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Optimal Placement of Line Surge Arresters Based on Predictive Risk Framework Using Spatiotemporally Correlated Big Data

M. KEZUNOVIC[1], T. DOKIC[1], R. SAID[2]
Texas A&M University[1], Vaisala[2]
USA

SUMMARY

Installation of line surge arresters on transmission towers can significantly improve the line lightning performance. However, it is not always economically beneficial to install the line surge arresters on every tower in the network. This paper proposes the method for optimal placement of line surge arresters that minimizes the overall risk of lightning related outages and disturbances, while staying within the required budgetary limits.

A variety of data sources was used: utility asset management, geographical information system, lightning detection network, historical weather and weather forecasts, vegetation and soil properties. The proposed solution is focused on predicting the risk of transmission line insulators experiencing an insulation breakdown due to the accumulated deterioration over time and an instant impact of a given lightning strike. The linear regression prediction-based algorithm observes the impact of various historical events on each individual component. In addition, the spatial distribution of various impacts is used to enhance the predictive performance of the algorithm. The developed method is fully automated, making it a unique large scale automated decision-making risk model for real-time management of the transmission line lightning protection performance.

Based on the observation of risk tracking and prediction, the zones with highest probability of lightning caused outages are identified. Then the optimization algorithm is applied to determine the best placement strategy for the limited number of line surge arresters that would provide the highest reduction in the overall risk for the network. Economic factors are taken into account in order to develop installation schedule that would enable economically efficient management of line lightning protection performance for utilities.

KEYWORDS

Asset management, big data, data analysis, geographical information system, insulation coordination, lightning detection network, line surge arrester, optimization, risk analysis, weather forecast

kezunov@ece.tamu.edu

INTRODUCTION

Increase in frequency of severe weather conditions and aging infrastructure are causing the rise in the risk of transmission network insulator failures. Insulator failures amount for more than 70% of total network outages and contribute up to 50% of the line maintenance cost [1]. In addition, due to the climate change, the amount of lightning caused outages is increasing every year. Instalment of the line surge arresters (LSA) presents a valuable solution for better lightning protection. Installing LSA on every tower is not economically efficient. Instead, comprehensive analysis should be performed to establish the optimal number and location of LSAs.

In [2], an unconstrained nonlinear optimization algorithm has been used in order to minimize global risk of the network exposed to lightning impact. The study in [3] uses multi-objective optimization method based on genetic algorithm to minimize both lightning and switching flashover rates. Genetic algorithms were also used in [4] to determine optimal number and location of LSAs in a distribution network. All of the methods are minimizing a statistically calculated risk function, considering insulator strength as defined by the insulator manufacturer.

We model the network and its surrounding impacts using multi-modal weighted graph that uses data coming from various sources. The developed risk model takes into account the accumulated impact of past lightning disturbances in order to produce more accurate estimate of insulator strength, and predicts insulator performances for the future lightning caused overvoltages using Gaussian Conditional Random Fields (GCRF) [5]. Linear programming (LP) is used to find the LSA placement for which the global risk function is minimal.

BACKGROUND

The insulation coordination study defines the insulator strength with the Basic Lightning Impulse Insulation Level (BIL). BIL is a voltage at which insulator has 10% probability of a flashover [6]. Current practice is to determine BIL by performing a set of standard tests for the standard atmospheric conditions. These tests are done by the manufacturer prior to the insulator installation. Because these tests are performed before any kind of field environmental exposure, they do not reflect the actual strength of the insulator after prolonged exposure. In addition, the BIL value is only true for the standard atmospheric conditions, and need to be recalculated based on the weather conditions at the time of the lightning strike.

There are two types of insulator failures, electrical and mechanical [7]. Electrical failures manifest as increased leakage current through the insulator. They are mostly caused by a high number of experienced flashovers. Mechanical failures are physical deformities to the insulator material. They are mostly caused by manufacturing defects or severe material erosion. Due to exposure to various environmental impacts the performance of insulators deteriorates over time. It is not always easy to observe the changes in the insulator lightning performances. Overhead line insulators are exposed to a variety of environmental impacts [8]: lightning strikes, temperature and pressure variations, ultraviolet radiation and ozone, wind impact, rain, humidity, hail, snow, fog, and pollution. In addition, vegetation presence around the line lowers the probability of flashover in the network, a phenomenon called “shielding by trees” [9]. In addition, lightning strikes are more likely to affect locations with higher altitude [10]. Thus, the elevation data is of importance. The tower grounding resistance also has an impact on overvoltage propagation on the line. This resistance is dependent on the type of soil at the tower location.

