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Real-Time Weather Hazard Assessment for Power System Emergency Risk Management

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SUMMARY

This paper focuses on the development of a weather impacts classifier embedded in a Geographic Information System (GIS). It is able to put together a massive variety of information, from historical outage and weather data, to real-time weather forecast and network monitoring, into a parameter known as weather hazard defined as a probability of occurrence of a weather threat of intensity T. It enables the real-time, just-in-time interpretation of the expected impacts of the severe weather conditions. It is developed to assist in evaluating the risk of weather impacts on the power systems operation and planning. Since the data comes with different spatial and temporal resolutions, it is critical to correlate all the data into a unified spatiotemporal model. As a result, a variety of features of interests can be extracted from such fused data, such as probability of lightning flashover on a tower, probability of vegetation coming in contact with power lines, severe storm probability, etc. A classification of weather impacts is based on a set of extracted features relevant to a given application. The unified hazard framework assigns a hazard probability to each location in the network for each moment in time. The hazard model is built to support the development of a predictive risk map based on weather impact assessment. The main goal of the model is to provide the capability of predicting various weather impacts and their expected levels of severity that will enable implementation of proactive mitigation measures for power system assets and outage management. In order to demonstrate the applicability of the model to solving problems in different sectors of electric utility, the developed model was tested on two different applications: one for prediction of transmission line lightning performance caused by deterioration of the insulators, and second one for prediction of distribution line performance caused by the impact of severe weather and vegetation growth.

KEYWORDS

Analytical models, weather impact, asset management, outage management, big data, geographic information system, meteorology, operation, risk analysis, smart grid.

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1. INTRODUCTION

The weather impact is described as severe if there is a chance that the weather conditions will cause damage, or endanger human life. Examples of severe weather are thunderstorms, tornadoes, hail, storms, etc. A special case of severe weather is catastrophic weather, characterized by the high potential for causing damage, serious social disruptions, and loss of human life. Another type of weather impact is extreme weather, which describes the event where one or multiple weather parameters has reached the extreme value, when compared to the historical distribution. The impact of different kinds of weather events to electric power system infrastructure has been addressed in some of the recent publications. Extreme weather impacts caused by storms and hurricanes have been analysed in [1]. The impact of extreme wind storms was quantified through the risk analysis in [2]. Several publications have analysed the impact of catastrophic events, such as Hurricane Sandy's impact analysed in [3]. In [4] the probabilistic framework was developed for evaluation of catastrophic weather impacts on power grid. A variety of studies are dealing with optimizing the post event restoration process. For example, in [5] the time-varying weight factors were used to estimate the restoration times. Damage forecast model for optimizing the restoration process was introduced in [6].

In contrast to the listed existing studies that either evaluate the weather events that have already occurred or provide support for restoration process, our study focuses on the development of a predictive model that will enable implementation of a pro-active mitigation strategy. Existing solutions for weather impact assessment are relying on a set of static pre-determined guidelines that do not follow the events in the network as they unfold but rather make an assessment based on a common practice. For example, the utility may have a 5-year plan for vegetation management around the distribution lines. This kind of plan does not take into account the network and weather events that are impacting the network in real-time over this time span. This study provides the means for development of a dynamic weather impact model that gets update as the time and impact progresses. In each moment of time the weather impacts are characterized with a unique hazard value for each network component. In addition, with the prediction model based on linear regression the system is capable of providing the hazard prediction for the future that is updated as the time progresses with the more accurate prediction. This enables the decision-making that results in dynamic allocation of resources and always relies on the most recent estimate of the network performances as it gets exposed to severe weather conditions.

2. WEATHER DATA SOURCES AND PARAMETERS

Variety of weather data sources and parameters has been used in this study. The goal of the unified hazard model is to provide the means for processing all types of weather data coming in different data formats with a variety of temporal and spatial resolutions.

