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DUBLIN 2017

# Big Data Uses for Risk Assessment in Predictive Outage and Asset Management

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## SUMMARY

Allowing better estimates of the risk associated with outages and asset failures is an ultimate goal since the cost of service interruption due to forced or planned outage can be substantial. This paper address how the risk calculation is improved by the use of Big Data related to weather and other environmental impacts that may lead to outages and asset deterioration. Big Data considered in this paper relates to various weather data services such as radar, satellite, land stations, specialized tracking systems (lightning), etc., as well as vegetation and topography. In addition, traditional utility measurement data coming from Intelligent Electronic Devices located in substations and along the feeders are integrated to get better assessment of the risk. Developing a framework that ties the data and physical network components together in time and space to obtain better predictions is an emerging area of research. Our innovative study opens several opportunities to address unique fundamental issues of how to effectively fuse weather and network data in time and space for the benefit of predicting likelihood of power network outages under severe weather conditions, which will lead to better maintenance and operation strategies.

The results are obtained using advanced predictive data analytics approach that incorporates spatiotemporal properties of the Big Data. To better visualize the risk assessment results, a Geographic Information System view of the power system components is offered. This view allows operators to immediately assess the risk in the face of unfolding weather conditions and take actions accordingly. The benefits of using Big Data to achieve such decision-making capability is contrasted with the legacy solutions and their mostly after-the-fact reactive actions. The Big Data utilization is part of a larger effort aimed at introducing various advantages to the utility industry based on the advanced data analytics. Several examples from the recent work done for the utility industry are given, using a real- life representation of their system and the associated events.

## KEYWORDS

Asset management, big data, outage management, risk analysis, tree trimming, vegetation management, weather impact.

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## 1. INTRODUCTION

The efficiency of implementing outage and asset management has a significant impact on the reliability and cost of utility operations. Weather conditions are very important in determining the power system operating conditions including the state of assets, and probability of outages [1]. Each type of weather-related event has a different impact on the power system. Differentiating between weather events and using the appropriate granularity of weather-related data in the prediction process is a critical component of a successful strategy to manage and mitigate the impacts.

Previous studies have focused on the predictions of hurricanes (tropical cyclones) and the resultant power outages. Guikema et al. [2] developed models to estimate the physical damage of a hurricane to power systems. Liu et al. [3] developed models to estimate the restoration times for hurricanes and ice storms related outages. Davidson et al. [4] studied outages caused by hurricanes and concluded that the relationship between the maximum wind gust and the number of outages is statistically significant. Nateghi et al. [5] examined various statistical models for estimating outage durations and validated the predictive power of these models. Quiring et al. [6] incorporated uncertainties in the hurricane forecast into outage modeling. Han et al. [7] developed statistical models to estimate the number of outages in grid cells of a utility service area in the gulf coast region for an approaching hurricane. In summary, Ref. [2-7] have studied outage predictions and durations by statistical models.

Shariatinasab et al. present optimal location method for surge arresters based on statistical analysis of insulation characteristics [8]. Orille-Fernández et. all use artificial neural networks to estimate risk of failure for lightning protection equipment [9]. In [10], Meliopoulos et al. present the overvoltage protection method based on Monte-Carlo analysis. In [11], Amarh et al. discuss a statistical method for insulator risk assessment used for prediction of flashover occurrences. The work in [12] predicts insulator flashover voltage based on the voltage surface resistance measurement. Previous studies [8-13] assumed constant insulator strength through the lifetime, and neglected insulator individual spatial and temporal characteristics. Same as in case of outage management, the conventional studies of insulation coordination are based on statistical models.

In contrast to previous studies based mainly on statistical modelling, this paper describes the development of a predictive decision making tools for utilities based on data mining. The outages and assets deterioration for variety of weather events, including seasonal events (thunderstorms, tornados), extreme daily variations (temperature, wind, precipitation), and catastrophic events (hurricanes, tornados) can be better managed by predicting the impacts. The focus is on incorporating weather predictions into two system applications: 1) Outage Management, particularly accurate prediction of fault location; and 2) Assets management, particularly accurate prediction of deterioration of insulators. An overview of the proposed implementation is presented in Fig. 1.