To improve the transmission line lightning performance, the line surge arresters (LSA) are installed in parallel with the insulator strings. The LSA limits the overvoltages on the line by discharging or bypassing the surge current [11]. There are two types of LSAs: 1) Externally Gapped Line Arrester that has an external series of air gaps, and 2) Non Gapped Line Arrester that has no air gaps, similar to substation surge arresters.

The insulator flashover voltage determines the appropriate selection of LSA characteristics, since the purpose of LSAs is to limit the voltage bellow insulator withstand limit. The locations where LSA are installed are of great importance. More about observations and experiences of LSAs installation in the field can be found in [12-14]. The study in [12] demonstrates that the LSAs do not show any line lightning performance improvement if they are installed at the wrong towers. Thus, in this paper we would like to introduce a solution for optimal placement of LSAs that could help utilities make smart planning decisions for improvement of line lightning performance.

METHODOLOGY

The proposed method in Fig. 1 combines the probability of a lightning strike as Lightning Hazard, and probability of the insulator breakdown as Network Vulnerability, to construct the lightning impact Component Risk. Then the Global Risk is calculated by averaging the risk over the entire network. The optimization algorithm is minimizing the Global Risk value while considering the Economic Limits and Tower Limits as constrains. The different scenarios of LSA locations are iterated until the optimal placement is found.

Data Preprocessing

Comprehensive geospatial analysis taking into account all environmental factors and their relations to the utility assets is developed using ArcGIS [15]. Transmission network data is spatiotemporally correlated with lightning, weather, vegetation, topography, and soil data. The overview of used data sets is presented in Table I where all non-weather parameters are listed. Table II provides more details about weather data sources and parameters. More details about spatiotemporal correlation of diverse data used for this study can be found in [7].

The rest of this section will describe two main preprocessing steps needed to prepare the data for the input in the risk analysis (including hazard and vulnerability) described in the next section. First step includes the spatial and temporal correlation of lightning, weather, and outage data. The second step will present the use of weather parameters for calculation of BIL under nonstandard atmospheric conditions.

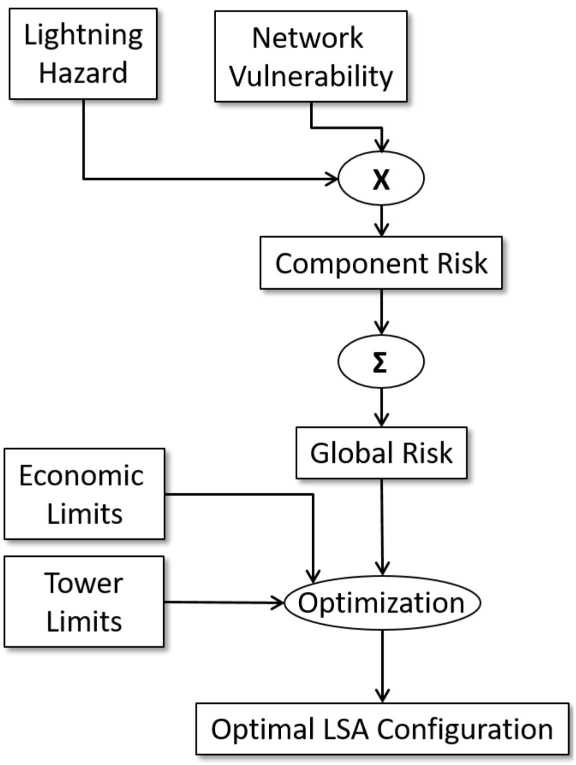

Figure 1. Overview of the proposed method

Table I. List of non-weather parameters

Historical Network Data	**Insulator Physical Characteristics**	**In-field Measurements**		**Other Environmental Parameters**
Outage Reports	Surge Impedances of Towers and Ground Wires	Leakage Current Magnitude	Corona Discharge Detection	Vegetation Index (presence and canopy height)
Maintenance Orders	Footing Resistance	Flashover Voltage	Infrared Reflection Thermography	Elevation
Replacement Orders	Component BIL	Electric Field Distribution	Visual Inspection Reports	Soil