The Automated Surface Observing System (ASOS) [7] is a vide area land-based system containing about 900 weather stations covering the continental USA, and operating since the year 2000. The system measures a variety of weather parameters: air temperature, dew point, relative humidity, wind direction, wind speed, altimeter, sea level pressure, precipitation, visibility, wind gust, cloud coverage, and cloud height. ASOS data is collected with three temporal resolutions: 1 hour, 15 min, and 1 min. The data is provided as a space-delimited table stored in the *DAT* format. The NOAA's radar database [8] contains several radar products such as Level-2 and Level-3 Next Generation Weather Radar (NEXRAD), as well as National Reflectivity Mosaic Maps. The NEXRAD data has been collected for the USA since 1991. Today it contains about 160 high-resolution Doppler radar stations that record data with 5 min temporal resolution. The NEXRAD Level-2 data can be downloaded from the Amazon S3 storage. A variety of satellite products, such as, cloud coverage, hydrological observations (precipitation, cloud liquid water, total precipitable water, snow cover, and sea ice extent), pollution monitoring, smoke detection, surface temperature readings, vegetation indices, etc. are also available [9]. The temporal resolutions of satellite data vary from hourly to monthly depending on the dataset, with spatial resolution of 4 km. The lightning data is collected separately by the Vaisala company [10]. Their National Lightning Detection Network (NLDN) has been collecting data starting with year 1989, for the USA, with the median location accuracy of about 200m. NLDN dataset contains following parameters: date and time, latitude and longitude, peak amplitude, polarity, type of event (cloud to cloud or cloud to ground). The data is stored as a space-delimited ASCII text file.

The weather forecast data used in this study comes from the National Digital Forecast Database (NDFD) [11]. The weather forecast is updated every three hours with predictions for up to 7 days in the future, where temporal resolution of data is 3 hours. Spatial resolution of data is 5 km. The following are the examples of parameters that are forecasted: wind speed, direction, and gust, temperature, relative humidity, probability of critical fire, probability of dry lightning, hail probability, tornado probability, probability of severe thunderstorms, damaging thunderstorm wind probability, etc. NDFD also maintains the historical weather forecast database for the last 10 years.

3. WEATHER IMPACTS ON POWER OUTAGES

3.1. Lightning Impacts

Due to exposure to different environmental impacts, the mechanical and electrical performance of insulators deteriorates over time. These changes in insulator performances are not always easily observable. The insulator deterioration can be classified into two stages, [12]: 1) the deterioration of hydrophobic properties where insulator may age chemically, but it still retains its electrical properties; 2) hydrophobic properties of insulator start to deteriorate causing the degradation in insulator electrical performance. Based on study presented in [13], the second stage can be further separated into three groups: i) weathered, with a small or moderate loss of hydrophobic properties, ii) mature with a very low hydrophobicity, and iii) at risk with a fully hydrophilic surface, or total loss of insulation properties. The overview of the deterioration rates is presented in Fig 1.

Overhead line insulators are exposed to variety of environmental impacts, [12]: i) lightning strikes, ii) temperature and pressure variations, iii) ultraviolet radiation and ozone, iv) wind impact, v) rain, humidity, hail, snow, fog, and vi) pollution. In addition, a variety of environmental factors affects the probability and characteristics of flashover. Vegetation coverage around the line will lover the probability of lightning strike affecting the network, the phenomena called “shielding by trees” [14]. Elevation data is of importance also, since lightning strikes are more likely to affect locations with higher altitude [15]. The type of soil at the tower location determines the tower grounding resistance, which has a big impact on overvoltage propagation on the line [16].

3.2 Vegetation Impacts

Vegetation growth rate is highly dependent on the environmental impacts. In order to estimate the expected growth rate, it is imperative to observe the historical weather impacts and relate them to the vegetation indices obtained by periodically collected high resolution imagery

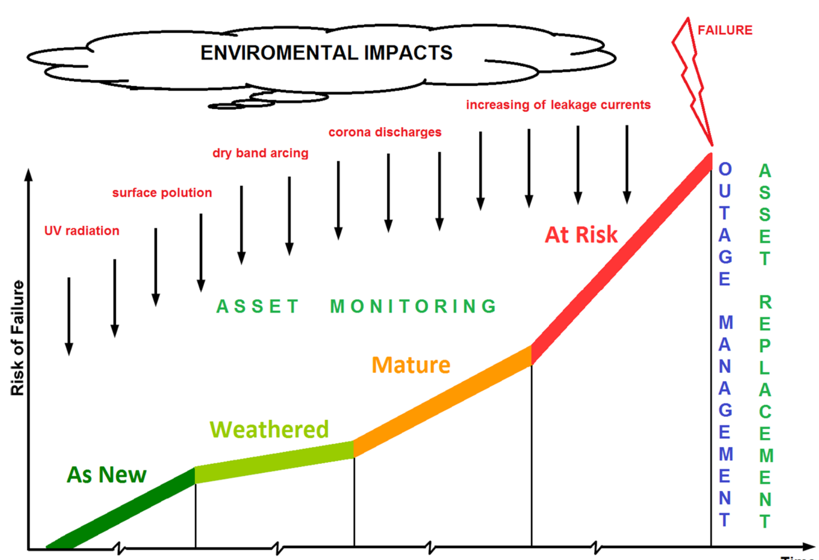


Figure 1. Environmental impacts on insulation coordination [13]

