Optimized Asset Management in Distribution Systems Based on Predictive Risk Analysis

Tatjana Dokic, Mladen Kezunovic
Department of Electrical and Computer Engineering
Texas A&M University
College Station, TX, USA
tatjana.djokic@tamu.edu, kezunov@ece.tamu.edu

***Abstract*— The paper introduces an optimal maintenance scheduler based on predictive assessment of risk of outage and equipment failure in distribution networks. The variety of severe weather conditions are observed and their impact on the network components is quantified. The equipment deterioration and failure rates are observed continuously across the space and time using heterogeneous data. The risk of weather-related outages for each component is generated in real-time, and can be extracted at multiple temporal and spatial scales depending on the application of interest. The optimal maintenance scheduling that minimizes the system risk while maintaining the economic investment limits is developed. The benefits of the framework are presented using a distribution network asset management example.**

Keywords*— *asset management, big data, data mining, geographic information system, meteorology, prediction methods, power distribution, risk analysis.

I. Introduction

The number of power outages in overhead distribution system in the USA is increasing in recent years mainly due to the following factors: 1) weather pattern change, 2) accelerated deterioration due to aging infrastructure. The variety of different weather data are being collected by various organizations, which opens an opportunity for the data intensive analysis of outage causes. Due to the high exposure of assets to environmental impacts it is expected that incorporating such data would be of great benefit, and could help in reversing the increasing trend of power outage occurrences by deploying predictive optimal maintenance practices. This brings up the question of how to efficiently merge electricity network data with variety of environmental data, while observing their spatial and temporal interdependencies. The key benefit is capability to determine likelihood of power network outages and asset deterioration rates under severe weather conditions, which is the key to developing better maintenance strategies.

Traditional assets condition monitoring relies on laboratory tests and filed assessment with periodic examinations [1]. Another approach often used in electric distribution is “run-to-failure”, where actions are taken only after the component malfunctions [2]. In recent decades, the intelligent electronic devices (IEDs) provide continuous on-line condition-based monitoring of equipment [3]. Such approach is still dominant in transmission, and rarely used in distribution. In [4-9] different approaches have been used for the risk-based allocation of maintenance resources to various distribution system assets with optimization of maintenance tasks.

The research in [10] has shown that more accurate predictions are possible by structured learning from merged heterogeneous Big Data. In [11] it is demonstrated that the assessment of equipment deterioration due to prolonged exposure to environmental impacts can lead to an improved on-demand maintenance strategy. In [12] the optimal maintenance strategy was developed for the tree trimming scheduling in distribution network. This paper extends the work reported in [10, 11] by introducing an optimal maintenance scheduler that generates just in time tree trimming maps based on the latest prediction of the state of risk of network components experiencing faults when touched by trees.

The key contributions of the paper are: a) integration of variety of data, b) the use of the risk maps to develop spatiotemporal assessment of the assets status, and c) development of an optimized maintenance strategy to mitigate the risk.

The rest of the paper is organized as follows. First the background on asset management approaches is summarized in Sec. II. Sec. III introduces the predictive asset management. In Sec. IV we describe optimal risk-based maintenance strategy based on predictive analysis. Examples of results are provided in Sec. V, and conclusions are summarized in Sec. VI.

II. Asset Management

Current practices use several approaches to asset maintenance scheduling [13]:

1) Run-to-failure where replacement is performed after component fails without any monitoring or maintenance during component lifetime,
2) Periodic maintenance where each component is serviced on a predetermined periodic schedule,
3) Condition-based maintenance using monitoring equipment where the equipment is repaired or repliced when needed,
4) Reliability-centered maintenance that relies on the likelihood of equipment failure for selection of the ebst maintenace interval.
5) Optimization techniques based on the reduction of economic impacts.