Table II. Weather Data Sources and Characteristics

Source	**Data Type**	**Temporal Coverage**	**Spatial Coverage**	**Temporal Resolution**	**Spatial Resolution**	**Measurements**
National Lightning Detection Network [16]	Lightning Data	1989-Present	USA	Instant	Median Location Accuracy 200-500 m	Date, Time, Latitude, Longitude, Peak amplitude, Polarity, Type of the event: C-C or C-G
Automated Surface Observing System (ASOS) [17]	Land-Based Stations Data	2000-Present	USA	1 min	900 stations	Temperature; Humidity; Pressure; Precipitation;
National Digital Forecast Database (NDFD) [18]	Weather Forecast Data	7 days into the future	USA	3 hours	5 km	Temperature, Relative Humidity, Precipitation, Prob. Dry Lightning, Probability of Severe Thunderstorms

Correlation of lightning, weather, and outage data:

Correlation of datasets is presented in Fig. 2. The weather parameters (temperature, precipitation, humidity, and pressure) are extracted from the ASOS [17], and geocoded into the network area as the raster with the 1 km resolution. The weather forecast data obtained from the NDFD [18] is already a polygon shapefile.

To correlate the lightning data obtained from NLDN [16], first all lightning strikes that are outside of the 1 km buffer around the transmission lines and towers are removed. Then the lightning strikes are spatially and temporally joined with the historical outages. For each historical outage the lightning strike closest in time and space is selected. The spatial limit is set to 1 km around the outage point, and temporal limit for (-2) min in reference to the reported outage start time. In case of multiple lightning strikes satisfying the criterion, the closest one is selected.

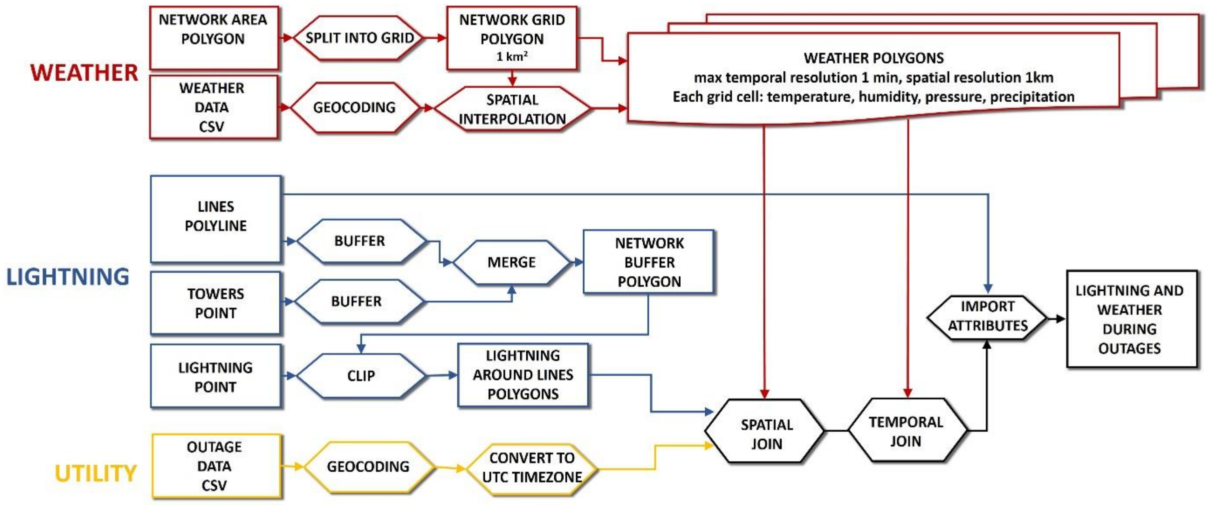

Fig. 2 Spatiotemporal correlation of data

<u>*BIL under nonstandard atmospheric conditions:*</u> For each lightning strike, the lightning protection parameters are calculated for the existing atmospheric conditions obtained from the historical weather data. Additional weather parameters (temperature, humidity, pressure, precipitation) are needed to calculate BIL under nonstandard atmospheric conditions [5]. First, the relative air density and humidity correction factor are calculated as (1) and (2) respectively:

$$\delta = \frac{P T_S}{P_S T} \tag{1}$$

$$H_C = 1 + 0.0096 \cdot \left[\frac{H}{\delta} - 11 \right] \tag{2}$$

where T_S and P_S are standard temperature and pressure respectively; T and P are measured temperature and pressure respectively. Humidity correction factor is equal to 1 for rainy conditions and for dry conditions is calculated using (2). Then the BIL under nonstandard atmospheric conditions is calculated as BIL_A:

$$BIL_A = \delta \; H_C BIL_S \tag{3}$$

where BIL_S is the standard BIL.

