Fuzzy Logic Approach to Predictive Risk Analysis in Distribution Outage Management

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***Abstract*—Weather impacts are one of the main causes of distribution outages. To devise strategies to mitigate weather impacts, a fuzzy logic system for decision making is introduced. It allows utility operators to achieve more precise outage predictions and optimize real time operation and maintenance scheduling. A novel approach for weather-driven risk framework is applied to process the data and produce risk maps for better decision making. The use of weather data in reducing fault location time, an important performance improvement in outage management, is also presented.**

***Index Terms*—Analytical models, big data, fault location, fuzzy systems, geographic information systems, meteorology, outage management, power distribution, risk analysis, smart grids.**

NOMENCLATURE

ATP	Alternative Transient Program
ASOS	Automated Surface Observing System
FL	Fault Location
GIS	Geographic Information System
GOES	Geostationary Operational Environmental Satellite
GPS	Global Positioning System
MF	Membership functions
MLR	Multiple linear regression
NOAA	National Oceanic and Atmospheric Administration
NCEI	National Centers for Environmental Information
NDFD	National Digital Forecast Database
OM	Outage Management
OMS	Outage Management System
WFS	Weather Fuzzy System.

I. INTRODUCTION

WEATHER impacts are the main causes of electrical outages in the U.S. [1], [2]. Moreover, the incidence and severity of weather conditions and major outages show a growing trend since 1992 [2], and they are projected to increase in the future due to climate change [3]. For instance, the number of outages grew by more than 12% from 2013 to 2014 [1]. The efficiency of OM represents a significant factor in increasing the reliability of distribution systems. Prospectively, higher demand for system reliability requires the utility industry to improve the existing OMS. Traditionally, utilities operate through manual exchange of data between departments and their independent data sources in order to identify the outage location and manage restoration. This approach poses disadvantages shown in Table I. By leveraging the properties of Big Data [4], there are opportunities to perform improved data management and analysis for better decision-making process.

TABLE I
DISADVANTAGES OF TRADITIONAL OM

Operation	Current State of Art	Disadvantages
Outage Reporting	Mostly customer calls; lack of effective automated outage reporting systems	Incomplete outage information without integration encumbers the whole OM process.
Identify Precise FL	Inaccurate/incomplete distribution network models	Individual customer outage is difficult to be identified.
Outage Mapping	Manual predictions of the outage locations	Inaccurate outage area mapping leads to poor crew dispatch (duplicate work orders and unnecessary truck rolls).
Restoration	Lack of comprehensive progress tracking system and management.	Slow restoration of multiple outages in wide area especially for severe-weather-related outages.
Asset Management	Lack of prediction-based asset management.	Aging features of equipment; higher failure rate during for potential outages.

Mitigating weather impacts to improve OM is a complex task. To locate the weather-related outages precisely, current utility OMS faces several challenges: (1) maintaining up-to-date distribution model, (2) integrating databases to receive and process multiple data sources, (3) predicting risks associated with potential outages. In addition, the complexity of distribution systems may prolong the time to locate faults. The outage risk mapping techniques become critical in reducing the search range for the maintenance crew in locating faults. Without utilizing weather data or relying on manual predictions only, the outage mapping results can be unreliable.

References [5] and [6] evaluate states of power system and analyze time varying factors to allocate resources and determine network reinforcement. References [7]–[9] propose the flow chart of OM for large scale outages, such as hurricanes and ice storms, and discuss estimated time for restoration and crew management. References [10] and [11] discuss outage

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TABLE II
WEATHER DATA SERVICES AND SOURCES

Data Sources	Portal	Services	Data Format
National Weather Service (NWS)	GIS (Portal)	• Real-time: Monitoring and Warnings; • Forecasts: Severe Weather Conditions; • Historical: Precipitation/flood/Hurricane data.	Import Data into GIS: Shapefile, KML files, and web services such as OGC format or geo-referenced image files (e.g. geo-gifs). Available access to watches, warnings, advisories, and other similar products in the XML/CAP and ATOM.
	National Digital Forecast Database (NDFD)	Real-time data available: gridded forecasts of sensible weather elements (e.g., cloud cover, maximum temperature).	Data access via web services FTP, HTTP, XML, or web browser. Graphical representation available.
National Centers for Environmental Information (NCEI)	Data Download Page	• Land-based data: QCLCD data, ASOS data, station metadata, climate data, etc; • Satellite data: atmospheric, cloud, oceanic from three operational Satellite (S-NPP, GOES, and POES) • Radar data: Level-II and -III products, historical reflectivity mosaics for the continental U.S.; • Severe weather data inventory.	
	Web Service	• Station climate data; • Climatological GIS products; • Severe weather data and reports.	Programmatic access for custom or standard implementations: OGC GIS Web Services (e.g. WMP, WFS, and WCS) and OPeNDAP. Data download formats: CSV, XML, Shapefile, KMZ, and NetCDF.
	GIS Portal	Data of real time and historical weather parameters in daily and monthly observations, climate Indices, radar data (Level-II and -III products).	View, access, and utilize in situ station data. Products available: Interactive maps, associated metadata, and OGC GIS Web Services (e.g. WMP, WFS).
Office of Satellite and Product Operations (OSPO)	Spatial Data Products for GIS	Satellite imagery products via FTP: GOES data, AVHRR data, winds data and metadata, SST data and metadata, and surface data.	

prediction improvement and preparation for extreme weather conditions. References [12]–[14] demonstrate development of Weather Research and Forecasting (WRF) Model and propose spatial temporal statistical modeling for outage and restoration predictions. References [15]–[19] analyze impacts of different weather conditions on particular distribution network components and related types of faults. References [20] and [21] show GIS usage for OM including crew dispatch, restoration process, software interfacing. The aforementioned papers focus on different aspects of OM, but yet fail to utilize both historical and close-to-real-time weather data, and consequently derive the risk of weather impacts on assets in a preventive fashion. To incorporate weather data, utilities use commercial weather data and forecast service vendors [22] but additional processing is needed to assess the risk.

