

GIS-Based Risk Assessment for Electric Power Consumers Under Severe Weather Conditions

Qin Yan, Tatjana Dokic, Mladen Kezunovic
Department of Electrical and Computer Engineering
Texas A&M University
College Station, TX, U.S.A

Abstract—This study incorporates the real-time weather changes into the models for evaluation of customer interruption cost (CIC) and implements the risk assessment of the impact on customers from the possible weather-caused power outage. The methods uses historical weather and weather forecast data to evaluate the risk for customers in case of different weather conditions that are predicted to affect a given area in near future.

Keywords—customer impact; data analysis; geographical information system; meteorology; risk assessment; smart grid

I. INTRODUCTION

Heavy rain, strong wind, unusual heat, thunderstorm, hail, tornados, etc. can lead to power outages. When a tree limb falls on a power line due to the bad weather condition, protective equipment may initiate a breaker operation to shut off the power flow. As a result, customers served by the interrupted feeder will be out of power until service is restored. The falling of power lines/poles can directly lead to power outage. The same consequence results from the vehicle crashes involving utility poles or equipment, which may be caused by dense fog leading to low visibility. According to the historical outage data (2012-2014), about 33.33% of the historical outages are caused by weather [1]. Electricity supply outage can result in substantial damage to customers because of spoiled perishable materials, production loss, broken equipment, health impact, income loss, extra expenses, etc. [2]

Customer Interruption cost (CIC) is essential for assessing the investments and quantifying the risk associated with operating and planning strategies. The CIGRE report [2] provided a brief summary regarding CIC assessment methods. Different methods to estimate CIC during power outages were proposed in the literature. The following evaluation methods are commonly used by engineers [3]: 1) Ratio of Economic Output to Energy Consumption, 2) Customer Survey (CS), 3) Amalgamated Customer Surveys, 4) Mapped Customer Survey, and 5) Blackout Case Study. References [4-6] used the ratio of a gross economic measure and electricity consumption measure by industry. The assumptions used are strictly limited and are often invalid. It is preferred by many economists to evaluate national economy impacted by electricity interruption. Literature [7-11] used surveys from industrial, commercial, residential and agricultural consumers to determine the interruption cost from the perspective of the individual consumer. Indices for different outage durations are summarized. When the surveys are designed and implemented

appropriately, the method can produce very reliable estimation due to the directly obtained data from customers. References [12, 13] integrated multiple CSs from various regions of a country into a big dataset for the whole country, while [14] used another variation of CS, which is to modify the CS from one country to suit the context of another country, so as to avoid high expense and time for another CS effort. The method in [15] is based on post-event analysis of specific interruptions, e.g. the 1977 New York City blackout, the US Northeast blackout of 2003.

In terms of reliability and power-quality issues, the customers' economic losses can be represented using the customer damage function (CDF). It was first proposed in [16] and improved in [17]. The evaluation of CIC in CDF is based on customer surveys. Nowadays, the methods to estimate CIC are mainly based on customer surveys statistics or analytical methods. But none of the above-mentioned methods considered the impact of real-time weather on the customer economic and health loss. Thus, this study uses the existing methods in evaluating customer cost during power outages, but also incorporates the weather factors into the models, evaluates customer financial and health impact, and develops the risk assessment of impacts caused by possible weather-caused power outages on different customer categories. The same risk framework in this study has been used for other power system applications. In [18] the weather driven GIS based risk assessment has been developed for predicting lightning related outages in electric transmission network. In [19] risk framework has been used to predict probability of severe impact of weather conditions on power apparatus.

This paper is organized as follows: Section II states the background for weather data, GIS, and customer impact are assessed. Section III describes the methodology for integrating the spatio-temporal data, and evaluating the risk of weather-driven customer impact. Case study is presented in Section IV and Section V summarizes the conclusions.

II. BACKGROUND

A. Weather Data

Meteorological data can be obtained from the following sources, [20]:

- *Land-Based Stations* are located sparsely over the area and contain measurement devices that track several weather indices such as temperature, precipitation,

This effort was funded by NSF CURENT ERC and contracted through University of Tennessee under the project titled "The Use of Big Data for Outage Management in Distribution Systems".

wind speed and direction, humidity, atmospheric pressure etc.

- *Radar* (Radio Detection and Ranging) provides accurate storm data using radio waves to determine the speed, direction of movement, range and altitude of objects. Based on radar measurements different reflectivity levels are presented with different colors on a map.
- *Satellites* generate raw radiance data. Unlike local-based stations, they provide global environmental observations. Data is used to monitor and predict wide-area meteorological events such as flash floods, tropical systems, tornadoes, forest fires, etc.