Risk

The Risk Framework [19] is capable of predicting risk in real time, as well as estimating the overall risk over a certain period of time. The Gaussian Conditional Random Fields (GCRF) prediction algorithm [20] takes advantage of spatial and temporal similarities between network nodes (transmission towers), and historical events (lightning caused outages). Impact of every historical outage is modelled by the change of line lightning protection performance, creating a dynamic real-time estimate of the insulator strength [21].

The risk is defined as:

$$Risk = Hazard \times Vulnerability \tag{4}$$

The weather impact on the network is modelled as a Hazard Map. In this map every location in the network area has an associated hazard value that represents the probability of a lightning strike at that location for a certain moment in time. The Hazard maps are generated automatically in real time, based on the most current weather forecast.

Network lightning performances are modelled with a Vulnerability Map. This vulnerability map represents the conditional probability of an insulator total failure in case of a lightning strike on its tower. Traditionally, insulator strength is considered to be constant during the insulator lifetime, and equal to the Basic Lightning Impulse Insulation Level – BIL determined in advance by the manufacturer through testing [5]. In our approach, the BIL value changes in time and space to take into account accumulated impact of all past lightning discharges in the particular network locations, as presented in Fig. 3.

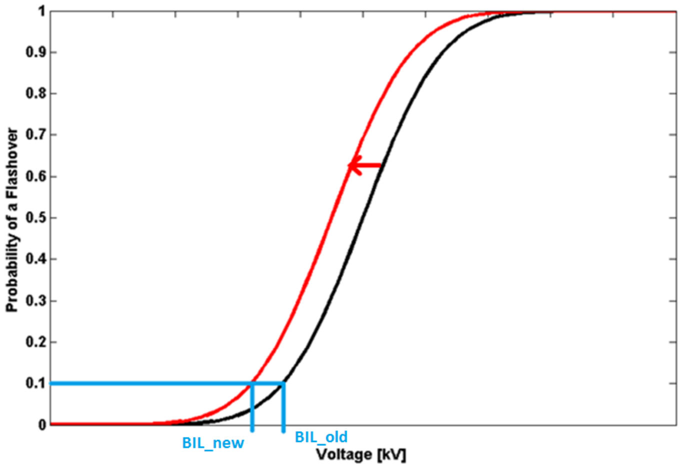

Fig. 3 Dynamic BIL Change

The vulnerability map is developed using predictive linear regression model that uses a variety of historical data including: historical outage, weather, lightning detection, vegetation, and assets. The data are correlated in time and space. The prediction model is based on the GCRF [20]:

$$P(\mathrm{y}\,|\,\mathrm{x}) = \frac{1}{Z}\exp\Big(-\sum_{i=1}^{N}\sum_{k=1}^{K}\alpha_k (y_i - R_k(\mathrm{x}))^2 - \sum_{i,j}\sum_{l=1}^{L}\beta_l e_{ij}^{(l)} S_{ij}^{(l)}(\mathrm{x})(y_i - y_j)^2\Big) \qquad (5)$$

The vector x represents the input data containing lightning parameters (peak current, polarity), weather parameters (temperature, precipitation, humidity, pressure), and insulator parameters (BIL). The output y is the predicted value of BIL after the impact of insulator backflashover has been taken into account. The second sum in eq. (5) represents the node inter-dependencies, where similarity between neighboring towers is expressed in terms of electrical impedance between them.

To solve eq. (5), the parameters α and β need to be estimated. This can be done by maximizing the conditional log-likelihood based on the collected training data from past outages:

$$L(\alpha,\beta) = \sum \log P(\mathbf{y}|\mathbf{x}) \qquad (6)$$

$$\left(\boldsymbol{\alpha},\boldsymbol{\beta}\right)=\underset{\boldsymbol{\alpha},\boldsymbol{\beta}}{\arg\max}\left(L\left(\boldsymbol{\alpha},\boldsymbol{\beta}\right)\right) \tag{7}$$