This paper is organized as follows. First the need for the more vigilant exploitation of predictive methods is justified in Section 2. Then, in Section 3, the predictive risk framework is described, with focus on two applications: asset, and outage management. Section 4 presents examples of results obtained using developed predictive risk framework. In Section 5, final conclusions are presented.

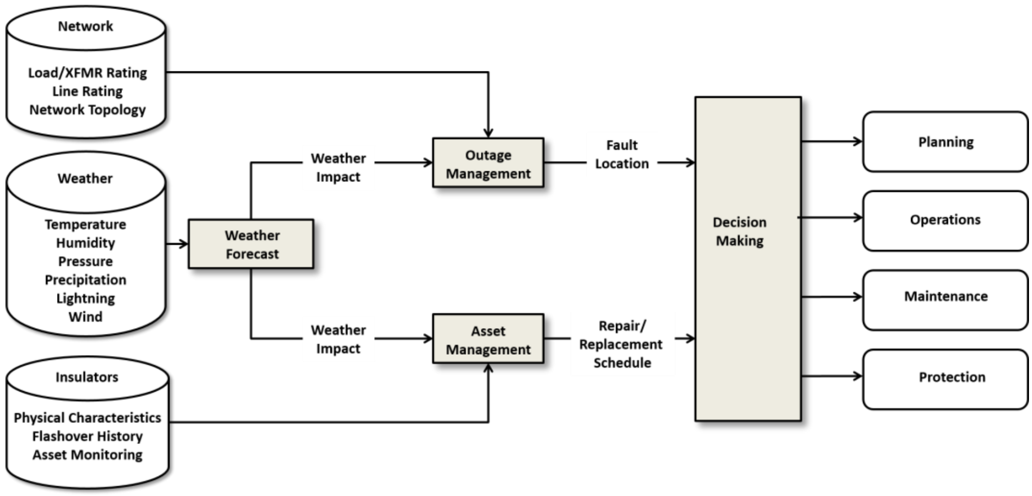


Figure 1. Overall Implementation Description

## 2. PREDICTIVE REQUIREMENTS OF SMART GRIDS

The analysis of weather impacts on the electricity grid requires a comprehensive examination of data, models and analytics, to support systematic integration of big data for power system applications. The measurements from the physical network and weather data exhibit various aspects of Big Data, such as large volume, high velocity, increasing variety and varying veracity [14]. The heterogeneity of data sources and data accuracy are additional challenges. For efficient condition-based asset and outage management, fast processing of large volumes of data is required.

Different smart grid applications may require different temporal characteristics, thus defining the temporal requirement of prediction algorithms. Asset management typically deals with long-term analysis (days, months, years). For outage management, real time operation is needed to locate faults, which is followed by repair and restoration, requiring a short-term analysis (seconds, minutes, hours).

Asset and outage management, have relied heavily on model-based solutions in the past [15-18]. The inability of such methods to reflect the dynamically changing weather impacts over time makes it difficult to assess the unfolding deterioration of power grid infrastructure, and locate faults. The advancements in smart grid measurement technologies have enabled the necessary condition for development of new data-driven solutions. While the new sensors can provide abundant information about the power system state, there is a lack of data analytics to extract knowledge needed to draw causal inferences between evolving power system events and the weather elements. The sufficient condition to derive such knowledge is to use adequate model-based approaches that directly incorporate big data. The framework proposed in this paper builds a hybrid system that utilizes both model- and data-driven solutions as two complementary parts necessary to observe the evolving weather impacts on the power system. Data helps calibrate the models, while models define necessary causal relations to reduce the impact of missing or low quality data.

## 3. RISK ASSESMENT

The goal of this research is to develop a predictive tool that can mitigate and reduce operational and asset economic losses derived from weather impacts on the grid. This will be achieved by assessing the Risk Factor (R) associated on distribution asset components (e.g. insulator) when impacted by likely combinations of weather threats. The Risk Factor here is defined as [19]:

$$R = P[T] \cdot P[C|T] \cdot u(C) \tag{1}$$

where:

- Hazard P[T]: The probability that a combination of weather threats' intensities (T) will affect the component (or a system of components), in such a way that the predefined and tolerable thresholds for its desired operation are exceeded or violated.
- Vulnerability P[C|T]: The probability of failure of the affected component exposed to a particular combination of weather threats' intensities.
- Economic Losses u(C): Associated economical losses in case of component failure (or system failure). That is, the total economic value of the asset if it is lost during operation.

