 statistics (min, max, mean) for each of the 7 clusters.

3.4 Lighting data preprocessing and feature extraction

To describe the lighting activity in the area we utilized a dataset from Vaisala National Lightning Detection Network (Vaisala, 2021). The dataset contained information about lightning strikes in the area of interest in the same time period as outages from a utility dataset. Lightning dataset contained date, time, latitude, longitude, peak current, rise time and cloud-to-ground or cloud-to-cloud distinction columns. The data was separated into cloud-to-cloud and cloud-to-ground strikes and then imported into geodatabase.

The outage can happen due to either a direct hit of lightning or due to induced voltage of an indirect hit. There are several characteristics that affect the probability of an outage from lightning strike: distance from a lightning strike to power lines, current magnitude and waveform, the configuration of a power line, and soil resistivity (Lazzaretti et al., 2015; Ravaglio et al., 2019). The induced voltage is proportional to the current derivative over time and inversely proportional to the distance. From the available data, we are able to calculate the approximation of a current derivative as the peak current divided by the rise time.

The distance is accounted for by creating 50-meter bands around cluster locations. That allows differentiation of lightning strikes by distance to feeders. We have created 8 bands in 50 meters increments around the clusters: 0 to 50 meters, 50 to 100 meters etc. and a band (0 to 400 meters) that encloses all of the other bands, to have a summation of the features within one cluster. Fig 2 illustrates the bands. The maximum band of 400m was selected based on the median accuracy of strike locations in the data, the 50m interval is selected to account for different distances from strikes to feeders.

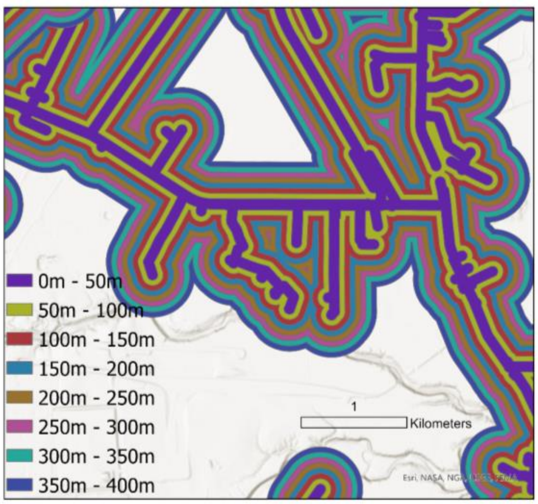

Figure 2. Bands around feeders

To create features that reflect lighting activity and its intensity, we aggregated the strikes into 6 hour windows throughout the period of the experiment. The time windows coincide with the time windows for outages and weather parameters. All strikes that occurred within the time window are then separated into respective 50m bands. Within each band the summary statistics of the strikes are calculated: the number of strikes, sum of the peak currents, maximum of the peak currents, sum of the current derivatives, and maximum of the current derivatives. For example, to calculate the maximum of the peak current for a given cluster in the 150m-200m band, we first select all the strikes that occurred between 150m and 200m from the feeder locations. Then from that selection, the value of a maximum current is used as a feature for a given 6h window.

In such a manner each time window for each of the clusters is characterized by 5 statistics for each band. For 2 types of strikes (cloud-to-cloud and cloud-to-ground) 5 statistics (number of strikes, sum of peak current etc.) are derived for each of the 9 bands (0m-50m, 50m-100m etc.) in each of the 7 clusters, resulting in 630 total lightning features. The features are then exported from geodatabase and saved as .csv files for use in the next steps.

For this experiment, we use actual lighting strikes during outages. As far as we know, the predictions of lightning strike locations, currents, and rise times are not available in the public domain at the moment, but the situation might change. Our goal is to determine whether lightning data of such nature can be used to improve the accuracy of outage SoR predictions. We hope that our study will serve as a guidance to other researchers.

3.5 Combination of processed datasets

Once all datasets have been processed, we combine them. Since each dataset uses the same temporal and spatial reference points, the combination is performed by joining datasets along the temporal and spatial axes. Our previous works show that 2 years of data is the minimum for training the SoR prediction algorithm (Baembitov et al., 2024). For this reason, 5 years of available data are split into 3 years of training and 2 years of testing. The split is temporal to ensure no data leakage. The effects of adding new features are evaluated on a test dataset unseen during training, as described in the next section.

4. ML Algorithm and Feature Importance

Once the outage, weather, and lightning data were extracted, preprocessed, and consolidated, the obtained training data was used to train different models. Our paper is focused on understanding the effects of adding new features. Therefore, we compare the performance with and without new lighting features and only then analyze features importance.

