Predictive Asset Management Under Weather Impacts Using Big Data, Spatiotemporal Data Analytics and Risk Based Decision-Making

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***Abstract*—This paper introduces predictive framework for asset management risk assessment that utilizes big data. It describes the data analytics required for integrating the big data in time and space. The proposed assets management framework is novel since it implements a dynamic proactive maintenance scheduling. The dynamic maintenance scheduling overpowers the conventional periodic scheduling, by taking into account variety of factors that are changing over time and generating up to date estimations of components' state of risk. The framework complements the condition-based maintenance scheduling by providing additional knowledge extracted from historical data and measurements taken from the sources besides the utility measurements, such as weather data. This enables the integration of various types of ever-changing environmental impacts into the assets failure assessment leading to prevention through optimized maintenance. The framework is demonstrated with the example of the predictive line insulator maintenance scheduling.**

Keywords—asset management; big data; reliability, resilience, risk analysis; weather forecast;

I. Introduction

The changing weather conditions and varying utility operating states caused by introduction of distributed generation and renewables create dynamic conditions that may be harmful to the assets due to the extreme stresses [1]. Under such conditions, the main asset management goal is to minimize the cost of the asset repair and replacement while maximizing the resilience of the system.

Traditional approach to assets condition monitoring is to perform laboratory tests to asses initial properties of the asset and its performance breakdown point, and then use it as a reference for the filed assessment when periodic examinations are done [2]. The frequency of field examination varies based on the device type and operating conditions and can range from several months to several years or even a decade. Another approach to assets management is "run-to-failure", where the components are never being inspected and actions are taken only after the component breaks [3]. In recent decades, technological advances have made it possible to closely monitor asset's states and characteristics using various sensors [4]. Today, these sensors are typically integrated with intelligent electronic devices (IEDs) and provide a continuous on-line condition-based monitoring of equipment [5].

Another approach is a risk-based maintenance scheduling illustrated by several recent studies. In [6] the risk-based allocation of maintenance resources to various distribution system assets is described. The method uses linear optimization to balance risk reduction and economic losses. Research in [7] uses decoupled risk factor and mixed-integer linear formulation for optimization of maintenance tasks. Work in [8, 9] demonstrates the application of the risk assessment analysis of a structured asset model with the function-oriented business process model. In [10] a nonparametric regression method is used to develop failure rate model based on proportional hazards modeling. Study in [11] develops risk assessment framework for the extreme events caused by simultaneous or cascading faults. All the mentioned studies are modeling the risk factor using statistical data. There is a lack of risk-based maintenance strategies that can incorporate all the different data collected by various sensors networks available today.

Our paper provides a new predictive framework for asset maintenance scheduling that combines the sensor monitoring data with the excessive sets of weather, lightning, vegetation, and GIS (Geographical Information System) data. Instead of statistical estimation of failure rates, the variety of data is used to train the prediction model based on linear regression. The state of the network assets is automatically updated resulting in the dynamic risk maps allowing optimized scheduling of assets based on dynamically unfolding risk assessment. The maintenance schedule is created whenever new set of data become available and component state is automatically updated over time. The advantages of this framework are illustrated using the intelligent monitoring and maintenance scheduling for transmission line insulators.

The rest of the paper is organized as follows. First, the background about asset management in general, and the insulator management in particular are introduced in section II. The stages for spatio-temporal correlation of data are described in section II, and the spatiotemporal predictive risk analysis with optimal maintenance scheduling in section III. The results are given in section IV and Conclusions in Section V.

II. Asset Management Approaches

There are several basic approaches to maintenance scheduling [12]:

- Run-to-failure (RTF): in this approach maintenance is only performed after the component fails. The advantage is that there are no expenses associated with the equipment monitoring and analysis but there is no mechanism to predict outages due to the equipment failure resulting in higher cost to re-instate service.
- Condition-based maintenance (CBM): this type of maintenance is initiated by the monitoring equipment indicating that certain performance degradation thresholds are exceeded requiring maintenance action. While this method allows prevention of an outage by "just in time" action, it is typically costly due to the requirement that each individual component is closely monitored.
- Reliability-centered maintenance (RCM): the maintenance schedule is prioritized based on the likelihood of equipment failure. This kind of maintenance scheduling does observe the whole system and prioritizes the maintenance area. However, in the existing RCM studies the likelihood is determined statistically and it is equal for all components, neglecting the variety of factors affected the individual components over the years.
- Optimization techniques (OT): the maintenance scheduling is optimized based on the economic impacts. This kind of maintenance takes into account restrictions such as: availability of maintenance crews, travel expenses, restricted time intervals but still does not get the benefit of the predictive risk assessment based on unfolding threats and vulnerabilities.