Optimal Placement of LSAs

The goal is to ensure that overall risk of the network is minimal while the economic impact of the solution stays bellow the acceptable budget limit. The global state of risk function is constructed as an arithmetic mean of the individual state of risk for each network component, and summarized over time:

$$R=\frac{1}{N}\sum_{n=1}^{N}R_n \tag{8}$$

Where R is a total risk for the entire network, N is the total number of towers in the network, and R_n is the individual risk for tower n. The optimization algorithm maximizes the global state of risk reduction by setting LSA positions as independent variables:

$$\begin{gathered}\max\left\{R=\frac{1}{N}\sum_{n=1}^{N}\Delta R_n\cdot F_n\right\}\\ F_n=\begin{cases}0, & \text{no LSA}\\ 1, & \text{LSA installed}\end{cases}\end{gathered} \tag{9}$$

where ΔR_n is a risk reduction on a tower n after installation of LSA. The available budget for the LSA installation is considered to be limited, adding an economic constraint:

$$\sum_{n=1}^{N}F_n\cdot C_n\leq TC \tag{10}$$

where C_n is a cost of installation of LSA on tower n, and TC is a total budget dedicated to the LSA installations.

RESULTS

The method has been simulated and tested on section of the network containing 36 substations, 65 transmission lines, with a total of 1590 towers. The historical outage and lightning data for the period of 5 years were observed.

The Fig. 4 shows an example of a Hazard Map generated for the time of the outage. The Vulnerability Map segment in the area of the outage is presented in Fig. 5. The Risk Map, shown in Fig. 6, is generated by combining the two maps, Hazard in Fig. 4 and Vulnerability in Fig. 5. For each moment in time, it is possible to generate a unique risk map. By averaging the set of risk maps for a period of time it is possible to develop a final risk map on a seasonal or yearly basis.

Based on the overall risk map created for a period of one year, and associated economic impact, the recommended number of line surge arresters (LSAs) is calculated to be 264, and optimal locations of the LSAs in terms of risk reduction are presented in Fig. 7. The presented configuration of LSAs is expected to reduce overall risk by 72%. This kind of result could help utilities make decision about installation of LSAs in an economically efficient way.