Based on the input features, three different ML models were fit to predict the SoR of outages: Random Forest (RF), Logistic Regression (LR), and Neural Network (NN). We selected the algorithms of different types (LR – linear algorithm, RF – tree-based non-linear algorithm, NN – non-linear algorithm) to be able to utilize different methods for feature importance. A previous study suggests that algorithms have similar performance on the task of predicting outages (Baembitov et al., 2024). Therefore, the comparison between the algorithms' performance falls outside the scope of this paper.

Two metrics used to evaluate the models on the test dataset are the F1 score and the Area Under the Receiver Operating Characteristics Curve (AUC-ROC) (Baembitov et al., 2024). After training the models on the input data, the importance of the various features for predicting the outages at any given location was calculated using various methods. Additionally, the effect of lightning data on these three models was observed.

4.1. Effect of lighting features

To determine the effect of lighting features on the algorithm performance, we repeated the experiment with and without lighting features. The values of each metric were determined for the cases with and without lightning features included in the training and testing data, and the difference in performance was observed. Weather data itself is helpful to predict outages. In this study, we focus on understanding the change in performance metrics when adding lightning features (Baembitov & Kezunovic, 2023). Each of the seven clusters was individually studied. The results are presented in Tables I and .

Table I. Average F1 score and ROC-AUC for all models with and without lightning features

Model	Lightning Features	F1	ROC_AUC
LR	absent	0.32	0.74
RF		0.38	0.8
NN		0.34	0.73
LR	present	0.32	0.72
RF		**0.45**	**0.81**
NN		0.41	0.73

Table II. F1 score and ROC-AUC for RF per cluster.

Cluster	Lightning Features	F1	ROC_AUC
0	absent	0.44	0.83
1		0.42	0.81
2		0.39	0.79
3		0.3	0.82
4		0.27	0.77
5		0.37	0.82
6		0.46	0.81
0	present	0.47	0.83
1		0.5	0.81
2		0.44	0.78
3		0.41	0.81
4		0.37	0.79
5		0.48	0.84
6		0.49	0.81

Despite the low absolute values of the metrics, one can see a positive change due to addition of new features. To have a better representation of the results, we have calculated the difference between metrics for the cases with and without lighting data. Then we averaged the obtained differences across clusters. In such manner mean difference in each metric was obtained to demonstrate the change of performance of the models. The results are shown in Fig. 3.

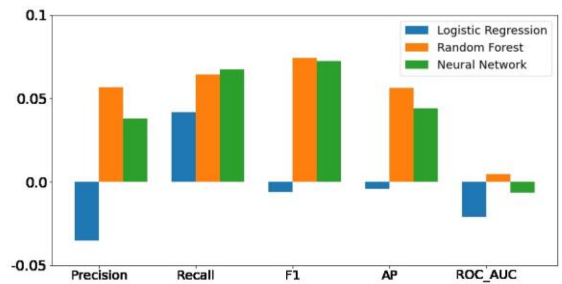

Figure 3. Mean difference in performance with and without lightning

From Fig. 3, it can be observed that the mean value of all the performance metrics over all the clusters improves in the case of Random Forest. All the metrics except for ROC-AUC improve when neural networks are used to predict the outages in the system. However, in the case of Logistic Regression, only the Recall scores improve with the inclusion of Lightning data. The average performance of the remaining metrics over the clusters decreases with the inclusion of lightning information for LR. We should note that the performance of LR on the given task is inferior to NN and RF. The linear model could not separate outages from normal operations, based on the given features. We also note that linear models perform poorly on highly correlated features. That is the case for lighting features, as all of them (current, derivative, count) appear all together when lightning strikes are present.

4.2 Determining feature importance

There are several methods used for calculating the feature importance. Most known are: feature importance based on the linear model's coefficients, impurity-based feature importance for tree-based models, and permutation-based importance that can be used for all types of models (König et al., 2021; Rajbahadur et al., 2022).

Since we have almost 800 features for each of the models, we grouped the lightning features by type: A – point count, B – max current, C – max derivative, D – sum of current, E – sum of derivative, F – altitude, G – wind direction, H – dewpoint, I – wind gust, J – atmospheric pressure, K – relative humidity, L – wind speed, M – temperature. We then added the importance coefficients for each of the feature types obtained from the specific cluster. Then, we present them as figures.

Through such an approach we can observe the relative feature importance of each type acquired from separate clusters.