Based on collected historical weather data and real-time measurements, weather forecast algorithms are developed. National Digital Forecast Database (NDFD), [21] provides short-term (next 3 – 7 days) and long-term (next year and a half) weather prediction for variety of weather parameters such as temperature, precipitation, wind speed and direction, hail, storm probabilities etc. NDFD uses Numerical Weather Prediction (NWP), which is taking current weather observations and processing it using different numerical models for prediction of future state of weather. Some of the numerical models that are used for weather forecast are [22]:

- *Global Ensemble Forecast System (GEFS)* uses 21 different forecasts to generate a global-coverage weather forecast model. The amount of uncertainty of the forecast is determined by generating ensemble of forecasts where each one is perturbed from the original observations.
- *Global Forecast System (GFS)* contains four different forecast models working together in order to provide accurate picture of weather changes.
- *North American Mesoscale (NAM)* is a weather forecast model developed for North America region. It generates multiple grids of weather forecast over the North America up to 12 km horizontal resolution. The basis for NAM is Weather Research and Forecast (WRF) model [23]

While National Oceanic and Atmospheric Administration provides data for most of weather parameters, the lightning data can be obtained from a company Vaisala that operates lightning detection network in US, [24]. Lightning data includes following parameters: date and time (UTC with milliseconds accuracy), location (latitude and longitude), lightning peak current (kA), polarity (+/-), type of event (cloud or cloud to ground). Median spatial accuracy is 200m and detection efficiency for cloud to ground lightning strikes that are of interest for power system applications is 95%.

Severe weather includes any meteorological phenomena that have potential to cause damage. Some of the conditions typically considered severe are: high winds, hail, excessive precipitation, thunderstorms, downbursts, lightning, tornadoes, waterspouts, tropical cyclones, etc. Catastrophic weather is a type of severe weather where events have exceeded the predicted amount of severity and caused tremendous damage to the area. In this paper regular severe weather (not the catastrophic type) is considered.

B. GIS

Geographical Information System (GIS) is designed to enable storage, manipulation, analysis and visualization of all types of spatial data. Together with Global Positioning System (GPS) it enables spatio-temporal analysis of extensive data sets that play the key role in integrating big data for various electric power system applications, [25]. Spatio-temporal databases offer the possibility of simulation or prediction of strategic events. GIS database contains two types of data: 1) *Spatial data* containing location and the shape of components on the map; 2) *Attribute data* containing features of objects on the map. There are two basic structures for storing and manipulating spatial data: 1) *Raster data* (grid data) is a grid of cells where each cell has a unique value of targeted information; 2) *Vector data* uses geometry rules to represent shapes using points, lines and polygons.

The key components of modern GIS software, such as ESRI ArcGIS [26] that enable spatial integration of data are:

- Data coming from various sources can be presented in several map *layers*.
- *Spatial relationships* such as *topology* and *networks*. Topology is used to manage boundaries between features, while networks describe connectivity between spatial objects.
- Extensive set of *geoprocessing tools* helps user to manipulate and combine different layers.
- *Extension Manager* allows user to develop and distribute additional processing tools and models.

C. Customer Impact

For residential customers, the most proper tools to estimate CIC are through customer surveys. But the problem with the customer filled surveys is that in most cases the customers cannot estimate their loss comprehensively. In addition, this method requires long period of time to complete and cost associated with the survey may be prohibitively high. On the whole, most of the estimation results are classified by different type of customers (residential, industrial, commercial, agricultural, etc.). Some of the results provide different values for different outage duration. However, none of the results considered important customers, i.e. health care centers, schools, as a customer category and neither included the estimated cost. In addition, none of the results differentiated and considered real-time weather conditions when the outage occurs. This may influence the level of customer costs tremendously including the health impact and economic loss. When quantifying customer impact, business interruption and property loss are usually considered. Indeed, it is hard to estimate the health impact on the customers. But it will be helpful to estimate the possible risk caused by the unusual weather elements for a possible upcoming event [27]. Thus, this study considers weather impact on different customer categories in different time steps, incorporates the weather factors into the models in evaluating the customer cost, and implements a risk assessment of customer impact caused by the weather-caused power outage.