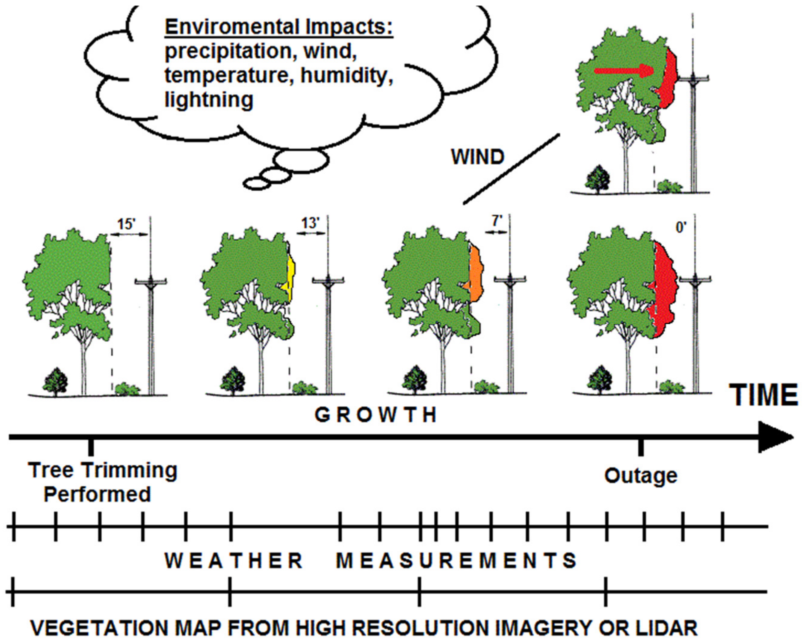


Figure 2. Environmental impacts on vegetation management

data. As presented in Fig. 2, the impact of tree to the line can occur due to the tree overgrowing into the line, or by the wind blowing the tree branches into the line.
The common procedure for vegetation management is to follow a predetermined periodic tree trimming schedule. This kind of approach ignores the changes to the network environment that may have occurred during the certain period of time.

The weather parameters that can impact vegetation related outages are: wind speed, direction and gust, precipitation, temperature, humidity, pressure. The impact can be either instant causing an outage, or prolonged if related to the tree growth rate. The type of soil also has the prolonged impact on the tree growth rate.

4. SPATIOTEMPORAL DATA

The State of Risk changes over time and has an assigned value in each location of the network, as demonstrated in Fig. 3. Thus, the state of risk R is a function of time and space as follows [17]:

$$\mathrm{R}\left(\mathrm{X},\, \mathrm{t}\right) = P\left[T\left(G, t\right)\right] \cdot P\left[C\left(G, t\right) \middle| T\left(G, t\right)\right] \tag{1}$$

where G represents the spatial location of a single component expressed in terms of longitude and latitude, and t represents a specific moment in time for which the State of Risk is calculated. The parameter T represents the threat intensity. The first term in (1) marked $P[T]$ is a hazard probability, calculated based on the weather forecast data for the specific time and location. The second term marked $P[C|T]$ is calculated based on the historical weather, as well as outage and assets data. The purpose of the second term is to estimate the network vulnerability for the given weather hazard.