The method we used to determine the feature importance for RF is Impurity-based analysis. The method is built in the class of Random Forest in the sklearn library (Breiman, 2001; *RandomForestClassifier*, 2024). This method helps us determine whether the feature enables the model to predict the output. It is performed on the training data, when the random forest is being trained, providing a benefit of fast estimation of the feature importances. A limitation is that in an overfitted model, the output of the impurity-based importance analysis is not as reliable. The importance of a feature is determined by counting the number of times it was used to split the nodes and reduce impurity after a tree is constructed. However, it favors features with more categories. In the absence of a correlation between the input features, the impurity measure can be used to identify the contribution of each feature (Scornet, 2023). The impurity-based feature importance for all target clusters using all available features is shown in Fig. 4 – Fig. 10.

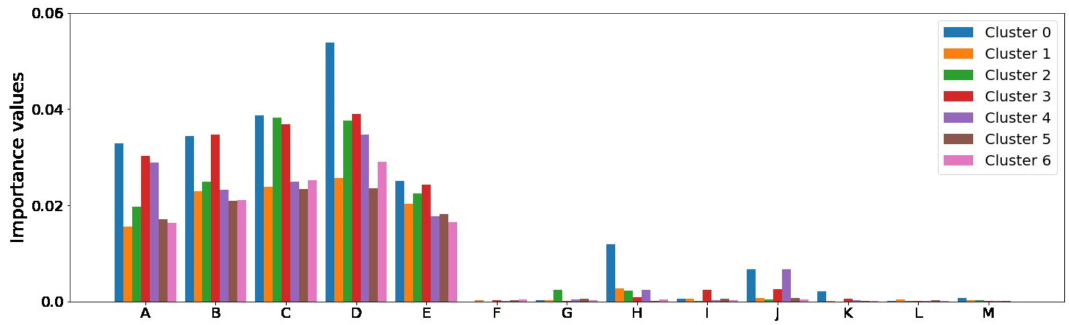

Figure 4. RF cluster 0 importance

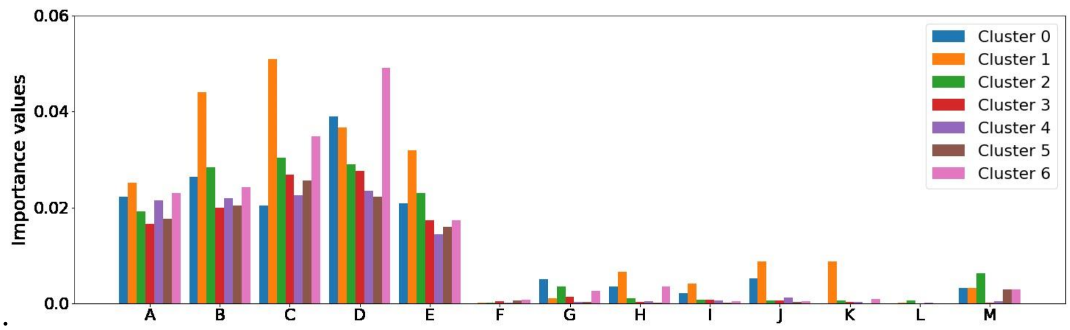