The objective here is to mitigate the economic losses through countermeasures, by reducing the vulnerability of a system. The benefits of predictive risk analysis are demonstrated on two applications:

- *Optimized Condition-Based Asset Management* capable of assessing equipment deterioration continuously across space and time, leading to an improved on-demand maintenance strategy;
- *Efficient Outage Management* capable of predicting fault location in real time, and determining strategies to reduce outage duration and restoration time.

### 3.1. Asset Management

The proposed tool can predict the failure of a component (or a system of components) over time, considering cumulative impacts from continuous weather exposures. In order to do so, the historical outage and disturbance data is used to train the prediction algorithm based on linear regression. As a result, available countermeasures for a given component (e.g. insulator) are defined as the preventive maintenance activities. The suggested tool is capable of comparing how different maintenance

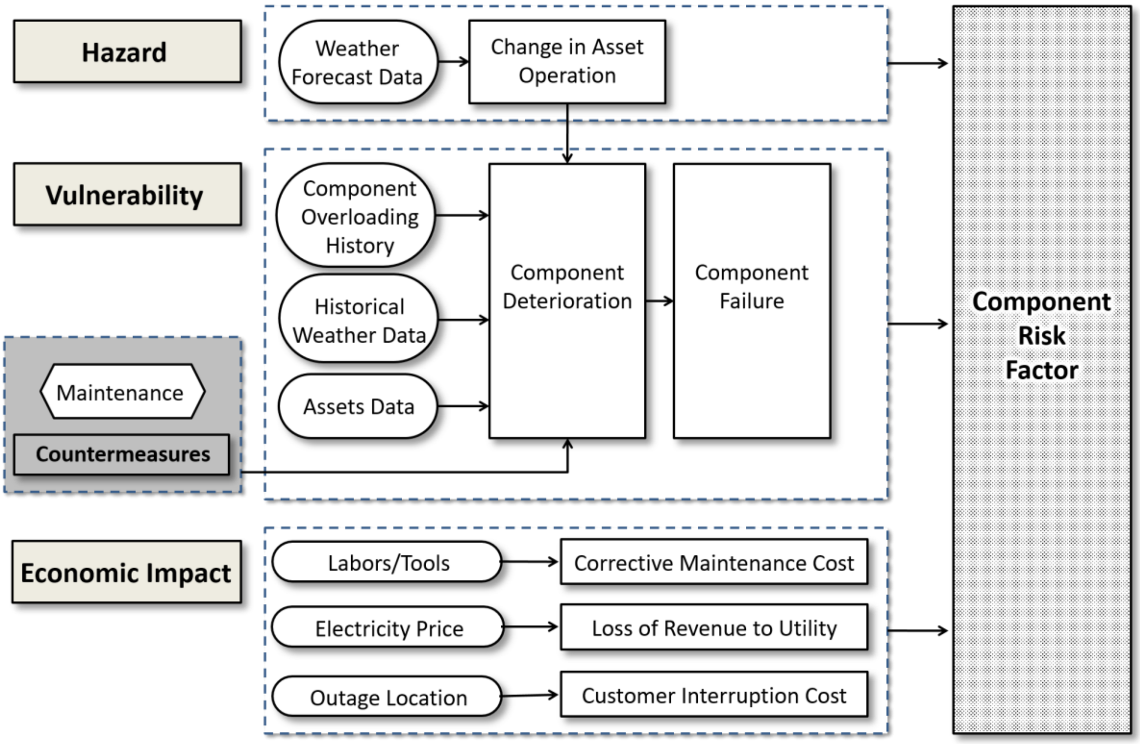


Figure 2. Component (Insulator) Risk Assessment

schedules will be reflected in the Insulator Risk Factor, and accordingly provides an optimal maintenance plan. A high level design of the proposed tool is shown in Figure 2, which introduces the notion of a component 'Risk Factor' at a given time and location, which will facilitate the implementation of the optimal maintenance plan. Hazard in Fig. 2 represent the outside impact on the network, thus is determined based on the weather forecast. The aim of Hazard is to determine what is the probability that the weather impact will be severe enough to affect the network components. Vulnerability, in Fig. 2 represent the probability of component failure in case the Hazard conditions exist. Vulnerability function uses historical data (ouatge, weather, assets data) to determine what will be the network response for a given Hazard. Economic impact, in Fig. 2, is a combination of several cost experianced in case of a component failure : 1) cost of maintenance, 2) loast revenue to an utility due to an outage, and 3) customer cost sue to an outage. The countermeasures are applied to reduce the vulnerability of the system. This includes: insulator maintenance and replacement, instalment and maintenance of line surge arresters.