This paper presents a novel fuzzy logic approach for predictive risk analysis utilizing both weather-related forecasts and power system-related operational data to improve the decision making processes of OMS. The benefit is an avoided cost in operating and maintaining the systems.

The rest of this paper is organized as follows. Section II describes the background. Section III demonstrates the decision-making applications for risk framework of OM. Section IV focuses on the historical weather data analysis. Section V discusses risk utilization for OM. Section VI contains the conclusion.

II. BACKGROUND

A. Risk Analysis Framework Formulation

The risk analysis framework [23], [24] for improving OM may be defined as a stochastic process using

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

where R is associated risk index for each component of the system, Hazard $P[T]$ is a probability of a Threat T affecting the system; $P[C|T]$ is the vulnerability of the component or the probability that Consequences C will happen if system is under the impact of a Threat T, and $u(C)$ is the utility (cost) of the consequences.

In the OM processes, this framework is applied such that R represents the overall estimate of expected risk associated with

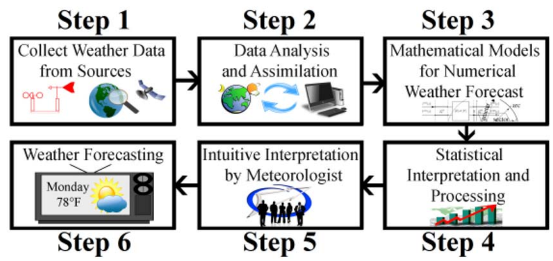


Fig. 1. A typical weather forecasting process.

power outages, T represents an intensity of weather impact that may cause an outage event, C represents an outage event. Hazard $P[T]$ represents a probability of a weather impact with intensity T. In this work, Hazard is represented spatially through the outage zone classifications where probability of a weather associated threat is quantified in different areas. Vulnerability $P[C|T]$ represents the probability of an outage under occurring weather conditions. Worth of Loss $u(C)$ represents the financial loss utility is experiencing due to the outage event. This study focuses on the Hazard and Vulnerability part of the risk analysis, which comprises the following part of the risk expression:

$$R = P[T] \cdot P[C|T]. \tag{1.b}$$

B. Weather Variables and Data

The measurements of weather variables and data collection infrastructures have been particularly designed and gradually improved for increasingly better operational weather forecasts in the past decades. Not only localized observations (e.g., radar detection of tornados) but also large-scale weather patterns are necessary for predicting the weather over a specific small area, because the localized weather is closely linked to meso-scale and planetary-scale dynamic meteorology processes such as baroclinic instability and tropical cyclones [25]. Typical weather data used in OM is shown in Table II.

A typical weather forecasting process is shown in Fig. 1 [26]. Firstly, the raw weather measurements are collected. Then they are processed for weather predictions. Data for utility use may come from: **Step 1** original data sources, **Step 4** interpolated data, and **Step 6**

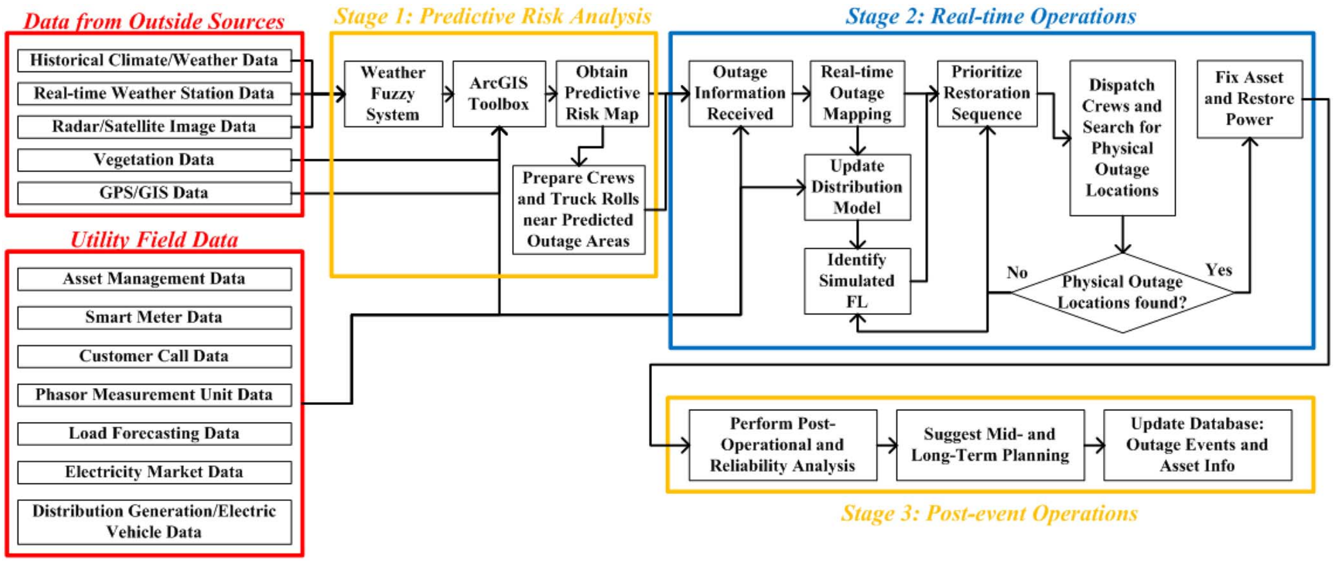


Fig. 2. OM flowchart with big data analytics.

weather application products. For different applications, suitable sources are selected.