TABLE I. COMPARISON OF ASSET MANAGEMENT APPROACHES

Approach/Feature	Run-to-failure/Periodic	Condition-based	Reliability-centered	Optimization techniques	Our Approach
Monitoring cost	No expenses	High	High	High	High
Cost of reinstating services	High	Low	Low	Low	Low
Preventive capability	No	Yes	Yes	Yes	Yes
System or component level	Component level	Component level	System level	Both	Both
Data	No	One or several different measurements	One or several parameters observed	One or several parameters observed	Big Data – wide variety of parameters
Predictive	No	No	Yes – statistical	No	Yes – better accuracy with machine learning
Spatiotemporal analysis	No	No	Limited	No	All data spatiotemporally referenced
Dynamic real-time assessment	No	Yes	Limited	Limited	Yes
Interdependencies between components	No	No	No	No	Geographical and electrical

The overview of characteristics of conventional asset management approaches and our proposed method is presented in Table I. Compared to other methods our approach: 1) introduces capability to process, utilize, and visualize larger amounts of data, 2) enables predictive analysis based on spatiotemporal data where spatial interdependencies between components are considered, and 3) introduces dynamic maintenance scheduling based on real-time observation of network components' states and surrounding conditions.

This paper focuses on two types of outages in distribution that combined cover more than 60% of total outages:

1) Due to instantenious impact of severe and catastrophic weather conditions on utility assets. These types of outages are designated as weather caused outages.
2) Due to deterioration as a result of exposure of assets to long term weather impacts. These types of outages are designated as equipment failure.

We propose a novel asset management that enables the following capabilities:

1) Assessing equipment deterioration continuously across space and time by learning from heterogenous data,
2) Real-time risk assessment on multiple temporal and spatial scales by assessing the hazrads and vulnerabilites,
3) Optimal on-demand asset management by developing a maintenace strategy that reduces the outage risk.

The goal is to integrate the environmental data into the power system models and studies, build a model that integrates and exploits all types of data, evaluate system and component risk in real time, and contrast the existing static asset management practices with the new dynamic approach.

III. PREDICTIVE ASSET MANAGEMENT

The study improves the current asset management practices at three levels illustrated by the environment shown in Fig. 1:

1) Data Level: The study includes a variety of different data coming from multiple data sources. The data is collected at multiple temporal and spatial scales. Data sets may contain bad and missing data. The uncertainty levels of data may vary from one set to another. We show how such cases may be handled.
2) Analysis Level: The study uses the prediction algorithm [14-17] capable of leveraging the spatial and temporal aspects of heterogeneous data as a knowledge source. Graph based machine learning methods are used for prediction. The analysis has to be robust to missing and bad data. We demonstrate such data analytics features.
3) Economic Level: The maintenance decision-making is focused on minimizing the risk level while maintaining the economic investment limits. While the cost of periodic maintenance stays the same, the reactive maintenance cost is optimized and reduced.

Other details about implementation of predictive risk-based asset management can be found in [10-12, 18].

IV. OPTIMAL RISK-BASED MAINTENANCE STRATEGY

The maintenance scheduler has a goal to minimize the risk for the whole network while spending only the predetermined maintenance budget. Two types of maintenance cost are identified: 1) planned maintenance typically has a predetermined budget, and is performed periodically, 2) reactive maintenance includes the actions that occurred after the unexpected outage or asset failure, and the budget is variable.

The specific optimization problem has to be defined separately for each distribution asset type (pole, transformer, insulator…) but the overall procedure can be defined as follows. Minimize the total risk for the network:

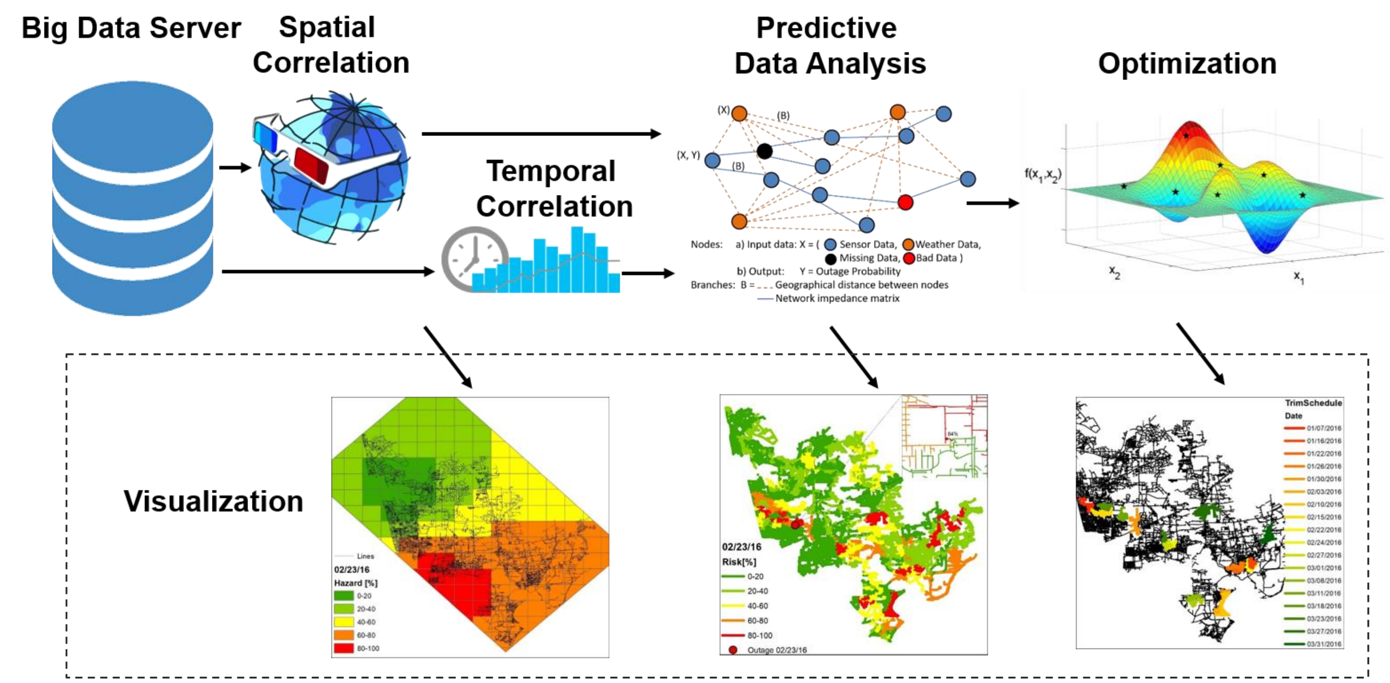

Figure 1. Weather testbed environment

$$max \left\{ R = \sum_{t=1}^{T} \frac{1}{N} \sum_{n=1}^{N} \Delta R_{n,t} \cdot A_{n,t} \right\} \quad (1)$$

$$A_{n,t} = \begin{cases} 0, & \text{no maintenance on asset } n \text{ at time } t \\ 1, & \text{maintenance on asset } n \text{ at time } t \end{cases}$$

subject to following economic constrain:

$$\sum_{t=1}^{T} \sum_{n=1}^{N} A_{n,t} \cdot C_{n,t} \leq TC \quad (2)$$

where $\Delta R_{n,\theta} = R_{n,(\theta-1)} - R_{n,\theta}$ is the difference in risk value for feeder n before and after the action is performed, R is a total reduction in risk, $C_{n,t}$ is the cost of maintenance of section n in the time instance t; and TC is a total budget allocated for the periodic tree trimming during the observed quarter. A total of T time instances is created. The risk is calculated for each of the N asset components.

The optimization problem solver will iterate various actions (component maintenance, component repair, component replacement, environment assessment such as tree trimming, etc.) until it finds the best asset management schedule. For each time step each component has an action flag that indicates if there is an action on that component and what type of action is performed. This makes the optimization problem nonlinear. In order to provide feasible solution in time, the heuristic solvers need to be considered.