The method presented in this paper is an extension of the RCM method. It calculates the risk reduction dynamically by mining large amount of data coming from various sources. Our method offers many advantages over previous methods. The larger scale implementation observing the entire network is feasible due to the spatiotemporal analytics that is scalable. Variety of relevant data such as weather, lightning, and vegetation data is used providing additional data relevant for asset "wear and tear". Prediction model is trained using historical knowledge extraction leading to advanced warning about potential asset failures. The method introduces the unfolding risk assessment allowing associated maintenance schedules to be created dynamically, both in time and space Using our method, every component is mapped with a unique state of risk, and geographical and electrical interdependencies between the components are taken into account.

A. Asset Management for Insulators

The insulator strength is quantified with the Basic Lightning Impulse Insulation Level (BIL). BIL is a voltage at which insulator has 10% probability of a flashover [13]. Conventionally BIL is determined by the manufacturer by performing a set of type tests for the standard atmospheric conditions. It should be noted that these tests are performed before any kind of environmental exposure of the insulator, so they do not reflect the actual strength of the insulator after the prolonged exposure.

Insulators exhibit two types of failures, [14]: 1) mechanical failures caused by physical deformities due to manufacturing defects or severe material erosion; and 2) electrical stress failures caused by increased leakage current mostly due to a high number of experienced flashovers. Due to exposure to different environmental impacts, the mechanical and electrical performances of insulators deteriorate over time. These changes in insulator performances are not always easily observable.

The insulator deterioration can be classified into two stages, [15]: 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 [14], 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.

There are multiple measurements that can be performed in order to estimate the conditions of network insulators. At the network level, the history of outages and disturbances can be used to quantify the insulator failure rates. At the component level, the individual insulator can be tested for its electrical and mechanical properties. The tests can be destructive (only performed in laboratory) or non-destructive (performed in field with system energized or not energized depending on the test type) [16]. Following parameters can be measured in a non-destructive way [14]: i) leakage current magnitude, ii) flashover voltage, iii) electric field distribution, iv) corona discharge, v) radio interference voltage. In addition, it is possible to characterize the insulator material by performing one of the following in-field tests [14]: i) visual inspection, ii) Infrared reflection thermography, iii) hydrophobicity, and iv) remote chemical analysis.

This paper focuses on the deterioration of electrical performances of insulators during the second stage of deterioration when the insulator is experiencing the loss of electrical strength. During this period, the manufacturer's (BIL) no longer can be used as the measure of insulator electrical

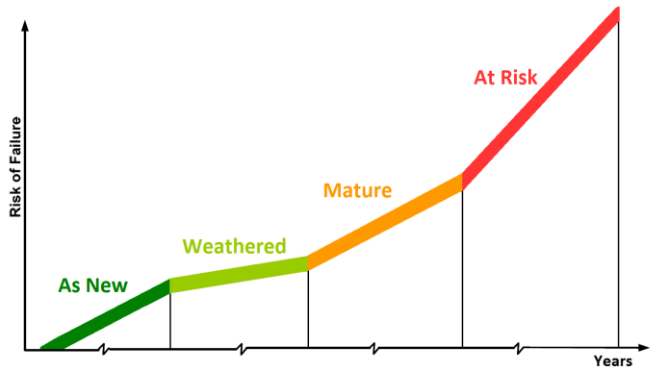

Figure 1. Insulator deterioration process, [14]

strength.

B. *Enviromental Impacts on Insulators*

Overhead line insulators are exposed to variety of environmental impacts, [r]: 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” [17]. Elevation data is of importance also, since lightning strikes are more likely to affect locations with higher altitude [18]. The type of soil at the tower location determines the tower grounding resistance which has a big impact on overvoltage propagation on the line [19].