In general, there are two situations with weather impacts: catastrophic (i.e., hurricanes) and extreme (i.e., seasonal changes). The data used by utilities may be classified into two categories according to the source [2]: field measurements that come from the grid and weather data that comes from outside sources (Fig. 2 input data). Our main focus is on the extreme weather impacts and risk assessment of such impacts on the operation of the power grid.

For specific types of weather events, the analytics require the most relevant weather data input. For instance, the gust speed may have a stronger relationship to damages rather than average wind speed [12]. In this paper, we use wind speed and gust speed as inputs to proposed WFS and create warning system as a storm approaches.

III. Predictive Risk Analysis for Distribution Outage Management

A typical overall process of OM involving the utilization of weather information is shown in Fig. 2. Firstly, the weather data is collected, analyzed, and correlated with power outages, providing utilities information to predict weather-related outages and prepare for mitigating activities. Then, utilities will receive outage information through customer calls (interactive voice response platform) and smart meter data (advanced metering infrastructure platform). With reported outage information, utilities can perform outage mapping within GIS and identify FL precisely. The crews then can be dispatched to potential FL and then restore the power back if fault damages are identified and repaired.

The key is the utilization of different data sources as highlighted in yellow color in Stage 1 Predictive Risk Analysis in Fig. 2. In Sections IV and V, the application of historical weather data analysis, automated WFS and GIS processing tool will be discussed, which have a direct impact on the availability and precision of weather data, and defines the values of Hazard $P[T]$ and Vulnerability $P[C|T]$. In Section IV, the weather hazards are calculated using historical weather data. In general, climatologists would analyze historical weather effects to a relatively large area (e.g., state of Texas), The contributions on the weather historical data analysis in this paper focus on the historical weather data analysis for a much smaller area. For a utility, the analysis which only focuses on their service area would be most beneficial.

In Section V, the weather information has been processed using fuzzy logic model. The Hazard analysis results then are analyzed using GIS toolbox to form a risk map as shown in eq. 1.b. The risk study results are demonstrated as spatial classification maps of probabilities of power outages. How the outage prediction results may be improved using risk analysis is discussed, and the automated OM data analysis framework is proposed.

FL is the critical component in OM. There are two categories of FL techniques [27]: outage mapping and distance to fault calculation. Outage mapping is a group of techniques that intend to narrow down the geographical area where the fault occurs (e.g., GIS). Distance to fault calculation comprises techniques that determine the precise location of the fault using field measurements (e.g., impedance-based FL method). The selection of precise FL algorithms is highly dependent on the available data from Intelligent Electronic Device (IED). More comprehensive literature survey regarding FL capabilities may be found in [28].

Due to the sparseness of available weather data, it is not always practical to utilize weather data as an input for precise FL algorithms. Instead, the weather data may be used for outage mapping, which in turn may reduce the execution time of FL algorithms (Section V) by considering detailed modeling, different types of faults, fault resistance estimation process, and complexity and large scale of distribution network [29].

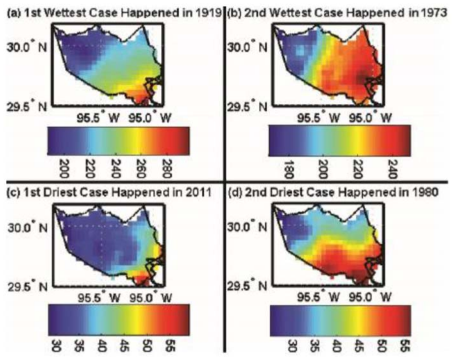


Fig. 3. The geospatial distribution of 4 extreme year summer rainfall data in each grid cell of Harris County.

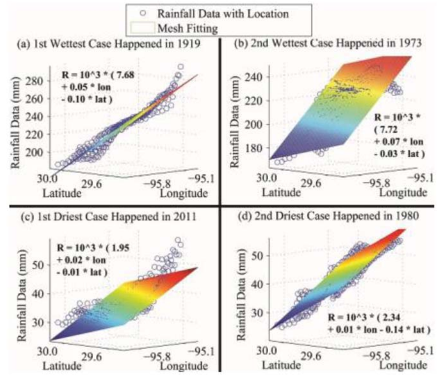


Fig. 4. 3-D data visualization of 4 years summer rainfall data in Harris County with MLR.

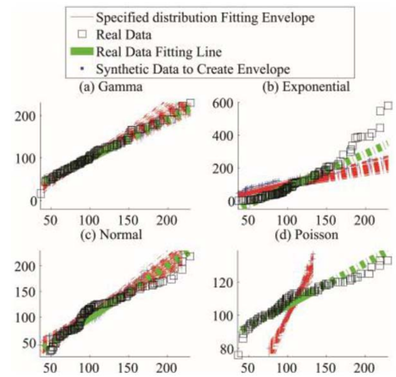


Fig. 5. Summer rainfall data between 1894 and 2013 fitting in 4 Q-Q plots; x-axes are synthetic data quantile of different distributions; y-axes labels are real data quantile.