Figure 5. RF cluster 1 importance

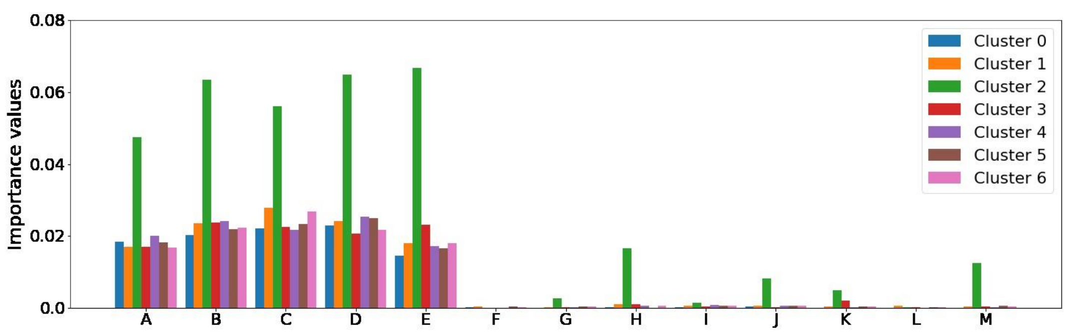

Figure 6. RF cluster 2 importance

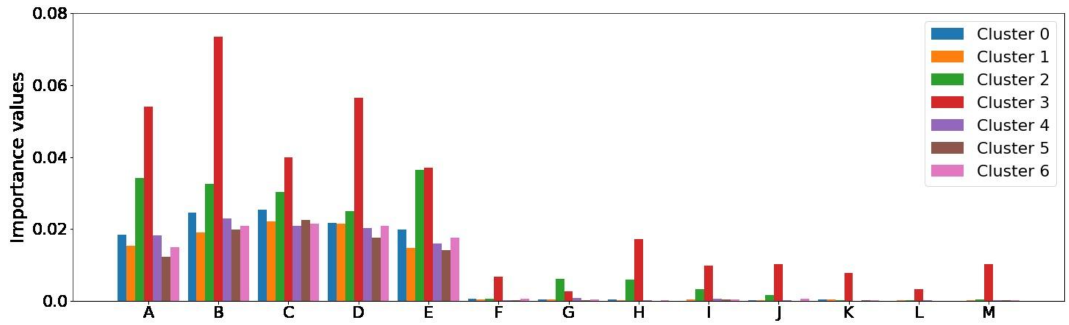

Figure 7. RF cluster 3 importance

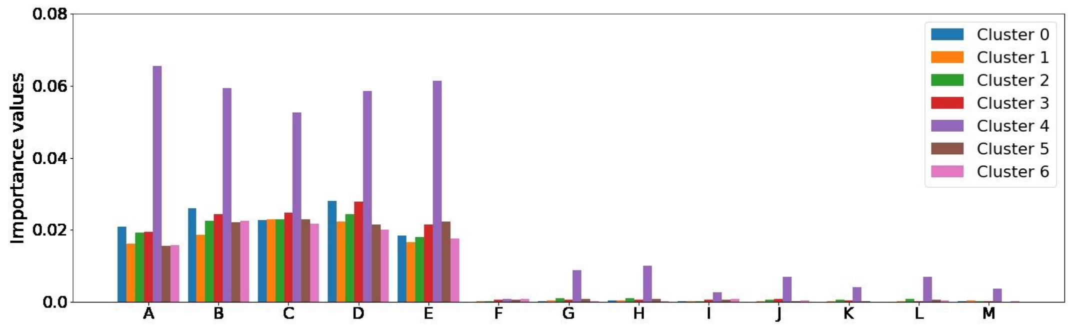

Figure 8. RF cluster 4 importance

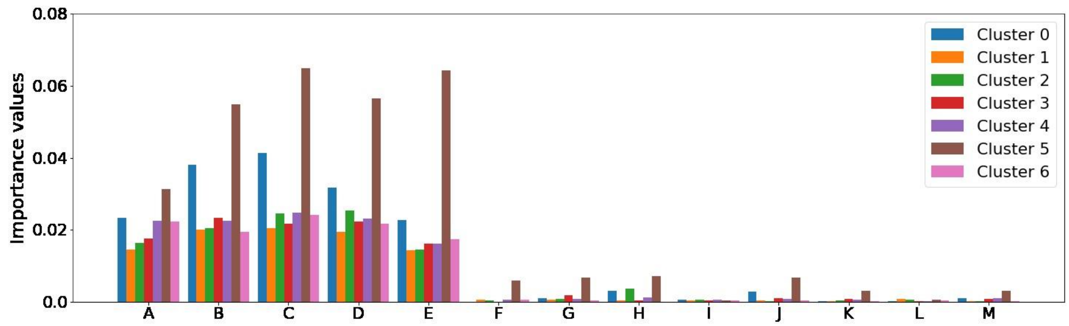

Figure 9. RF cluster 5 importance

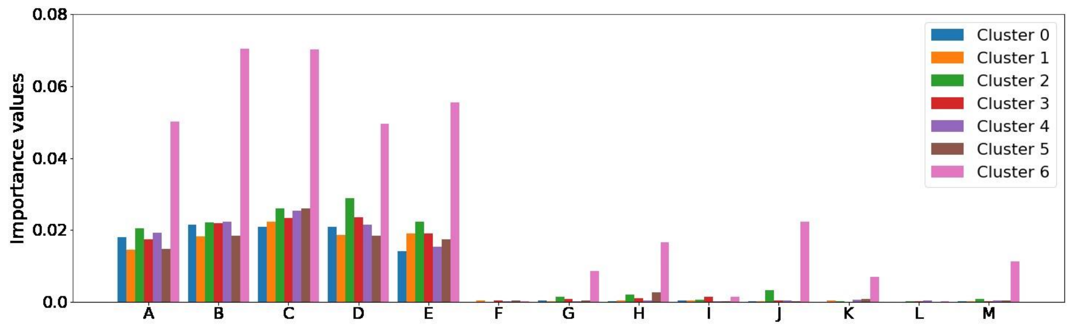

Figure 10. RF cluster 6 importance

From the figures above for RF, we can observe two different phenomena. First, we can see that the importance of the lighting features (A-E) is much higher than that of the weather parameters (F-M) as determined by the height of the bars on all of the Figures. Besides, it is visible that the lightning features of the same cluster for which the model is developed are more important in most cases (except for cluster 0, which also provides significant importance to features from other clusters, see Fig. 4). RF tends to distinguish and prioritize the features related to the target cluster and assign less importance to features coming from neighboring clusters. That is consistent for both weather and lightning features.