III. DATA PREPROCESSING

A. *Feature Identification*

First step is to identify all the parameters of interest for the development of the predictive risk model. There are six groups of parameters: insulator physical characteristics, insulator deterioration group and in-field measurements, weather, lightning and other environmental factors, historical network data. The Table I lists all the parameters.

B. *Spatial data analytics*

Spatial correlation of data is done using ESRI’s ArcGIS platform [20]. Any kind of data with a spatial component can be integrated into GIS as another layer of information. As new information is gathered by the system, these layers can be automatically updated. Two distinct categories of GIS data, spatial and attribute data, can be identified. Data which describes the absolute and relative context of geographic features is spatial data. For transmission towers, as an example, the exact spatial coordinates are usually kept by the operator. In order to provide additional characteristics of spatial features, the attribute data is included. Attribute data includes characteristics that can be either quantitative or qualitative. For instance, a table including the physical characteristics of a transmission tower can be described along with the attribute data.

In terms of the spatial data representation, raster and vector data can be used. In case of vector data, polygons, lines and points are used to form shapes on the map. Raster presents data as a visual grid where every cell is associated with one type of data classification. Typically, different data sources will provide different data formats and types. One thing to consider is the spatial resolution of data. In most cases different data sets come in different spatial resolutions.

The geospatial data model is presented in Fig. 2. Utilities maintain geodatabase with the locations of all towers, substations, and lines. These are typically stored as shapefiles. Based on the network geodata the area of interest for correlated weather data can be selected. This area is then split into 1 km blocks and all weather parameters are interpolated to the locations of these blocks. The final weather data contains a set of shapefiles with polygons where each time step has one shapefile assigned to it.

Vegetation data is clipped to the buffer around the lines. This data identifies the parts of a circuit that have tree coverage and are not likely to have lightning caused outages. The vegetation, elevation, soil, and lightning frequency data is added to the tower shapefile one by one performing a spatial join in order to extract the features of selected file that are closest to the tower point features. Insulator physical characteristics, in-field measurement locations, and historical network data are already geocoded to the tower points so their attributes can simply be added to the tower attribute table. In-field measurements and historical network data (including historical outage, maintenance, and component replacement data) have temporal component. Thus, for each tower the pointer to the location of historical file on the disk is created and added to the attribute table.

The final product of spatial correlation of data are the following datasets:

- Weather Dataset, contains one file for each time step. Every file is a shapefile containing polygons associated with the locational weather parameters.
- Tower Dataset, contains all the parameters projected to

TABLE I. LIST OF PARAMETERS

Historical Network Data	**In-field Measurements**	**Weather**	**Lightning**
Outage Reports	Leakage Current Magnitude	Temperature	Peak Current
Maintenance Orders	Flashover Voltage	Humidity	Polarity
Replacement Orders	Electric Field Distribution	Pressure	Type of Lightning
Insulator Physical Characteristics	Corona Discharge Detection	Wind Parameters (speed, direction, gust)	**Other Environmental Parameters**
Surge Impedances of Towers and Ground Wires	Infrared Reflection Thermography	Pollution (sodium chloride)	Vegetation Index (presence and canopy height)
Footing Resistance	Visual Inspection Reports	UV index	Elevation
Component BIL	Radio Interference Voltage	Precipitation	Soil