IV. Historical Weather Data Analysis

Since the early research in 1950s, numerical models have been developed and improved for weather prediction. The WRF is currently most widely used model for making regional short-term weather forecasts. However, not only the short-term (e.g., 2-day), but also the long-term (e.g., 1-month) weather prediction can benefit OM. For instance, if a hotter-than-average upcoming summer is predicted, one may expect a higher demand for electricity and hence an increased pressure on OM. Nino 3.4 represents the sea surface temperature of a specific region: central and east-central of Equatorial Pacific Ocean [30]. The anomaly of unusual warmer temperature (positive Nino 3.4) is called El Nino, and the anomaly of unusual colder temperature (negative Nino 3.4) is called anti-El Nino (i.e., La Nina) [30]. El Nino events are often associated with wetter-than-average precipitation conditions in U.S. Golf Coast area, and anti-El Nino events are opposite.

Despite the richness of global meteorological measurements, the weather data may be too sparse to provide the initial and boundary conditions for doing numerical weather predictions. Given the large amount of available weather data, the key issue is how to interpret the most relevant input data from the available data pool. In this study, we show the linkage between Nino 3.4 and rainfall over Harris County of Texas in a seasonal scale. According to 2010 census data from U.S. Census Bureau, Harris County is the most populous county in Texas as well as the third most populous county in the U.S. This linkage gives an example of how predicting long-term weather impacts using historical weather data in smaller targeted geographical areas may be useful as an input to WFS (Fig. 2 input historical weather data to WFS in Stage 1).

The historical long-term weather data, as an input to WFS, contains useful information for OM. Figs. 3 and 4 show the results of rainfall data analysis, where the subfigures (a) to (d) show the rainfall features in the summers of 1919, 1973, 2011, and 1980, which are the two wettest and two driest summers from the historical record, respectively. Fig. 3 shows the geospatial distribution of summer rainfall data in each grid cells of Harris County. Fig. 6 shows the grid cell data in 3-D (longitude verses latitude verses rainfall amount) using MLR analysis.

In Fig. 3, all 4 cases show a similar pattern where the precipitation amount decreases from the southeast (coastal area) to northwest. Such a pattern can be viewed more clearly in the 3-D visualization in Fig. 4 using MLR analysis. The linear relationship between longitude, latitude (i.e., explanatory variables), and the rainfall data (i.e., response variable) is modeled as:

$$rainfall = \beta_0 + \beta_1 \cdot longitude + \beta_2 \cdot latitude \qquad (2)$$

where $\beta_0, \beta_1, \beta_2$ are the regression coefficients. The model corresponds to a regression plane in the 3-D space for each case.

Fig. 5 shows the historical summer rainfall data between 1894 and 2013 fitting in 4 quantile-quantile plots, where the x-axes represent synthetic data quantile of 4 different probability distribution functions. The best fit is Gamma distribution, in agreement with the results proposed in [31] that applies Gamma distribution for rain-related models.

Fig. 6 shows percentage of prediction accuracy verses number of wettest or driest cases, where a prediction is regarded as accurate if Nino 3.4 in the winter of the previous year is in phase with the rainfall in the summer of this year. For instance, the prediction accuracy for the 5 years having the top 5 rainfall amounts is 60%. Fig. 7 (a) shows the time series of normalized summer rainfall in Harris County and extended Nino 3.4 in winter between 1894 and 2013. The extended Nino 3.4 data is from [32], where for each year it is the mean of Dec. of this year, and Jan. and Feb. of the next year. Fig. 7 (b) shows an

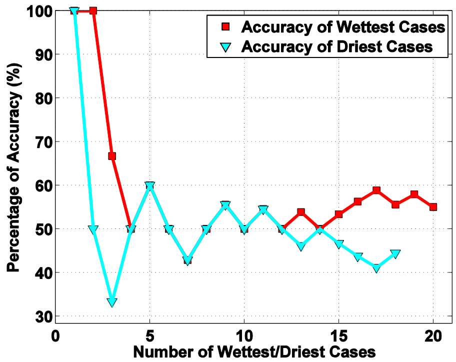
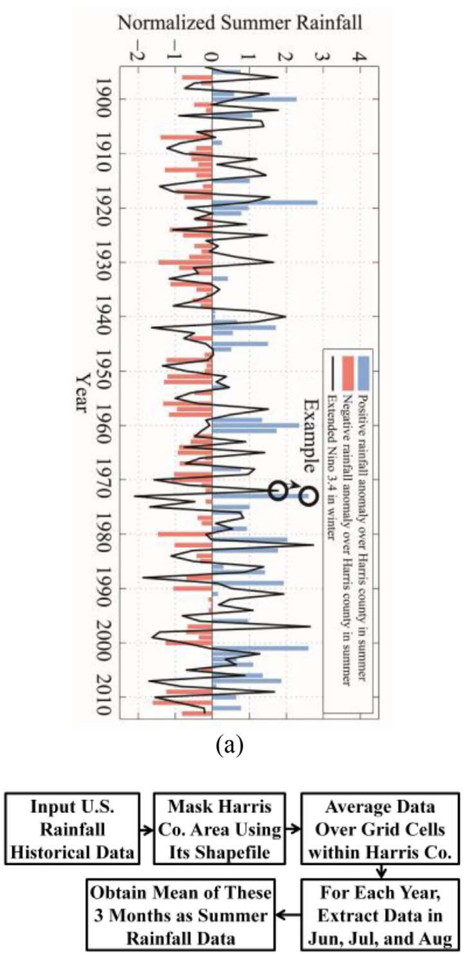


Fig. 6. Percentage of accuracy verses number of wettest or driest cases; x-axes representing the order of wettest/driest case.



(a)

(b)

Fig. 7. (a) Time series data of Nino 3.4 and rainfall. The negative rainfall represents the rainfall data below average. (b) Process to extract summer rainfall data in Harris County area, Texas, U.S.

example of how to process and integrate weather data using the summer rainfall data [33].