### 3.2 Outage Management

A predictive outage management requires the involvement of weather data where the grid data is associated with (Fig. 3). At first, the historical weather and asset data is gathered and layered to predict the faults in order to mitigate the impacts. Then, the operator will obtain other related information extracted various resources and identify the outages within the geographical information system and identify the precis fault location.

## 4. RESULTS

### 4.1 Asset Management

For this study one part of a larger power network was analyzed. The part of network under study contains ten substations that are interconnected with twelve transmission lines. Total number of insulated transmission towers is 170. Every network tower is geospatially referenced as presented in Fig. 4, and has a Risk Factor associated with it. For each time step new Risk Map is created that has a current risk factor value.

The next step is to create the optimal placement strategy for line surge arresters that minimizes the probability of insulator breakdown and associated economic losses that are calculated as part of risk analysis. For the purpose of this study 10 line surge arresters are placed in the network. Fig 5. shows the optimal location of surge arresters, while in Fig. 6. the risk map after the installation of 10 surge arresters is presented. With the calculated optimal line surge arrester configuration, overall risk of insulator breakdown was decreased by 36%.

### 4.2 Outage Management

While simulating fault location algorithms, there are various uncertainties may impact the accuracy of results. With predictive approaches proposed, the outage area may be narrow down for faster fault location algorithm execution. The time for execution of one scenario to map the outage location is defined as how long the program searches through the given network within given geographical area and locate the outage.

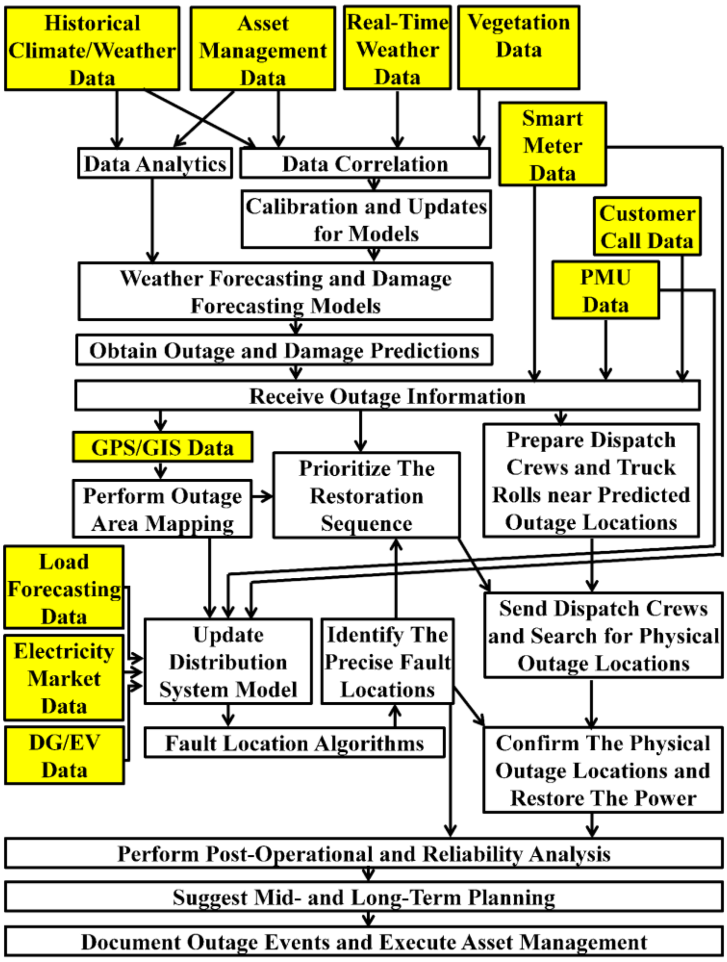


Fig. 3. Outage management flowchart with big data analytics.