For calculating the importance of the logistic regression model, the process is straightforward when the classification is binary - we only have a set of coefficients. However, in the case of multiclass classification, separate coefficients exist for each unique class. We calculate the feature importance for the multiclass logistic regression model by taking an average of coefficients across all the classes for each of the input features to the model. This technique results in an inaccurate estimation of feature importance when the features are highly correlated (Filho, 2024). In our case, we predict the outages for each cluster using the available features, and there are only two possible outcomes: either an outage occurs or it doesn't.

The feature importance obtained from the LR model for each cluster according to the model coefficients is very similar to the RF results and is presented in online appendix, available at (Appendix, 2024).

Based on the results for LR, we confirm that the coefficients for lightning-related features (A-E) are higher than the weather-related features (F-M). However, the importance of source clusters does not always correlate with target clusters as it does in case of RF, which can be explained by an overall worse performance of LR.

The third method that we considered for this study is permutation-based analysis. The permutation-based feature importance extraction method is independent of the model (Breiman, 2001; Mi et al., 2021). This method randomly shuffles an input feature to observe the model's performance change. A greater drop in performance after shuffling indicates greater importance of the feature for prediction purposes. Using the test data, a trained model is used for calculating the importance based on this method. The randomization effectively nullifies the effects of the variable as if the coefficients of a linear model were set to zero; however, it is not the same as removing the variable to create a new model (Hastie et al., 2009). Using error ratio rather than error difference for evaluation might be a good idea because the feature importance problems are comparable across different problems. The permutation-based method doesn't require us to retrain the model and gives the feature importance evaluation over consistent models. However, if the features are correlated, it can cause biased importance estimation (Molnar et al., 2020). The results obtained by the permutation-based method were inconclusive and thus were omitted from this study.

4.3. Discussion

The presented results demonstrate that the addition of lightning strikes data to the rest of the weather data positively affects the models' performance. The sensitivity study of the feature importance analysis reveals that lightning data plays a critical role in outage predictions. The sensitivity study also reveals that the lightning features of the target cluster itself are most valuable for the models. That may indicate the presence of relatively localized areas of lightning activity, which can be captured by the lightning detection network. However, the challenge of producing highly accurate locations of lightning strikes remains to be resolved.

Different methods for determining feature importance have relevant strengths and weaknesses. The usage of LR coefficients is straightforward and intuitive, providing an opportunity to explain how model operates to the stakeholders. However, LR is a linear algorithm. RF addresses that issue, as it is non-linear. It is also computationally effective as the importance is derived from the training process. However, such a method can only be used for decision trees-based algorithms. A more general method of permutation can be applied to any model. But it is more computationally intensive and as is the case in our study, may produce inconclusive results.

If one wants to address the inconclusive results of permutation-based analysis, one way would be to reduce the number of features either by sampling a smaller number of bands and/or reducing the number of calculated parameters. This topic is left for future research.

Future research steps would be to identify the parameters within available weather forecast models that can replace the actual lightning strikes. The performance improvement of such an approach might be lower than using actual data, but, nevertheless, should not be ignored.

In summary, the study demonstrates the importance of lightning features for outage SoR estimation. It provides a strong foundation for the conclusions that follow.

5. Conclusions

In this study, we analyzed the effect of the inclusion of lightning-based features on the performance of the SoR prediction algorithms. We then analyzed the feature importance for the models. Based on the results, we can draw the following conclusions.

1. Incorporation of lightning-based features positively affects the performance of models for predicting outage SoRs that are caused by thunderstorms in the area.

2. The lightning-based features have a bigger weight when targeting lightning-caused outages as compared to weather conditions available through ASOS network.
3. There is not a single pronounced feature within lightning-based features that is more important than the others. Thus, a selection of the features should be based on their availability.
4. Since the current state-of-the-art does not have a way of predicting accurate lightning strike locations and its parameters, a proxy features should be used instead. Weather forecast models capable of predicting cloud formation and thunderstorms activity would be the first candidates.

6. Acknowledgment

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