In summary, one may expect a higher frequency of the thunderstorm occurrence over the southeast of Harris County if a wettest summer is predicted. If a utility is interested in a distribution system located inside certain grid cells, spatial data analysis can be further carried out for specific tasks. The historical summer rainfall data having the best fit for

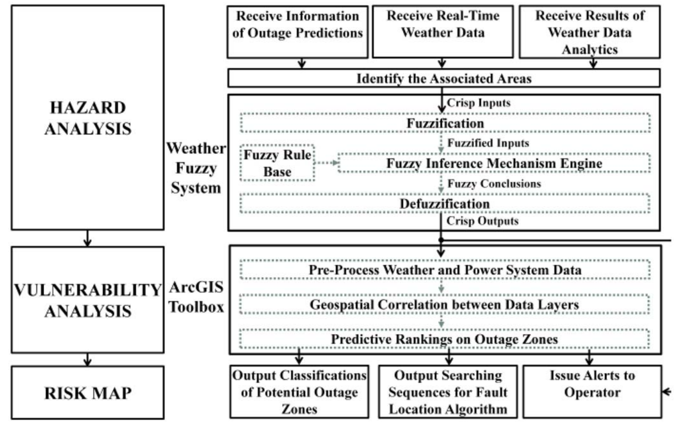


Fig. 8. Proposed WFS and GIS toolbox for data analysis framework.

Gamma Distribution shows that the most extreme rainfall events—severest droughts and floods—occur least frequently. Also, Nino 3.4-related effects on rainfall of U.S. southwest grid plain have been well documented in the literature. The correlation between Nino 3.4 and rainfall over Harris County is not adequately strong. The main reason is the increased randomness of rainfall in a smaller area. This indicates more factors (i.e., other historical weather data) may need to be considered such as Pacific Decadal Oscillation (PDO) and Atlantic Multidecadal Oscillation (AMO) to improve prediction accuracy.

V. Network Vulnerability for OM

In this section, a data analysis framework is proposed including weather data processing (using proposed WFS) and geospatially correlated with power system data in a GIS platform (using proposed ArcGIS toolbox) as shown in Fig. 8. For practical purposes, the weather data for weather fuzzy system should be online (updated periodically). In our example, we show that by using historical weather data from two different airports for demonstration purposes.

A. Hazard Analysis Using Weather Fuzzy System

There is a substantial financial impact of deploying crew management in utilities. In this case, in the preparation for outages, predicting which zone may have the highest impact probability is critical for an operator. The WFS is used to identify the area where most likely the weather may have highest impacts on the system, and then process the weather data using fuzzy logic.

The WFS receives the real-time weather data along with other additional information such as weather forecasts (e.g., severe weather alerts), weather hazard analysis from historical weather data analysis, and outage predictions in a continuous manner (all weather-related input). The outage prediction information is like the satellite and radar image analysis. Then, the WFS will identify the areas associated with the grid which includes the integration and refreshing of various weather data layers—having different data properties—into the target area of interest at the location of the distribution network.

Typical components of a fuzzy logic decision-making system are demonstrated in Fig. 8 (components from

TABLE III
IMPACTS OF WEATHER VARIABLES ON DISTRIBUTION SYSTEMS

Weather Variable	Distribution System Type	Impacts
Lightning	Overhead	**Cloud-to-ground lighting** hits on the poles or in the vicinity of the line and **high frequency transients** are generated on the lines.
Ice, snow, and sleet	Overhead	Ice would **accrete** on the overhead cables and may damage cables when they are heavy, especially in the **presence of strong wind**.
	Underground	While snow melt, the water containing impurity will infiltrate into underground and it may create **current flow between the burned-off cables**, where the short circuits may cause fire and explosions of manhole.
Freezing, fog, and frost	Both	The control panels of equipment may be damaged by **freezing when not fully drained**. This is one of the main reasons of causing equipment failure.
Wind and gale	Overhead	They can **swing the cables** contacting each other and cause the short circuit. They can lead to the **falling down of tree limbs** and damage the cables and/or poles. In the coastal area, wind and drought can result in **salt accretion on cables** and damage the insulation.
High temperature	Both	The **thermal insulation of substation equipment** should be taken into account to minimize the effects of outdoor temperature. The high temperature has significant impact on **transformer failure interruptions**.
Low temperature	Both	The plastic material may contain static charges on the surface under low humid at low temperature. These charges may have **hazard effect in gas environment** and other potential issues with electronic equipment. Moreover, for meters with plastic surface, these charges may result in **inaccurate readings**. The intention of installing cables at low temperature may bring damages to cables as well.
Precipitation	Underground	Severe precipitation can lead to flood that may **annihilate the equipment** (e.g. transformer, and equipment in manholes and substations).

Fig. 2 Stage 1). Fuzzy logic can be understood as a superset of traditional Boolean logic devised in order to handle partial truth values (between completely true and false). Therefore, fuzzy sets and fuzzy logic are used to heuristically quantify the meaning of linguistic variables, values, and rules that are specified by an expert [34]. Some common impacts of different weather factors on distribution system components are summarized in Table III [15]–[19]. In general, the choice of weather variable will depend on the localized nature of weather phenomenon. The impact of weather variables on the assets will determine the design of linguistic rules.