The analysis is done by using voltage sag based fault location method with an assumed presumed outage mapping accuracy. The real distribution network used for study, feeder branch and area labelling, and the hardware used for simulation are presented in [20]. We simulate new 5625 cases in ATP-EMTP while assuming 4 different group of presumed accuracy of mapping (10%, 25%, 60%, and 90%). can be found in [20]. Fig. 7 demonstrates 4 groups of different mapping accuracy probabilities from random sampling. While the accuracy increases from (a) to (d), the number of cases having shorter execution times increases as well. The bar shifted significant left while better prediction of outage location saves more time on the program execution.

## 5. CONCLUSION

In this paper the predictive method for outage and asset management using Big Data is proposed. The effective use of Big Data in power grid applications requires exploiting spatial and temporal correlations between the data and the physical power system network. Following are contributions of the paper:

- Requirements of predictive methods for outage and asset management are identified.
- New framework for outage and asset management that utilizes large amount of data is introduced.
- Instead of statistical methods used in conventional studies, the data mining was used.
- Predictions of outage locations and assets failure were made based on spatio0temporaly correlated historical weather, network, outage and assets data.
- Risk based insulation coordination method is defined. Results of risk factor calculation were presented. Optimal placement of line surge arresters based on developed risk analysis is demonstrated.
- Predictive outage management that utilizes weather data is introduced. The improvement in fault location with additional data is demonstrated.


Fig. 4. Risk map before the line surge arresters instalation.

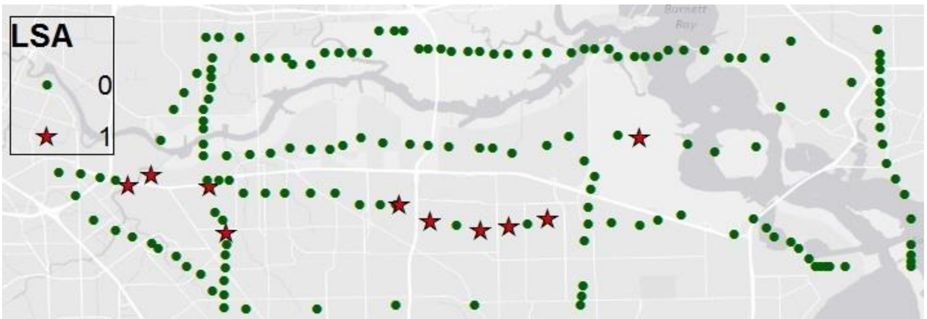


Fig. 5. Optimal locations of line surge arresters base on risk analysis.


Fig. 6. Risk map after the line surge arresters linstalation.

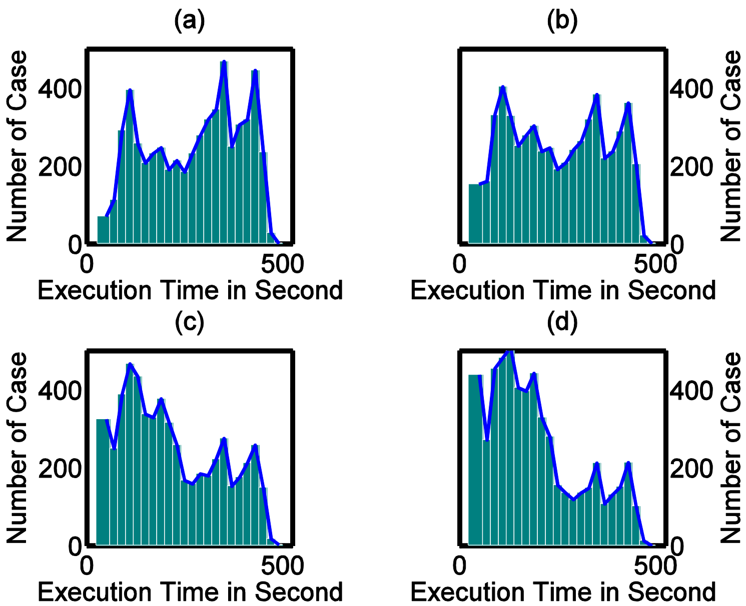


Fig. 7. Simulated scenarios execution time, histogram from different uniform distribution probability: (a) 10%; (b) 25%; (c) 60%; (d) 90%.

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