The impacts of the environment and component vulnerabilities for each moment in time are accumulated in the dynamic risk value we are trying to minimize. The limits of the budget for periodic (planned) actions are taken into account as constrains.

The last component, reactive maintenance, is target for minimization, and it is used for validation and testing of this approach performance. Our goal is to, by minimizing the network overall risk, also minimize the cost of reactive maintenance. As part of validation, after the optimization problem is solved, we compare the reactive asset management cost that was spent during the period of interest to the evaluated reactive maintenance expense that would be spent if optimal asset management schedule was followed.

Following are the required steps of the optimal maintenance scheduler, as presented in Fig. 2:

1) Generate risk maps based on the historical data and weather forecast and store the risk value for each component in the network. This step containes three tasks:
   a) Calculate weather hazard using weather forecast [19]. In this step we are evaluating the expected unfolding weather conditions that will affect the network in a certain moment in time.
   b) Calculate network vulnerability using historical data and current profile of the network and environment. In this step we learn from the historical outage and weather data [20,21] what the vulnerabilities of the network are, and we calculate based on the knowledge from the past what is the probability of an outage under an existing unfolding weather conditions.
   c) Generate action on a specific component. By performing any of the countermeasures it is possible

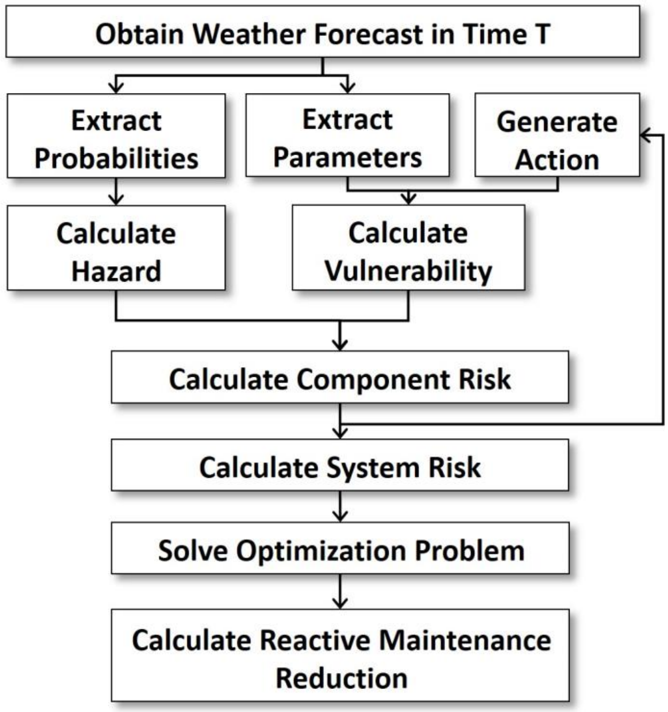

Figure 2. Optimal Risk-based Scheduler

to reduce the network vulnerability to the unfolding weather conditions. Optimization algorithm will iterate multiple *generate action* configurations until it finds the optimal schedule.

2) Calculate the system risk by averaging or sumarizing the risk over all components.
3) Define the optimization problem that minimizes the calculated system-level risk. In this step the objective countermeasures need to be selected. For example, if we are observing vegetation management, the main countermeasure would be tree trimming. In another example, if we are targeting insulators, countermeasures may include insulator cleaning, insulator repair, insulator replacement, etc.
4) Set the optimization constrains to limit the periodic asset management expense. In this step the specific practices followed by utility need to be observed in order to set the realistic economic constrains.
5) Solve the nonlinear optimization problem by applying the heuristics (for example Lagrangian Relaxation, Support Vector Machine, Neural Network, etc.).
6) Calculate the reduction in reactive maintenance cost after the outage. During the validation process the reduction in reactive maintenance can only be estimated. After the deployment in the field the testing process can observe the changes in reactive maintenance expense before and after dynamic maintenance scheduling.