The impacts of wind speed on potential faults caused by inadequate tree-trimming are demonstrated here. Concluded from [35]–[37], the wind speed may have a more significant impact at the boundary values of 39, 44, 49, and 64 knots, and the gust speed may have more significant impacts at the boundary values of 54 and 81 knots. Therefore, the output warning class here is categorized into a 5-classes-15-levels scale as shown below:

- Rare Tree-trimming Fault Alert: Class 1, Level 0-3
- Small Tree-trimming Fault Alert: Class 2, Level 3-6
- Medium Tree-trimming Fault Alert: Class 3, Level 6-9
- Large Tree-trimming Fault Alert: Class 4, Level 9-12
- Extreme Tree-trimming Fault Alert: Class 5, Level 12-15

Let $x_1(t)$ and $x_2(t)$ be the wind and gust speeds in unit knot collected at time instant t, then the designed linguistic weather rules are:

1. **If** $0 \leq x_1(t) < 39$ **Then** Issue Warning = "Class 1"
2. **If** $39 \leq x_1(t) < 44$ **And** $0 \leq x_2(t) < 54$ **Then** Issue Warning = "Class 2"
3. **If** $39 \leq x_1(t) < 44$ **And** $54 \leq x_2(t) < 81$ **Then** Issue Warning = "Class 3"
4. **If** $39 \leq x_1(t) < 44$ **And** $81 \leq x_2(t)$ **Then** Issue Warning = "Class 4"
5. **If** $44 \leq x_1(t) < 49$ **And** $0 \leq x_2(t) < 54$ **Then** Issue Warning = "Class 3"
6. **If** $44 \leq x_1(t) < 49$ **And** $54 \leq x_2(t) < 81$ **Then** Issue Warning = "Class 4"
7. **If** $44 \leq x_1(t) < 49$ **And** $81 \leq x_2(t)$ **Then** Issue Warning = "Class 5"
8. **If** $49 \leq x_1(t) < 64$ **And** $54 \leq x_2(t) < 81$ **Then** Issue Warning = "Class 4"
9. **If** $49 \leq x_1(t) < 64$ **And** $81 \leq x_2(t)$ **Then** Issue Warning = "Class 5"
10. **If** $64 \leq x_1(t)$ **Then** Issue Warning = "Class 5"

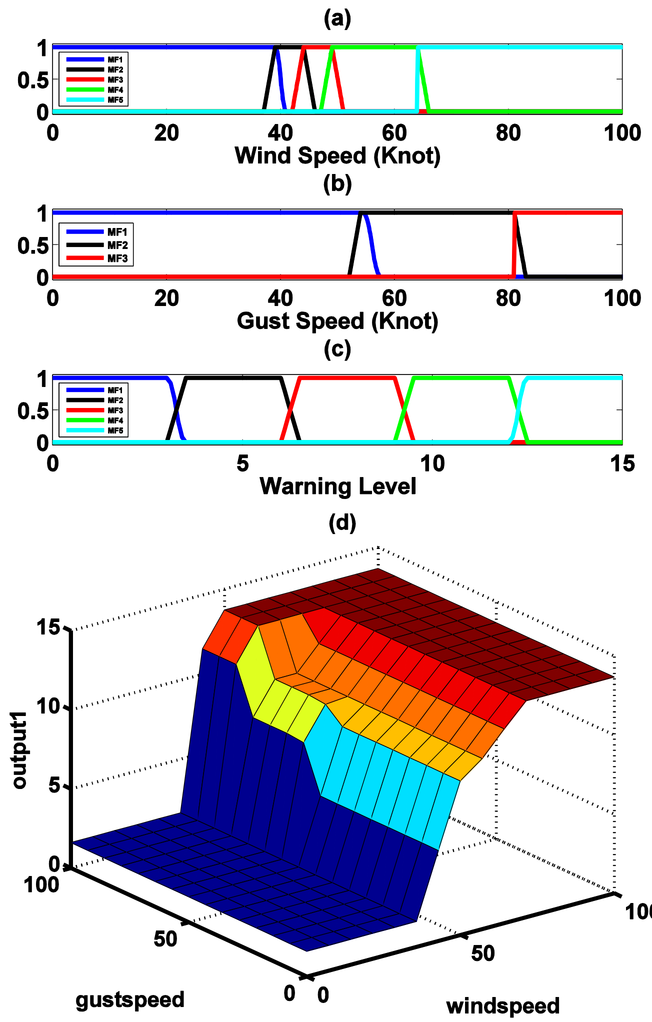
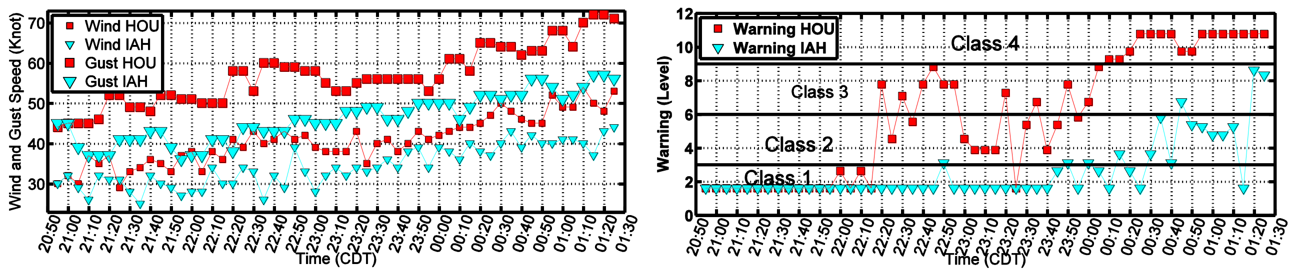


Fig. 9. Fuzzy system design: (a) MFs of input wind speed data; (b) MFs of input gust speed data; (c) MFs of output warning level; (d) surface plot of fuzzy system input-output relationship.