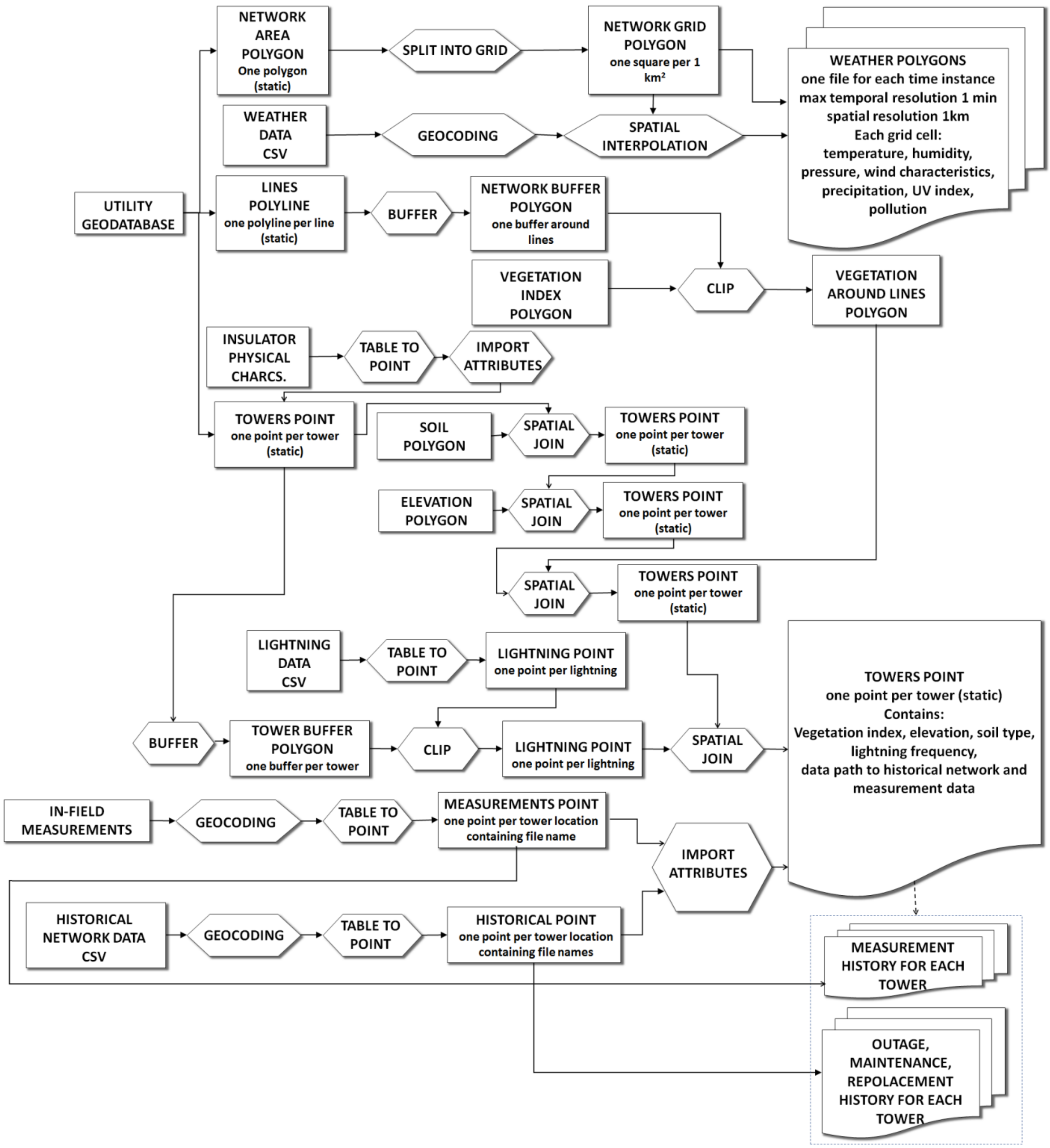

Figure 2. Spatial Correlation of Data

the tower location as a point. In addition, tower dataset contains the link to the historical dataset repository.

- Historical Dataset, which is not a geospatial dataset. Each tower in the network has a set of four files inside historical dataset that list all the events of interest that occurred in the tower's history.

Spatial correlation of data is performed only once as a part of preprocessing. After the initial setup of database, the information is automatically updated with every timestep, as described in the following chapter.