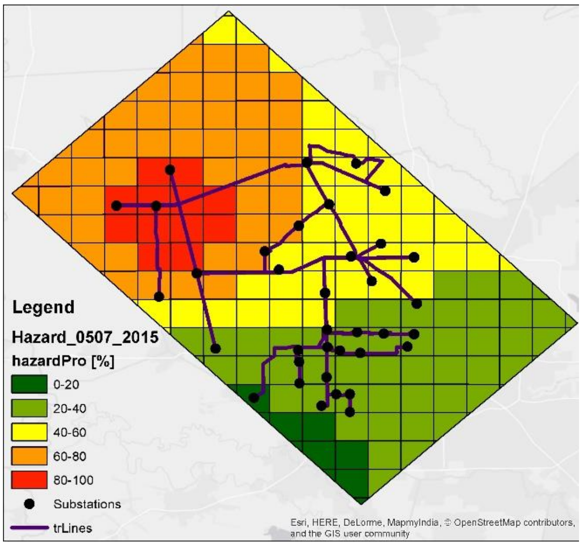

Fig. 4 Weather Hazard Map

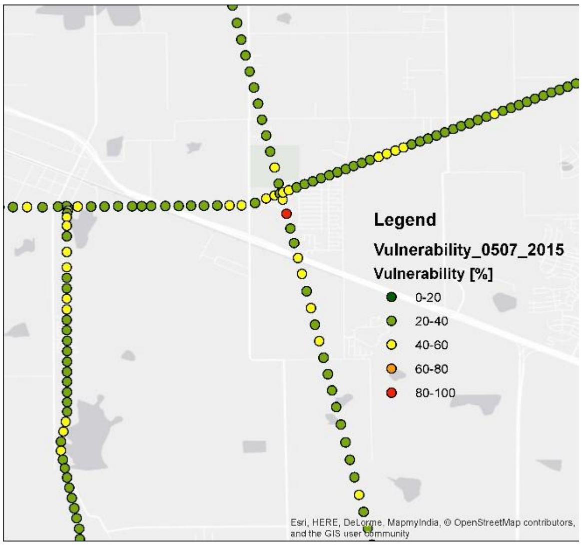

Fig. 5 Tower Vulnerability Map

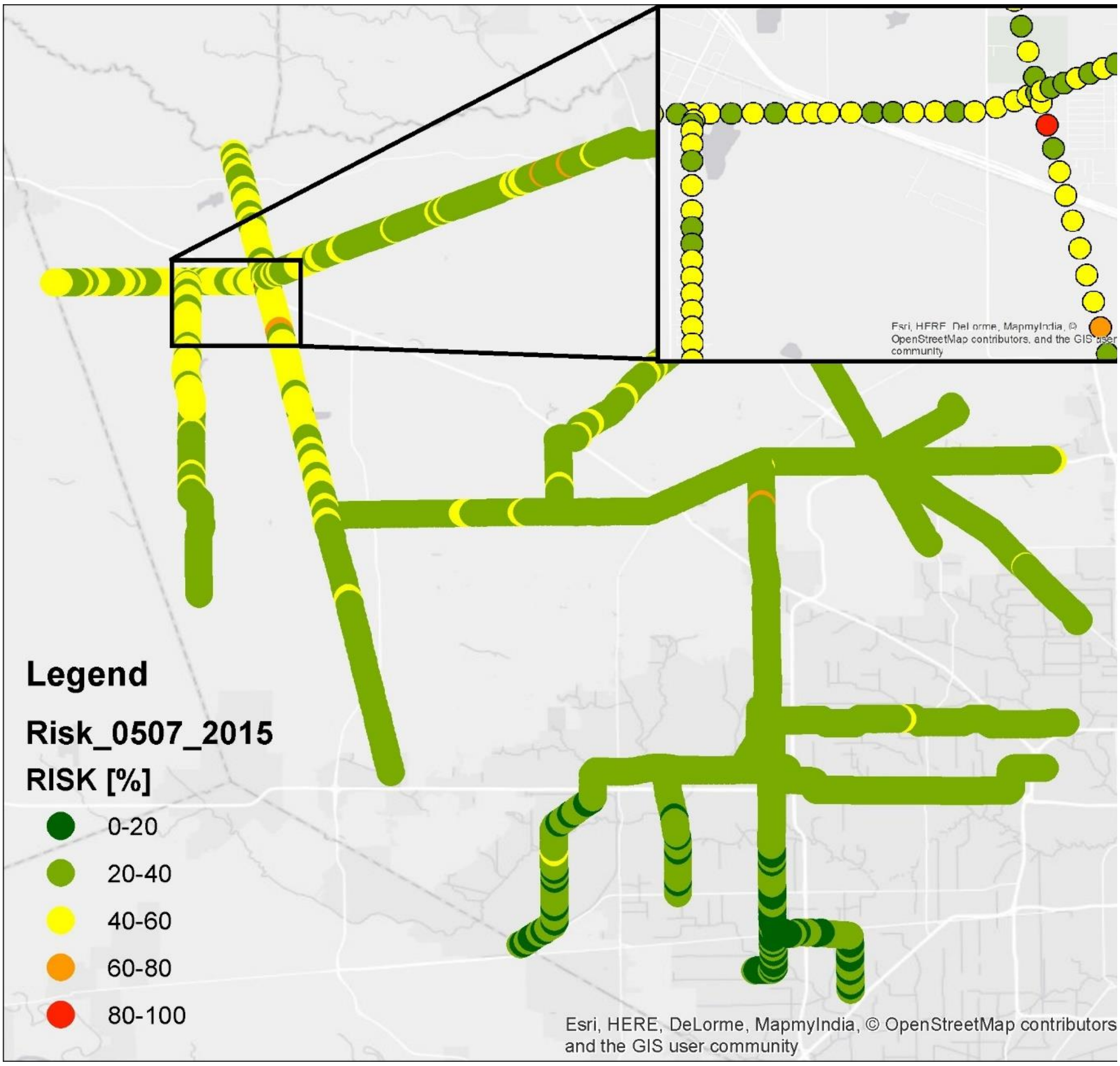

Fig. 6 Risk Map of the Network

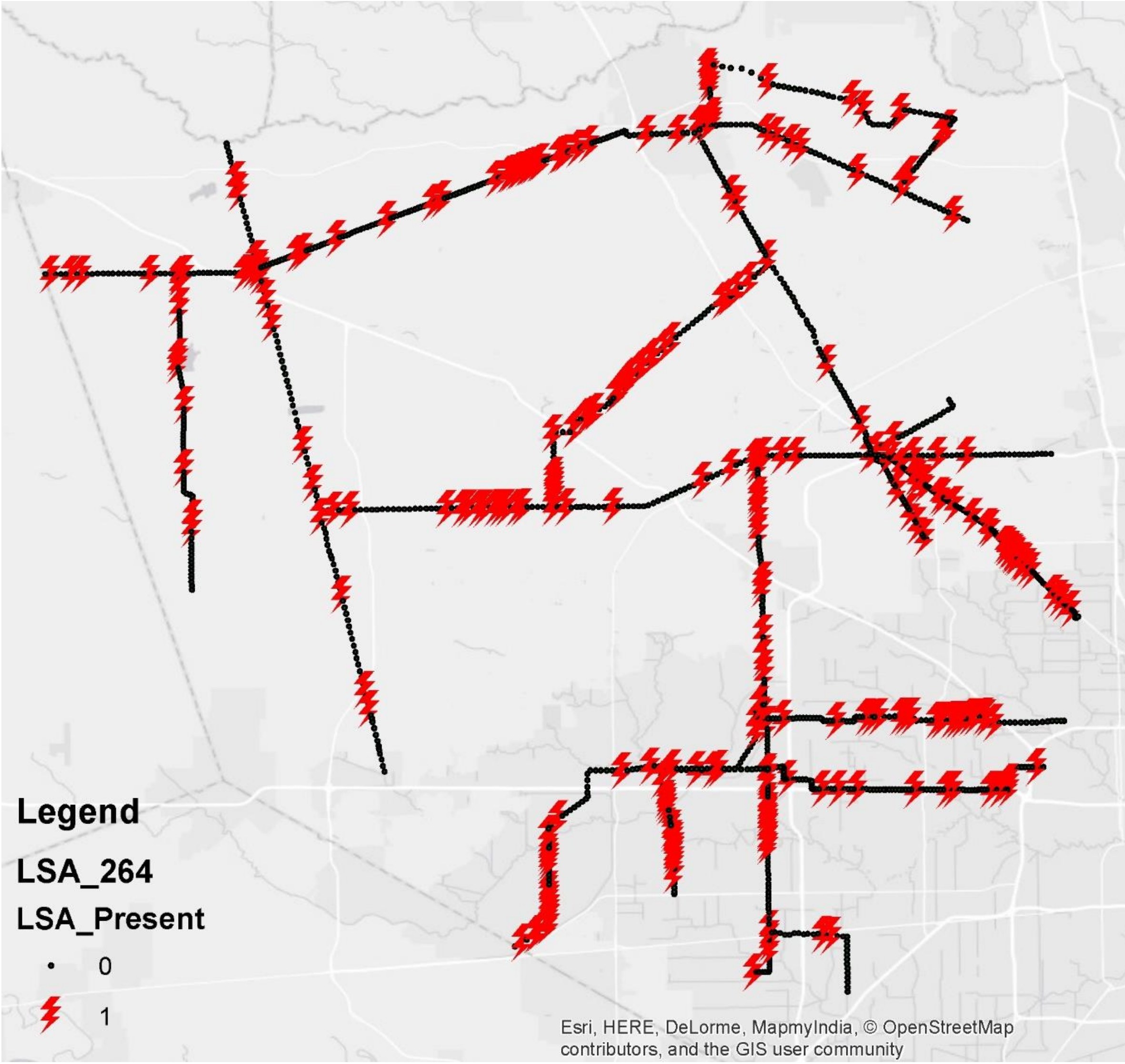

Fig. 7 Locations of 264 Line Surge Arresters

CONCLUSIONS

This paper presents a decision-making method for optimal placement of line surge arresters in the transmission network based on the predictive risk analysis. The outcomes of this research are:

- Lightning data obtained from the NLDN is correlated in time and space with variety of network and weather data.
- The study of insulator lightning strength takes into account the weather conditions at time of the outage, which reflects cumulative strength deterioration over time.
- The real-time risk framework that enables observation of unfolding weather conditions through the Hazard, and their impact of network outages through the Vulnerability was developed.
- The predictive risk method based on Gaussian Conditional Random Fields is used to estimate the network vulnerability to lightning caused outages.
- The predicted risk maps for the transmission network are used to determine the optimal location for line sure arresters that would provide the maximum decrease in risk level while maintaining the budget and physical limits.

BIBLIOGRAPHY

[1] R. S. Gorur, et al., “Utilities Share Their Insulator Field Experience,” T&D World Magazine, Apr. 2005, [Online] Available: http://tdworld.com/overhead-transmission/utilities-share-their-insulator-field-experience

[2] A. L. Orille-Fernandez, et al., “Optimization of Surge Arrester’s Location,” Power Delivery, IEEE Transactions on, Vol. 19, No, 1, pp. 145-150, January 2004.