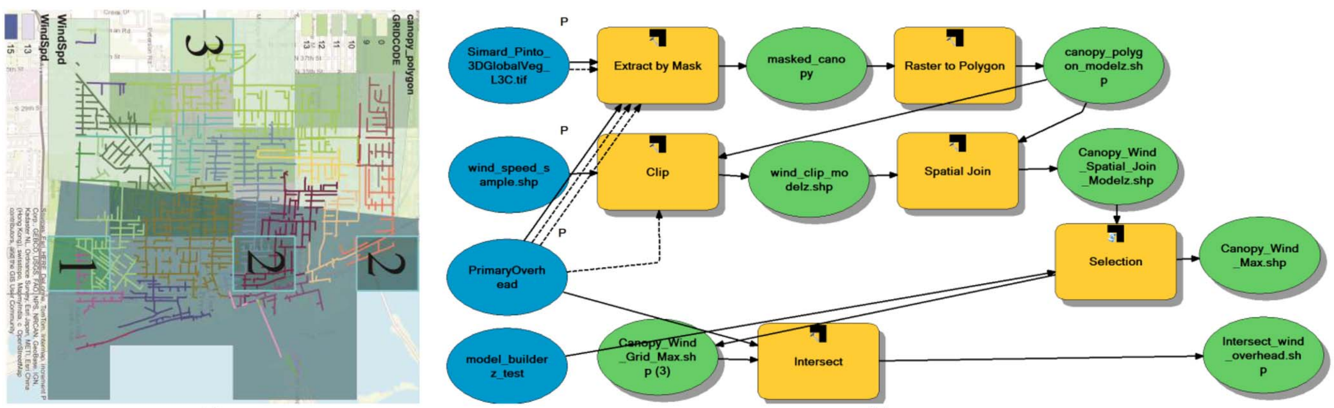
The designed MFs of wind and gust speed data (two inputs) and warning level (one output), as well as surface plot of input-output relationship are depicted in Fig. 9. In Fig. 9 (d), each colored area represents one tree-trimming fault alert. For the defuzzification, the centroid-of-area method is applied, which returns the center of an area under the curve.

The 5-minute ASOS data [38] from 2 ASOS stations IAH and HOU in Houston prior to landfall of Hurricane Ike [39]



(a) (b)

Fig. 10. Example of WFS system. (a) Input data: 5-minute ASOS data [28], wind and gust speed on Sep. 12-13, 2008; (b) output warning and class.



(a) (b)

Fig. 11. (a) Predictions of outage zone classification; (b) Automated toolbox for correlating weather and power system data layers.

in 2008 are used. The effectiveness of the proposed WFS is demonstrated in Fig. 10. Fig 10 (a) shows the time series of wind and gust speed measured at the 2 stations from 20:55 to 01:25 central division time (CDT) on Sep. 12 to 13 as inputs, and Fig. 10 (b) shows the corresponding output warning class levels. As the hurricane approaches and become closer to landfall, different warnings may be sent out to the operators.

For practical purposes, the weather data for WFS should be available online (updated periodically). Regarding implementation, the challenges are the different spatiotemporal resolutions for different types of weather data. Some weather data may be made into a static map data layer and used directly as input to GIS (wind data in GIS toolbox). If better temporal resolutions are needed (e.g., hourly updates for wind data), then the data itself may be used directly as inputs to WFS.

In the real-time operations, WFS may provide search sequence as inputs to FL algorithms. The key of WFS is the fuzzy system that emulates the human decision making process. While its distinct advantage is being computationally fast, it is also suitable for decision making on a large scale where the various data sets describe the weather conditions and the states of power grid.

B. Vulnerability Analysis Using GIS

Fig. 11 (a) shows an example of risk R calculated for a geographical map [40] using the hazard $P[T]$ and vulnerability $P[\mathrm{C}|T]$ analysis. The hazard part represents probability of a harmful weather condition. The hazard $P[T]$ is obtained from analyzing the wind speed in the associated area. The area with darker blue color represents higher wind speed. The vulnerability part represents probability of how the particular types of asset may be impacted by a given weather condition. The vulnerability $P[\mathrm{C}|T]$ is obtained from analyzing the impacts of the wind speed on the tree lamb (Section V-A). The area with darker green color represents taller canopy height. Then, the risk R in each grid cell can be calculated from $P[T]$ and $P[\mathrm{C}|T]$. It will represent a rank of the potential geographical outage zone for dispatching purposes.

In general, GIS tools enable a user to work with raster and vector data and provide functionality for geo-spatial processing such as classification of grid data and perform logical and relational operations [41]. An automated geospatial toolbox (Fig. 11 (b)) in ArcGIS [42] is proposed so that the correlation analysis may be done as an automated fashion. The proposed ArcGIS toolbox enables a predictive geospatial analysis platform to automate the routine tasks of correlating weather and power system data. Such vulnerability analysis leads to a prediction of risk map for OM on a continuing basis.

C. Improvement on Fault Location Algorithm Execution Time

Various uncertainties may exist in the FL results as aforementioned in the introduction. In this subsection, we simulate the cases running different FL scenarios and show how the program running time for a particular FL algorithm may be beneficial for WFS while narrowing down the outage search areas.