C. Temporal data analytics

All data must be time referenced in a unique fashion. Following factors are important for time correlation of data:

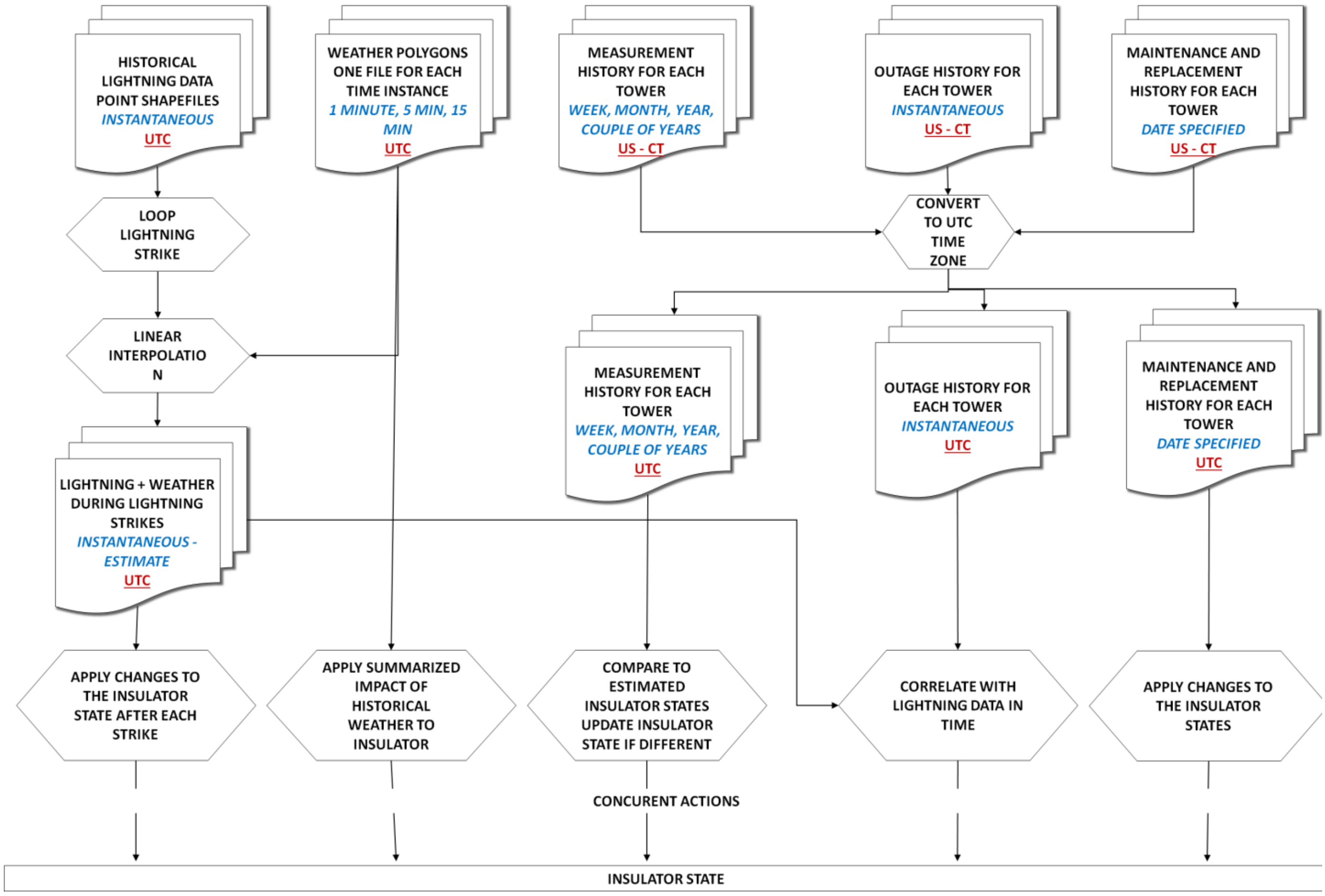

Figure 3. Temporal correlation of data

- Time scales: data can be collected with different time resolution: yearly, monthly, daily, hourly, once every few minutes or even seconds. In addition, different applications may require different rates of data acquisition.
- Atomic Time: Variety of different data sources use different atomic time standards [21], such as UTC – Coordinated Universal Time, GPS Satellite Time, and TAI – International Atomic Time. All time calculations have to be set into a unified time frame.
- Synchronization protocols: Accuracy of a time stamp is highly dependent on the type of the signal that is used for time synchronization. Different measuring devices that use GPS synchronization can use different synchronization signals, such as NTP – Network Time Protocol [22] or PTP – Precision Time Protocol [23].