V. Example of Results

The model is tested on the real distribution network, experiencing ~500 outages during the period of 5 years from 2011 to 2015. The data obtained for the first four months in year 2016 was used for testing of optimal maintenance scheduler.

Fig. 3 presents the predicted outage probabilities for multiple events in year 2015, including all weather related outages caused by lightning, vegetation, rain, etc. 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. For most outage occurrences the corresponding predicted outage probability value is higher than the predicted outage probability value when there was no outage.

In our work we were able to achieve accuracy of outage probability prediction greater than 64%. Our experience for applications in transmission shows accuracy greater than 75% [10-12, 22]. We can conclude that the predictive capabilities in distribution are still significantly behind our capabilities to predict risk in transmission. This is due to distribution network being smaller in size and denser, thus requiring better spatial and temporal resolution of input data that is not available for all datasets. Also, a number of measurement that are collected in transmission is much more than what is collected in distribution, which reflects on the number of input parameters that can be used for predictions. The trends are changing in recent years with an increase in data available for prediction in distribution, in addition to many datasets improving their spatial and temporal resolutions over time. We expect the performances on prediction of outages in distribution to come closer to the performances in transmission soon.

The example of risk map is presented in Fig. 4. The risk maps are created dynamically, so there is a separate risk map for each moment in time. The example in Fig. 4 presents the risk map generated for March 30th, 2016, when the network experience the outage. These maps are generated every three hours, and contain risk values for each component individually. The risk maps could be of great value to Distribution System Operators since they provide a prediction of areas that may experience outages in the future. With this kind of information, the operator can make better decisions about allocation of maintenance crews in the network.

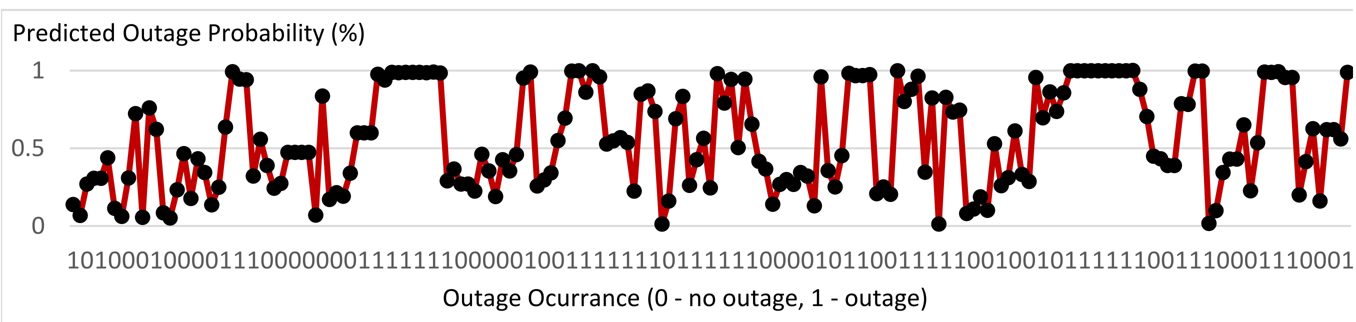

Figure 3. Outage probabilities predicted in 2015 based on the training data from 2011 to 2014 for weather outages.