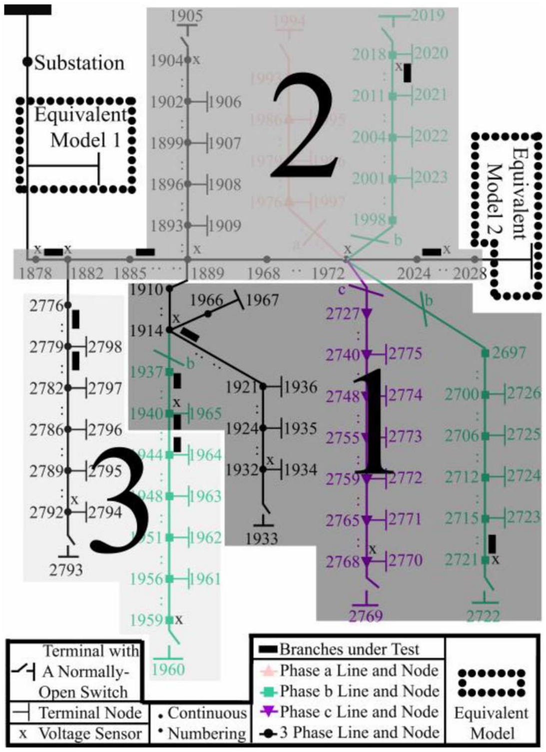


Fig. 12. Distribution network with labeled areas.

TABLE IV
INFORMATION OF THE OVERALL SYSTEM

Total Number of Components	4352
Number of Line Components	1828
Total length of Line Components (Foot)	655617.6
Total Connected Load (kVA)	33606

TABLE V
FEEDER BRANCH LABELING FOR AREA DIFFERENTIATION

Service Area Number	Nodes Containing (Node ID)	Number of Simulated Case
1	1878 - 1889, 2776 - 2793, 1910 - 1960	5625
2	1889 - 1905, 1968 - 2019, 2024 - 2028	
3	2727 - 2769, 2697 - 2722	

The execution time of a correct outage mapping case is defined as the time the algorithm takes to search through the nodes and lines within the given geographical area and locate the fault. The execution time is analyzed through coupling voltage sag based FL method and presumed outage mapping accuracy [29]. A real distribution network with underground lines is used (more details in [29]). The distribution model is shown in Table IV [29]. For practical simulation purposes, only one part of the whole network is chosen for this study as shown in Fig. 12 [29]. The feeder branches are separated and labeled individually as shown in Table V where 5625 experiments are simulated. One experiment is defined as performing one FL scenario. All experiments were simulated in ATP using a desktop having six processors which are Intel Xeon CPU W3670 operating at 3.20 GHz and installed memory (RAM) 12 GB. Each experiment is simulated under the fair condition to obtain the most accurate execution time.

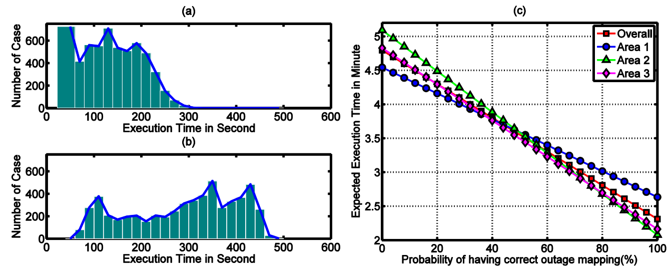


Fig. 13. (a) Histogram of execution time of all cases with 100% correct outage mapping; (b) histogram of execution time of all cases with no outage mapping; (c) expected time vs. probability of having correct outage mapping.

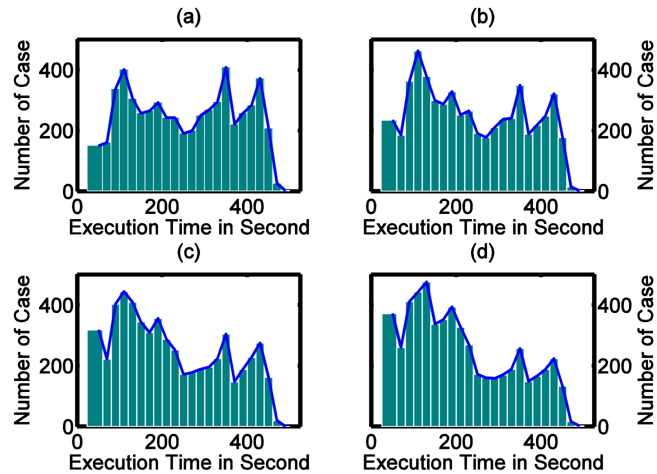


Fig. 14. Histogram of execution time of simulated cases, with uniform distribution of: (a) 25% correct outage mapping; (b) 40% correct outage mapping; (c) 55% correct outage mapping; (d) 75% correct outage mapping.

Fig. 13 (a) and (b) show the histograms of execution time of simulated experiments with 100% correct and no outage mapping, respectively. Fig. 13 (c) shows the expected execution time versus the probability of having correct outage mapping. Fig. 14 (a) to (d) show 4 groups of outage mapping accuracy probabilities from a random sample process: each sub-figure represents the histogram of execution time of simulated experiments.

Comparing Fig. 13 (a) and (b), the bar shifts left essentially indicating more cases have reduced execution times with 100% correct outage mapping. In Fig. 13 (c), the expected execution time decreases as the probability of correct outage mapping increases. In Fig. 14, while the percentage of correct outage mapping increases from (a) to (d), the bar shifts toward left, which is indicative of increased cases that have shorter execution times.

VI. CONCLUSION

This paper presents a new approach to risk-based decision making using weather impacts. Several contributions are made in this paper:

- A novel approach to quantify the Hazard and Vulnerability measures in the context of a weather-driven risk framework for OM is proposed.

- The historical weather data analytics in the cases of extreme weather events are employed through the geospatial techniques
- The proposed WFS and automated ArcGIS toolbox are proven to be an efficient mechanism to integrate various weather data sources into utility decision-making influenced by different weather conditions.
- The suggested framework may improve the OM process by enabling the operator to be automatically alerted when a severe weather condition is approaching for more effective inspection, repair and restoration decisions.

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