Fig. 3 demonstrates the steps in temporal correlation of data. Different datasets are collected in different time zones. The UTC time standard has been chosen, and all the temporal data was converted to the UTC time zone. The lightning data needs to be temporally correlated with: 1) weather data, by interpolating weather parameters at the time instance of the lightning strike, and 2) historical outage data, by identifying which lightning strike corresponds to the historical lightning outage.

Following actions are performed automatically as concurrent processes:

- Lightning Impact: After each lightning strike the changes are applied to the lightning performance characteristics of the insulator and insulator state is updated accordingly.
- Weather Impact: After each month, the weather impacts on the insulator are summarized and the insulator state is updated.
- Measurement Based State Update: Whenever the measurement in the field is performed the predicted state of insulator is compared to the measured characteristics. If there is a difference the state of insulator is calibrated to the measured value.
- Outage Impact: Based on the collected outage data the severity of lightning strike impact on the insulator is determined.
- Maintenance/Replacement: Whenever there is a restorative action in the network the associated insulator state is refreshed to the repaired value in case of

maintenance, or new component value in case of replacement.

IV. Geospacialy and Temporaly Referenced Risk Assesment

The State of Risk is represented as a stochastic process [24] that changes over time and has an assigned value in each location of the network. Thus, the state of risk R is a function of time and space as follows:

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

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) $P[T]$ is a hazard probability, calculated based on the weather forecast data for the specific time and location. The second term $P[C|T]$ is calculated based on the historical weather, outage and assets data. The purpose of the second term is to estimate the network vulnerability for the given weather hazard.

A. Hazard

Table II presents the threat levels for different environmental impacts, while the Table III demonstrates hazard classification based on likelihood and threat intensity. Threat describes the severity of the event. In case of the lightning impact, threat can be quantified by lightning peak current value. For the rest of the threats the level of threat is determined based on the length of exposure to the severe impact. While threat in case of lightning strike is instantaneous, the exposure to other weather parameters is summarized over time (months, years) in order to construct the threat level. Based on the weather forecast model the probability of a specific weather event or amount of exsposure is estimated.

TABLE II. THREAT CLASSIFICATION

Threat level	Lightning strikes	Temp. variations	UV radiation	Catastrophic events	Pollution
0					
1					
2					
3					
4					
5					

TABLE III HAZARD CLASSIFICATION

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

B. Vulnerability

For the prediction of network vulnerability levels the Gaussian Conditional Random Field (GCRF) algorithm is used [25]. 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:

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

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, lightning polarity, temperature, humidity, pressure, precipitation, temperature variations, UV, and pollution experienced during time step Δt, presence of catastrophic event, leakage current magnitude, flashover voltage, corona discharge detection, radio interference voltage, flag for inspection changes detected, BIL, and insulator state. The output y of the prediction algorithm is predicted insulator state after the time step Δt. Based on the predicted insulator state the insulator is placed in one of four groups (as new, weathered, mature, and at risk), and the probability of insulator failure is determined from the function presented in Fig. 1.

C. Optimal Maintenance Scheduling

The purpose of maintenance scheduler is to provide balance between system reliability and the maintenance costs. The scheduler is trying to maximize the risk reduction for a system while minimizing the expenses of insulator replacement and maintenance. The available maintenance actions are classified into three groups: do nothing, perform maintenance, or replace component. For each time instance, every insulator in the network can be assigned one of these three values. In order to reduce the number of permutations only insulators that have risk value higher than 60% are considered for maintenance, and those that have risk higher than 80% are considered for replacement. The rest of the network is assigned the "do nothing" action. The maintenance and replacement actions are varied in the selected insulator set until the best maintenance plan is found.