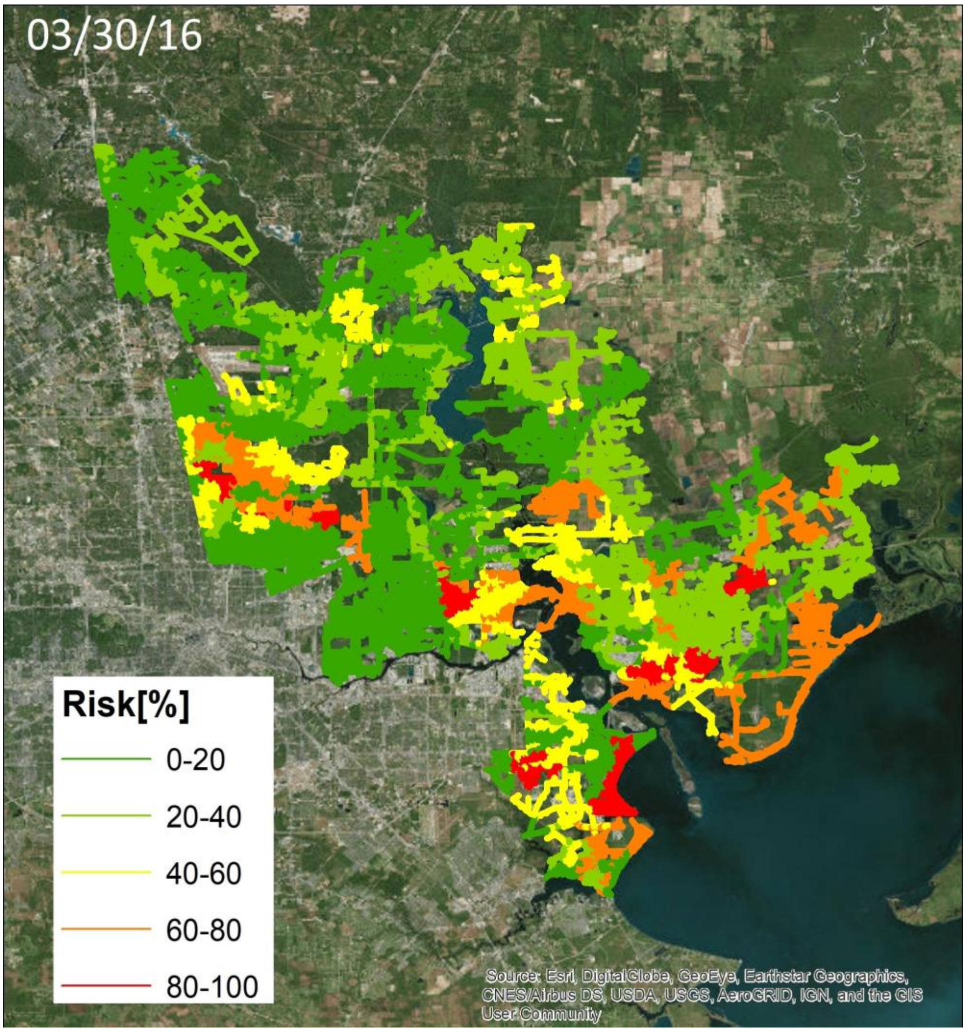

Figure 4. Risk Map

A collection of risk prediction maps for the month of January 2016 was used to create optimal maintenance schedule. Total of 248 risk maps in different time points were created and used as inputs to optimization algorithm. The optimization objective was to reduce overall risk for the network including both insulators and vegetation. The economic limits for insulators and vegetation management were observed separately, as two independent constrains.

Fig. 5 presents example of optimal asset maintenance schedule for one month in 2016. The chosen actions that were used in the optimization are tree trimming, insulator replacement, and insulator repair. In addition to selecting the asset (pole, feeder section) that needs to be maintained, algorithm sets the deadline by which the action should be performed to achieve maximum risk reduction.

VI. CONCLUSIONS

This paper introduces a new framework for optimal maintenance scheduling based on predictive risk assessment for distribution assets. More specifically, the following are the specific innovations:

1) The study uses variety of datasources, some collected by utility such as outage and assets data; and extensive set of enviromental data, such as weather station data, weather forecast, vegetation, lightning.
2) The temporal and spatial interdependencies between component and events in the network are levaraged for the improvement of prediction algorithm accuracy, and its capability to deal with bad and missing data.
3) The dynamic asset management system based on optimization was build to reduce the predicted risk of outages and component failure while mainteining predetermined economic investment in periodic asset maintenance.
4) The method is applied to the real utility data and the prediction performance in a real life setting is evaluated.