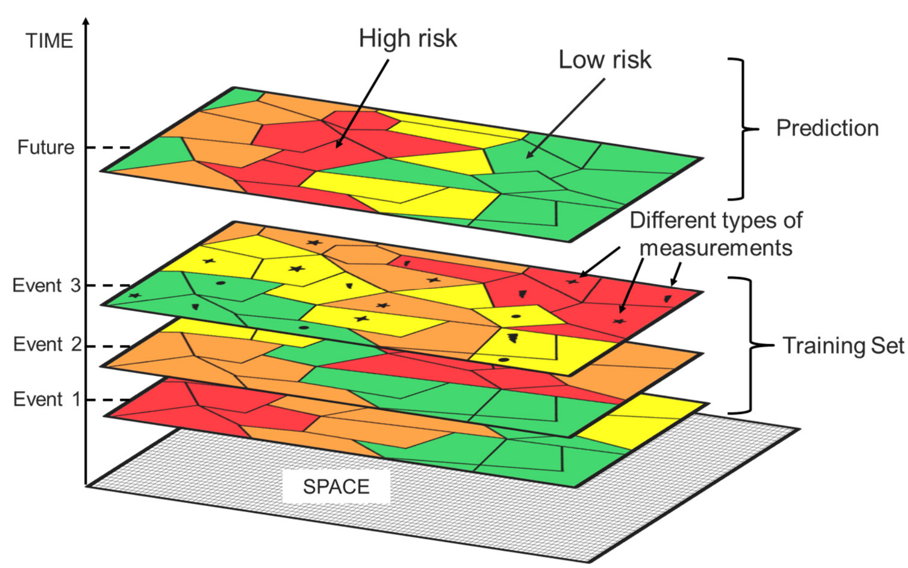


Figure 3. Spatiotemporal Prediction Model

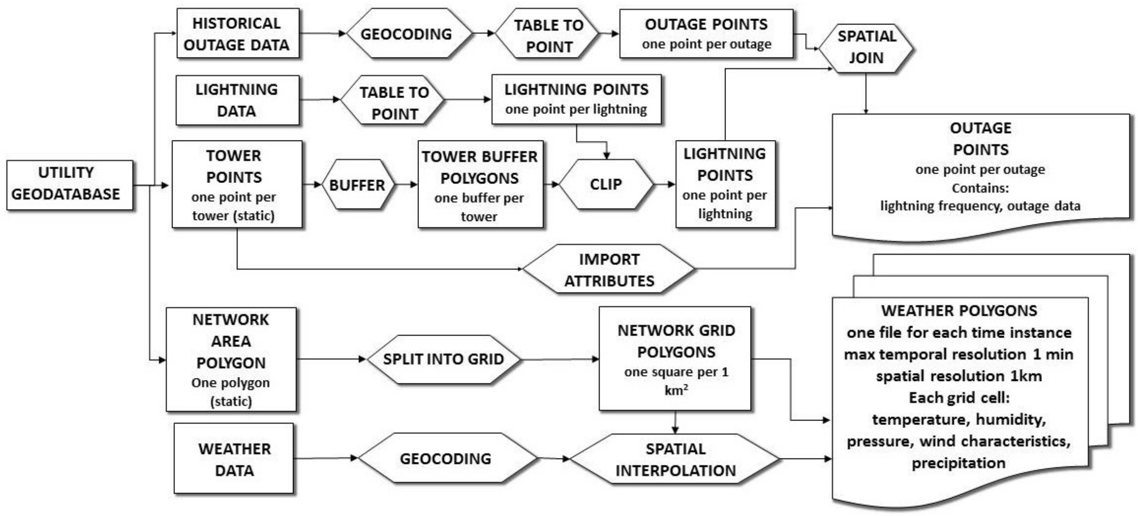


Figure 4. Spatial Correlation of Data

Spatial correlation of data is presented in Fig. 4. The locations of the utility network assets of interest are contained in the utility's geodatabase. This geodatabase is first extended with historical outage data that are geocoded into a point shapefile. Lightning data obtained from Vaisala contains geographical location in the csv file, which is converted to the lightning point shapefile, and added to the database. For each network tower, the lightning frequency is calculated from the historical data.

Weather data is also associated with the weather stations. The network area is split into grid. The weather parameters are estimated for each grid cell based on the closest three weather stations' data. For each lightning outage, the set of lightning strikes in its vicinity is generated and transmitted to the temporal correlation procedure presented in the next section. The final output of the spatial correlation is a set of weather parameter maps for each observation, and a historical outage map with all the attributes integrated in the outage shapefile.