The optimal solution for maintenance plan is determined by solving the following optimization problem that maximizes the system risk reduction:

$$\max\left[\sum_{a=1}^{N}\Delta \mathrm{R}_{\mathrm{M}}(a) SM(a) + \sum_{a=1}^{N}\Delta \mathrm{R}_{\mathrm{R}}(a) SR(a)\right] \qquad (3)$$

With following constrains:

$$\sum_{a=1}^{N} SM(a) MC(a) \leq MA \tag{4}$$

$$\sum_{a=1}^{N} SR(a) RC(a) \leq RA \tag{5}$$

$$SM(a) + SR(a) \leq 1, a = 1,2,\ldots,N \tag{6}$$

Where a is a selected insulator, N is a total number of insulators in the network, $\Delta R_M(a)$ is a reduction in risk for an insulator that was under maintenance, $\Delta R_R(a)$ is a reduction in risk for an insulator that was replaced. $SM(a)$ is 0 if there was no maintenance action and 1 if there was maintenance; $SR(a)$ is 0 if there was no replacement action and 1 if there was replacement, $MC(a)$ is a cost of maintenance for a component a, MA is a total allocated maintenance found, $RC(a)$ is a cost of replacement of component a, RA is a total allocated replacement found.

V. Examples and Advantages

The method has been simulated and tested on a 36 substation, 65 transmission lines section of a network, with a total of 1590 towers. The data coming from three weather stations [26] located in the vicinity of the network was used, and lightning data was obtained from the National Lightning Detection Network operated by Vaisala [27]. Weather forecast data used in this study was downloaded from the National Digital Forecast Database [28]. Soil data was obtained from [29]. Vegetation indices were calculated based on the study presented in [30].

In Fig. 4 the example of Hazard map is presented. Hazard map is created based on the interpolated weather data and presented as a polygon grid where each block has an assigned hazard probability. Example of Vulnerability map is presented in Fig. 5. Each tower has a vulnerability value assigned to it. The vulnerability value represents the probability of an insulator failure if presented Hazard in Fig. 4 has occurred.

In Fig. 6 the example of risk map for one time instance is presented. The advantage of this method is that risk maps are generated continuously over time. At each moment new data is available; the appropriate risk map is assigned based on the current weather forecast and current conditions of network assets.

Based on the overall risk map created for a period of one year, and associated economic cost, the optimal maintenance plan is presented in Table IV. The presented maintenance plan is expected to reduce overall risk by 56% during one year of application. With this method, the asset maintenance schedule is determined dynamically and it differs based on different environmental impacts on the network. The dynamic scheduler is constantly learning, hence adjusting the maintenance schedule to include the impact of all the events in the network.

VI. Conclusions

This paper described a dynamic maintenance scheduling for predictive asset management of geo-spatially and temporally referenced data. Following are the contributions of this paper:

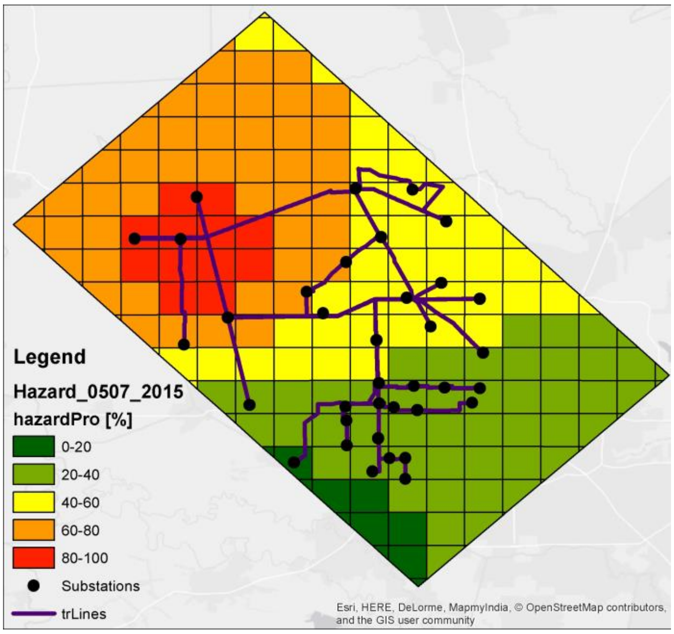

Figure 4. Weather Hazard Map

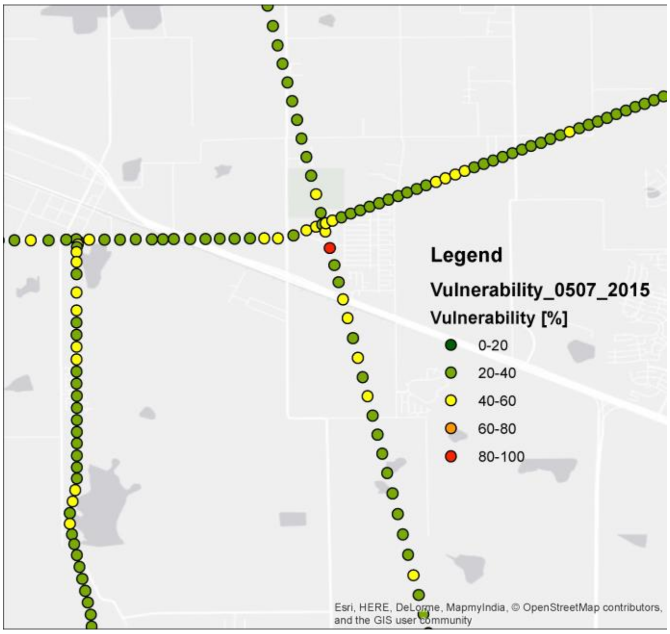

Figure 5. Tower Vulnerability Map

- A novel predictive asset management framework is proposed that optimizes the maintenance schedule based on the dynamically created State of Risk.
- The spatial and temporal integration of input data results in locational assessment of asset deterioration over time.
- The model is capable of predicting the future State of Risk based on the GCRF model, which is scalable to include large number of asset components.

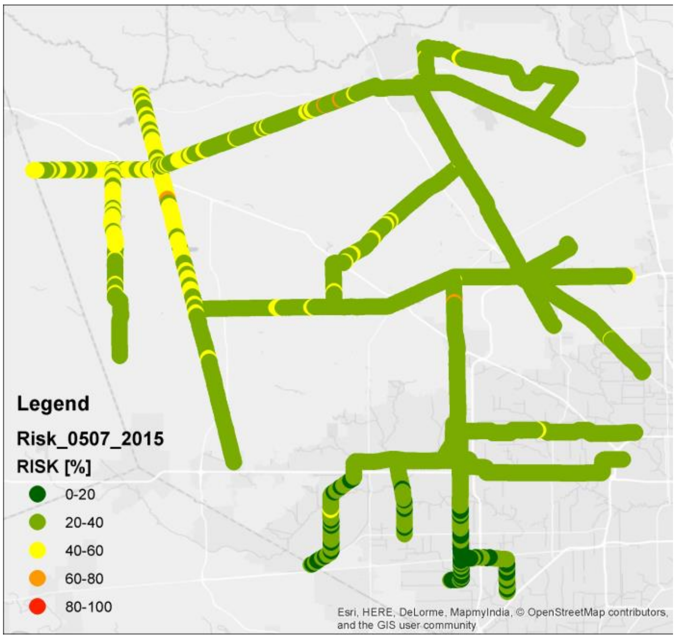

Figure 6. Risk Map of the Network

TABLE IV. OPTIMAL MAINTENANCE SCHEDULES

Time step (month)	**Insulator ID**	**Type of action**	**System Risk Reduction[%]**
1	1528, 924, 949, 321, 1111	M	18.02
	152, 954	R	
2	333, 851, 29, 1374, 854, 376	M	15.13
	34, 641	R	
3	525, 241, 384, 964, 464, 56	M	17.52
	944	R	
4	309, 1191, 1352	M	5.27
	861	R	
5	1506, 1208, 592, 559, 243	M	28.24
	185	R	
6	1389, 1443, 1064, 1009, 345, 127	M	13.13
	528, 74	R	
7	511, 130, 1008	M	10.54
	1181	R	
8	574, 254, 367	M	22.84
	497, 98	R	
9	1435, 1471, 502, 1535, 131	M	26.51
	771, 1313	R	
10	612, 1244, 787	M	7.89
	654	R	
11	217, 70, 369, 137	M	30.02
	184	R	
12	1524, 1475, 1232	M	12.44
	1485, 1501	R	

- The prediction model takes into account the spatial interdependencies of the input data, providing the additional knowledge for more precise prediction of the State of Risk.
- The method combines sensor data used for condition monitoring with additional data obtained from sources outside of electric utility, such as weather data, which gives more precise assessment of asset ageing problem.

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