REFERENCES

[1] J. Endrenyi, et al., “The present status of maintenance strategies and the impact of maintenance on reliability,” IEEE Trans. on Pwr Sys, Nov. 2001, pp. 638-646.

[2] Nelson, W. (1971). Analysis of accelerated life test data-Part I: The Arrhenius model and graphical methods. IEEE Transactions on Electrical Insulation, (4), 165-181.

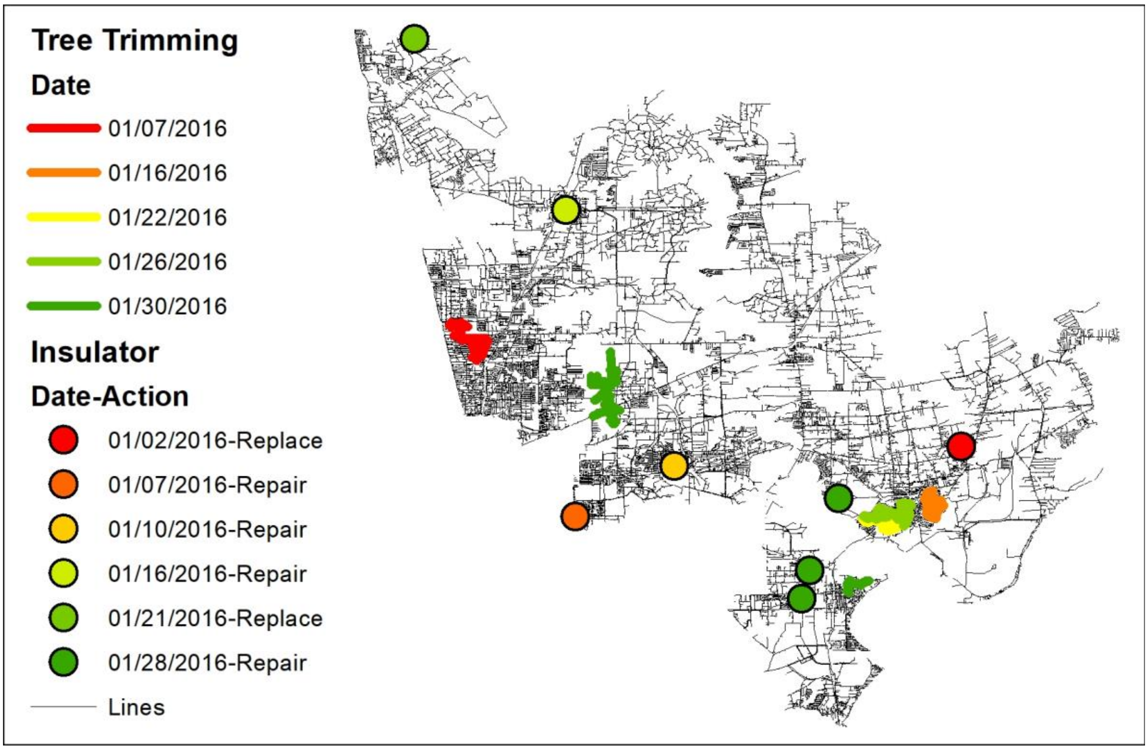

Figure 5. Asset Maintenance Scheduler

[3] S. Natti, M. Kezunovic, "Assessing Circuit Breaker Performance Using Condition-based Data and Bayesian approach,"Electric Power Systems Research, Volume 81, Issue 9, pp. 1796-1804, September 2011.

[4] Yeddanapudi, S. R. K., et al. (2008). Risk-based allocation of distribution system maintenance resources. IEEE Transactions on Power Systems, 23(2), 287-295.

[5] Abiri-Jahromi, et al., "An efficient mixed-integer linear formulation for long-term overhead lines maintenance scheduling in power distribution systems." IEEE transactions on Power Delivery 24.4 (2009): 2043-2053.