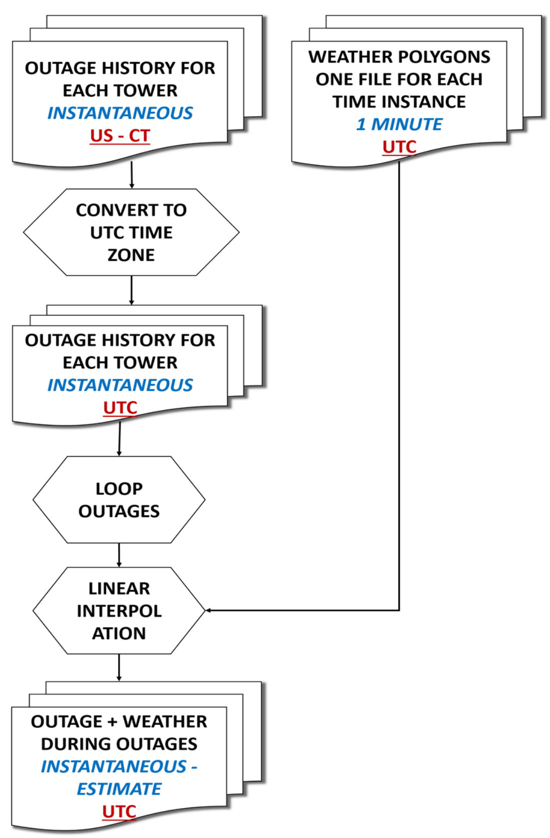


Figure 5. Temporal Correlation of Data

Temporal correlation of data is presented in Fig. 5. The goal of temporal correlation is to associate all the necessary parameters with each historical outage. First, the time zone conversion is performed to ensure unique UTC time reference. Then, each outage is set through the loop that extracts the weather parameters based on the specified time of the outage. It is necessary to perform linear interpolation to estimate the exact value of weather parameters at the time of an outage. The final product of the temporal analysis is a historical outage file containing all the necessary weather parameters for each outage. This file has all the necessary data for calculation of weather hazard for multiple applications.

5. UNIFIED HAZARD MODEL

Table I presents the threat levels for different environmental impacts, while the Table II demonstrates hazard classification based on likelihood of a threat intensity. The threat describes the severity of the event. The level of threat is determined based on the length of exposure to the severe impact. Based on the weather forecast model the probability of a specific weather event or amount of exposure is estimated.

For the prediction, the Gaussian Conditional Random Field (GCRF) algorithm is used [18]. The advantages of this algorithm are: capability to model the network as interconnected graph with assigned geographical locations and time reference; and capability to model the interdependencies between different nodes in the network. The GCRF can be expressed in canonical form as follows:

$$P(\mathrm{y} \mid \mathrm{x}) = \frac{1}{Z}\exp\left(-\sum_{i=1}^{N}\sum_{k=1}^{K}\alpha_k (y_i - R_k(\mathrm{x}))^2 - \sum_{i,j}\sum_{l=1}^{L}\beta_l e_{ij}^{(l)} S_{ij}^{(l)}(\mathrm{x})(y_i - y_j)^2\right) \tag{2}$$

Where x is a set of input variables, y is a set of outputs, R_k are unstructured predictors, S_{ij} represent similarities between outputs determined based on their geographical locations, and α and β are learning parameters.
Input variables x include: lightning peak current and polarity, temperature, dew point, relative humidity, wind direction, wind speed, altimeter, sea level pressure, precipitation, visibility, wind gust, cloud coverage, and cloud height, reflectivity, vegetation index, probability of dry lightning, hail probability, tornado probability, probability of severe thunderstorms, damaging thunderstorm wind probability, presence of catastrophic event. The output y of the prediction algorithm is predicted hazard value after the time step Δt.

6. RESULTS

The system is tested on a part of a utility network covering an area of ~2,000 km^2. The distribution system consists of ~200,000 poles, and ~60,000 lines. The historical outage and weather data were collected for the period from the beginning of 2011 up to the end of 2015. Over these five years, 505 weather related outages have been observed in the area. Table III summarizes the outage history.

For the insulator example, the main hazard is considered to be lightning, and only the lightning caused outages are observed by the prediction model. The weather hazard is the probability of a lightning caused outage of an insulator on a specific tower in the network. The goal of insulator management task is to assess the risk for each individual insulator in the network for each moment in time. The output of the developed hazard prediction model is used to calculate the risk for each individual tower and the results are presented as the risk map in Fig. 6.
The weather hazard for outage management is illustrated with the

Table I. Threat classification

Threat	Thunderstorm	Severe Wind	Hurricane	Hail	…

Table II Hazard Classification

Likelihood [%]	Threat level					
	0	1	2	3	4	5
0-20						
20-40						
40-60						
60-80						
80-100						

Table III. Historical weather caused outages

Type	Count	Outages Impact
vegetation	321	0.072
lightning	120	0.017
other	64	0.069