[3] R. Shariatinasab, et al., “Probabilistic Evaluation of Optimal Location of Surge Arresters on EHV and UHV Networks Due to Switching and Lightning Surges,“ Power delivery, IEEE Transactions on, Vol. 24, No. 4, pp. 1903-1911, October 2009.

[4] E. Bullich-Massague, et al., “Optimization of Surge Arresters Location in Overhead Distribution Networks,” Power Delivery, IEEE Transactions on, Vol. 30, No. 2, pp. 674-683, April 2015.

[5] M. Kezunovic, et al., "Predicating Spatiotemporal Impacts of Weather on Power Systems using Big Data Science," Springer Verlag, Data Science and Big Data: An Environment of Computational Intelligence, Pedrycz, Witold, Chen, Shyi-Ming (Eds.), 2017.

[6] A. R. Hileman, “Insulation Coordination for Power Systems,” CRC Taylor and Francis Group, LLC, 1999.

[7] Rowland, S. M., and S. Bahadoorsingh. "A Framework Linking Insulation Ageing and Power Network Asset Management." Electrical Insulation, 2008. ISEI 2008. Conference Record of the 2008 IEEE International Symposium on. IEEE, 2008.

[8] M. Kezunovic, T. Dokic, "Predictive Asset Management Under Weather Impacts Using Big Data, Spatiotemporal Data Analytics and Risk Based Decision-Making," 10th Bulk Power Systems Dynamics and Control Symposium – IREP’2017, Espinho, Portugal, August 2017.

[9] A. M. Mousa, et al., “Effect of shielding by trees on the frequency of lightning strokes to power lines,” IEEE Transaction on Power Delivery, Vol. 3, No. 2, pp. 724-732, April 1988.

[10] T. Sadovic, et al., “Expert System for Transmission Line Lightning Performance Determination”, CIGRE Int. Colloq. on Power Quality and Lightning, Sarajevo, Jun. 2012.

[11] CIGRE Working Group C4.301, “Use of Surge Arresters for Lightning Protection of Transmission Lines,” ISBN: 978-2-85873-128-2, December 2010.

[12] I. M. Rawi, M. Z. A. A. A. Kadir, “Effectiveness of Line Surge Arrester Application on the 132kV Kuala Krai – Gua Musang Line,” CIGRE Session 35th, Paris, France, August 2014.

[13] P. Bunov, et al., “High energy line surge arresters to improve reliability and protection against switching surges on a 500kV transmission line,” CIGRE Session 35th, Paris, France, August 2014.

[14] S. J. Hsiao, et al., “Lightning Transient Analysis of a 69kV Transmission Line with Externally Gapped Line Surge Arrester under Normal Open Circuit Breaker System,” CIGRE Session, Paris, France, January 2012.

[15] Esri, “ArcGIS Platform,” http://www.esri.com/software/ arcgis

[16] Vaisala, “National Lightning Detection Network – Technical Specification,” 2017 [Online] Available: http://www.vaisala.com/en/products/thunderstormandlightningdetectionsystems/Pages/NLDN.aspx

[17] National Oceanic and Atmospheric Administration, “Automated Surface Observing System (ASOS),” [Online] Available: https://www.ncdc.noaa.gov/dataaccess/land-based-station-data/land-baseddatasets/automated-surface-observing-system-asos

[18] National Digital Forecast Database (NDFD), NOAA. 2017 [Online] Available: http://www.nws.noaa.gov/ndfd/gis/ndfd_tutorial.pdf

[19] Z. Medina-Cetina and F. Nadim F, "Stochastic Design of an Early Warning System", Georisk: Assessment and Management of Risk for Engineered Systems and Geohazards, vol. 2, no. 4, pp. 223 – 236, 2008.

[20] J. Stojanovic, et al,. "Semi-supervised learning for structured regression on partially observed attributed graphs," SIAM International Conference on Data Mining (SDM 2015) Vancouver, Canada, April 30 - May 02, 2015

[21] T. Dokic, et al., "Risk Assessment of a Transmission Line Insulation Breakdown due to Lightning and Severe Weather," HICCS – Hawaii International Conference on System Science, Kauai, Hawaii, January 2016.