[6] Liu, Nian, et al., "Asset Analysis of Risk Assessment for IEC 61850-Based Power Control Systems—Part I: Methodology." IEEE Transactions on Power Delivery 26.2 (2011): 869-875.

[7] Liu, Nian, et al., "Asset analysis of risk assessment for IEC 61850-based power control systems—Part II: Application in substation." IEEE Transactions on Power Delivery 26.2 (2011): 876-881.

[8] Qiu, Jian, et al. "Nonparametric regression-based failure rate model for electric power equipment using lifecycle data." IEEE Transactions on Smart Grid 6.2 (2015): 955-964.

[9] Liu, Xindong, et al. "Risk assessment in extreme events considering the reliability of protection systems." IEEE Transactions on Smart Grid 6.2 (2015): 1073-1081.

[10] M. Kezunovic, Z. Obradovic, T. Dokic, B. Zhang, J. Stojanovic, P. Dehghanian, and P. -C. Chen, "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.), ISBN 978-3-319-53474-9, 2017.

[11] M. Kezunovic, Z. Obradovic, T. Dokic, S. Roychoudhury, "Systematic Framework for Integration of Weather Data into Prediction Models for the Electric Grid Outage and Asset Management Applications," The Hawaii International Conference on System Sciences - HICSS, Waikoloa Village, Hawaii, January 2018.

[12] T. Dokic, M. Kezunovic, "Predictive Risk Management for Dynamic Tree Trimming Scheduling for Distribution Networks," IEEE Transactions on Smart Grid, in review.

[13] J. McCalley, et al., "Automated Integration of Condition Monitoring with an Optimized Maintenance Scheduler for Circuit Breakers and Power Transformers," PSerc Report #06-04, January 2006.

[14] Stojanovic, J., Jovanovic, M., Gligorijevic, Dj., Obradovic, Z. (2015) " Semi-supervised learning for structured regression on partially observed attributed graphs" Proceedings of the 2015 SIAM International Conference on Data Mining (SDM 2015) Vancouver, Canada, April 30 - May 02, 2015.

[15] V. Radosavljevic, S. Vucetic, Z. Obradovic, "Neural Gaussian Conditional Random Fields," Proc. European Conference on Machine Learning and Principles and Practice of Knowledge Discovery in Databases, Nancy, France, September, 2014.

[16] V. Radosavljevic, Z. Obradovic, S. Vucetic, "Continuous Conditional Random Fields for Regression in Remote Sensing, " Proc. 19th European Conf. on Artificial Intelligence, August, Lisbon, Portugal, pp. 809-814, 2010.

[17] N. Djurovic, V. Radosavljevic, Z. Obradovic, S. Vucetic, "Gaussian Conditional Random Fields for Aggregation of Operational Aerosol Retrievals," IEEE Geoscience and Remote Sensing Letters, Vol. 12, No. 4, pp. 761 – 765, 2014.

[18] M. Kezunovic, T. Dokic, R. Said, "Optimal Placement of Line Surge Arresters Based on Predictive Risk Framework Using Spatiotemporally Correlated Big Data," CIGRE Paris 2018.

[19] National Digital Forecast Database (NDFD) Tkdegrib and GRIB2 DataDownload and ImgGen Tool Tutorial, NWS, NOAA. [Online] Available: http://www.nws.noaa.gov/ndfd /gis/ndfd_tutorial.pdf

[20] National Centers for Environmental Information, "Automated Surface Observing System (ASOS)," [Online] Available: https://www.ncdc.noaa.gov/data-access/land-based-station-data/land-based-datasets/automated-surface-observing-system-asos

[21] Vaisala, "National Lightning Detencton Network - NLDN", [Online] Available: https://www.vaisala.com/en

[22] T. Dokic, M. Pavlovski, Dj. Gligorijevic, M. Kezunovic, Z. Obradovic, "Spatially Aware Ensemble-Based Learning to Predict Weather-Related Outages in Transmission," The Hawaii International Conference on System Sciences – HICSS 2019, in review.