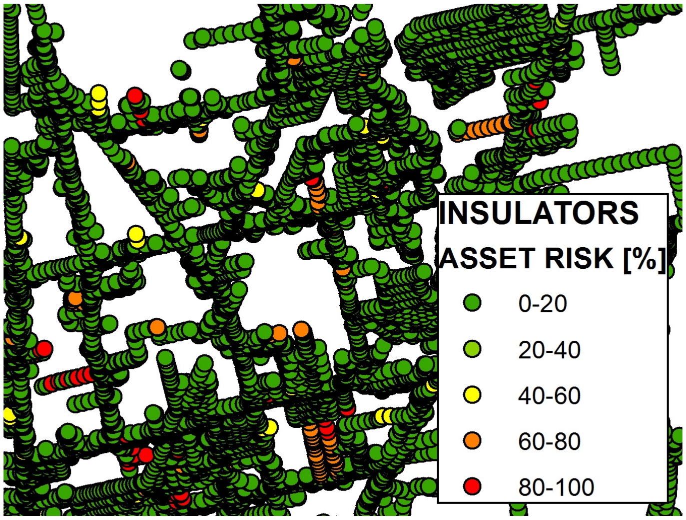
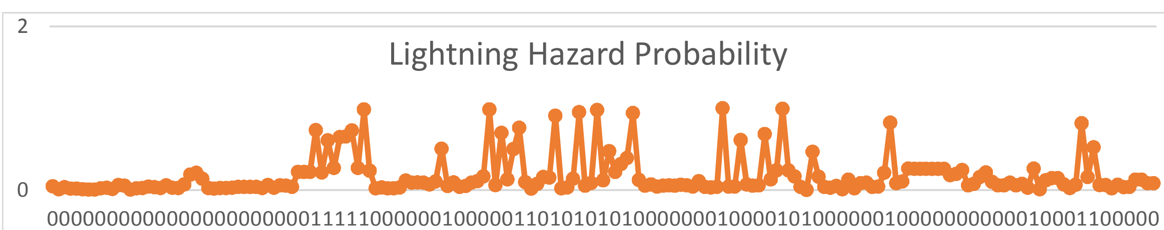


Figure 6. Insulator Risk Map

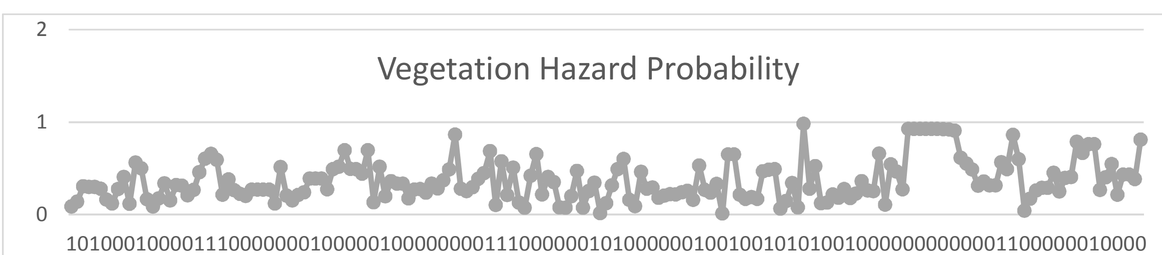
Figure 7. Vegetation Risk Map

vegetation outage application. In this case, the hazard is considered to be the probability of an outage caused by combination of vegetation growth and tree limb movement under severe weather conditions. The benefit for the outage management task is the prediction of the tree trimming section where the outage is expected to happen. This allows for a proactive maintenance of the targeted area in order to prevent the outage. Alternatively, the maintenance crew can be directed to the vulnerable network area and wait for the outage to happen in order to provide fast restoration response. The output of the hazard model is used to calculate the risk associated with each tree trimming zone. Example of the result is presented in Fig. 7.

Fig. 8 presents the predicted hazard probabilities for multiple events in year 2015. The binary values on *x* axis correspond with "1" for the occurrence of the type of event, and "0" for the absence of observed type of event. It can be observed from the Fig. 8 that for most of outage occurrences the corresponding predicted hazard value is higher than the predicted hazard value in the periods when there was no outage.



a)



b)

Figure 8. Hazard probabilities predicted in 2015 for a) lightning, b) vegetation

7. CONCLUSION

The paper describes a predictive weather hazard framework allowing pro-active assessment of electric power system emergencies. Following are the main contributions of the paper:

- The variety of weather data (historical and weather forecast models) is integrated into a unified database.
- The spatiotemporal correlation of weather data with the utility outage and asset data is developed.
- Prediction of weather hazard was done based on the linear regression model.
- The accuracy of the prediction is larger than 75% for all cases that were studied.
- The use of the predictive weather hazard is presented with two examples:
    - Insulation coordination study that predicts the deterioration of the dielectric strength of insulators based on the historical weather, outage, and assets data.
    - Vegetation management study that assigns risk to the various the network areas based on the predicted probability of vegetation caused outages.

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