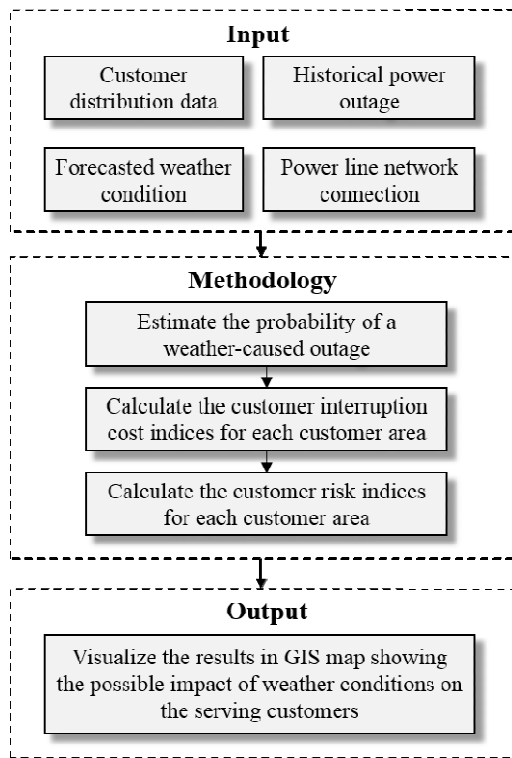


Fig. 1: Customer Impact Evaluation Framework

III. METHODOLOGY

Customer data has been integrated with weather and GIS data in order to develop framework for prediction of impact of different weather conditions on customers. Prediction model has been trained using historical outage data that are spatially and temporally correlated with weather parameters measured at the time of outage. Then, real-time weather forecast data has been used to predict risk to customers in case of a predicted

weather conditions. Overview of the proposed method is presented in Fig. 1.

A. Risk Analysis

The risk assessment framework used in this research presented in Fig. 2 is formulated as follows, [19]:

$$R = P [T] \cdot P [C|T] \cdot u(C) \quad (1)$$

Where R is the *State of Risk* for the customer impact of the upcoming weather conditions, *Hazard* P [T] is the probability of a *Threat* intensity T (i.e. a certain weather condition that may cause power outage), *Vulnerability* P [C|T] is the probability of power supply failure in that area (estimated according to the correlation of historical outage data and historical weather data), and *Worth of Loss* u(C) is an estimate of customer interruption losses in case of the power supply failure.

Following the outline in Fig. 2 *Hazard* map is developed based on historical weather data. Probabilities for a specific severe weather condition are estimated based on historical frequency of occurrence of such events in an area. The main data that drives building of *Vulnerability* map is historical outage data. Based on this information the probability that specific weather condition will cause the fault and loss of power to the customer is estimated. *Worth of loss* takes into account customer information, i.e. how many customers are disconnected and what is the expected duration of outage, what is the type of customer in the area (residential, commercial, industrial), are there any points of special interest (hospitals, schools etc.).

B. Weather Driven Customer Impact Analysis

In this work the historical weather data together with customer indices have been used to develop a predictive model that estimates what is the risk for customers in case of a weather conditions predicted by national forecast services. Two

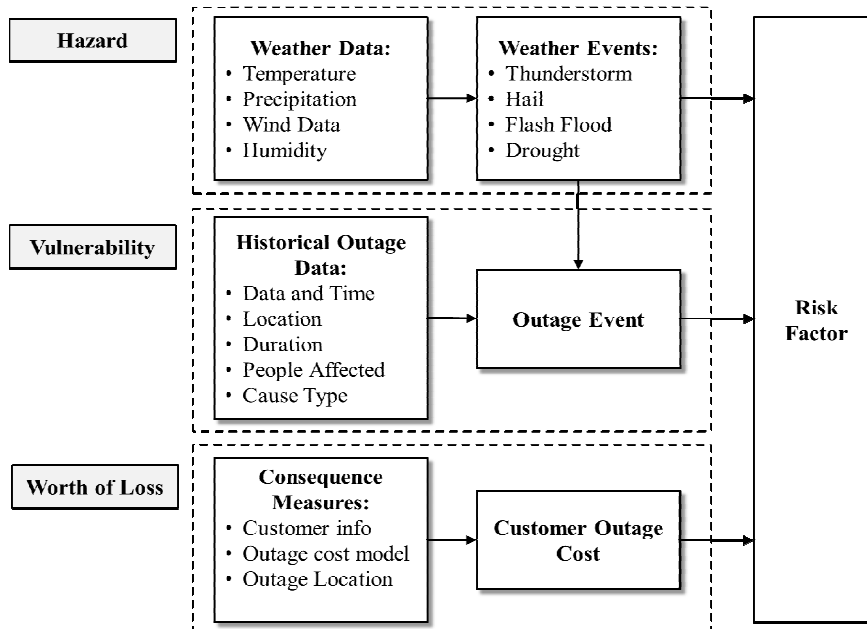


Fig. 2: Risk Analysis for Customer Impact

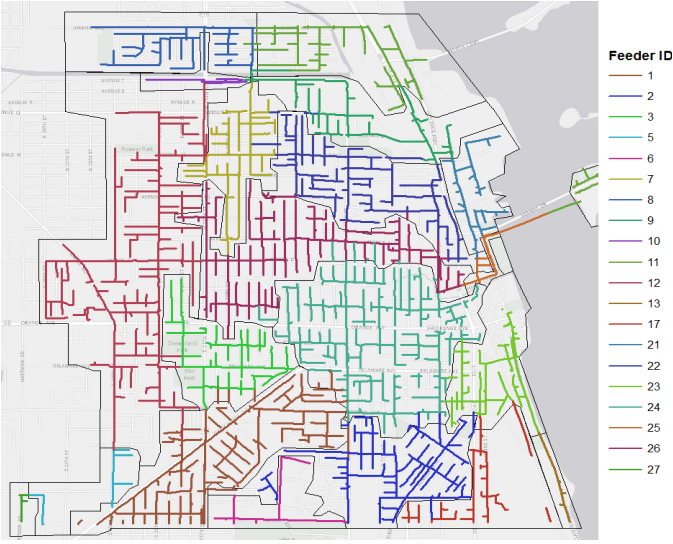


Fig. 5: Studied Distribution Network

kinds of weather data are used in this work:

- Historical weather data coming from weather stations:
 - Ft. Pierce Arc (temperature, precipitation, wind)
 - St. Lucie County International Airport (temperature, precipitation, wind)
 - Fort Pierce 2.8 SSE (precipitation)
 - Ft. Pierce (temperature, precipitation)
 Historical data for the period of 5 recent years were obtained starting from January 1st 2010 until December 31st 2014.
- Weather forecast data coming from National Digital Forecast Database (NDFD). Data for temperature, humidity, precipitation and wind for the future 3 days is used for prediction model. Data is updated every 3 hours. Data resolution is 3 hours.

From the perspective of customers, the CIC is correlated with the degree of the customers' dependence on the electricity [2]. It is stated to be a function of customer characteristics and interruption features. If weather condition is taken into consideration, then the formulation needs to be improved. Thus, in order to evaluate the customer loss in terms of weather-caused power failure, besides the previous model of estimating the economic cost during an outage, the total cost also needs to include the additional financial impact that the bad weather condition may bring to increase the original cost and the health impact the weather condition may cause for the customers without electricity supply. The total costs are formulated in (2) comprising of three monetary terms.

$$C_{total}^{t,FA} = CDF_{d,s,dy,w,cc}^{t,FA} + AC_{EA,cc,d}^{t,FA} + HC_{EA,cc}^{t,FA} \quad (2)$$

where the estimated total cost value at time t is calculated for each feeder area FA , due to the radial topology of distribution system. CDF is the customer damage function. d represents the interruption duration, s represents the season, dy represents the time of a day, and w represents the day of a week. cc represents the customer characteristics which may include the customer category, size, time schedule, presence of interruption-sensitive

equipment, presence of back-up equipment, etc. AC is additional cost that the weather may bring to the customers compared with normal condition. EA is environmental attributes which is the weather conditions at the time we are about to estimate the cost. HC is the health cost that the customers' personal life may be impaired.

To be specific, the three terms in (2) are defined as follows:

$$CDF_{FA}^t = \sum_{\substack{l=1 \\ l \in FA}}^L ICL_{d,s,dy,w,cc}^l \cdot EENS_t^l \quad (3)$$

$$CDF_{FA}^t = \sum_{\substack{l=1 \\ l \in FA}}^L ICE_{d,s,dy,w,cc}^l \quad (4)$$

Where ICL represents the interruption cost per kWh (\$/kWh) which has the similar meaning with value of lost load, L is the total customer number in each feeder area, $EENS$ represents the expected energy not supplied value which can be predicted reliably based on smart meter measurement, and ICE represents the interruption cost per event. CDF can be estimated by either (3) or (4) depends on the availability and accuracy of the data source.

$$AC_{FA}^t = \sum_{\substack{l=1 \\ l \in FA}}^L \{AICL_{d,s,dy,w,cc}^l \cdot AENS_{EA,t}^l + A_{EA,t}^l\} \quad (5)$$

Where $AICL$ represents the interruption cost for additional energy not supplied $AENS$ caused by bad weather condition for each customer, and A represents additional financial loss.

$$HC_{FA}^t = \sum_{\substack{l=1 \\ l \in FA}}^L f_{cc}^l(temp, humi, stm, wds, prec, other) \quad (6)$$

Where HC represents the health cost, and f is the function to calculate the health cost for each customer in terms of the customer characteristics and the expected environmental attribute. The terms in the bracket are the weather condition parameters that may influence the customer cost, including temperature, humidity, storm type, wind speed, precipitation, and others.

IV. CASE STUDY

To implement the study, firstly, the Florida network has been selected to demonstrate the results since the distribution lines information is available [28]. Then, the customer distribution data has been collected. Such data are customer population distribution, customer type, facility locations, etc. Next, the network is split into small polygons as customer service areas per distribution feeder. Then all the customer data layers are clipped to each area and the customer info are summarized based on the clipped data layers (customer population, customer types and corresponding numbers for each type, and disable people numbers). The customer info in each area is imported to the models of customer cost, and the corresponding risk index for each area is calculated based on the risk assessment theory. Last step is to demonstrate the risk indices in the GIS map and use different colors to indicate severity of the customer cost impact.

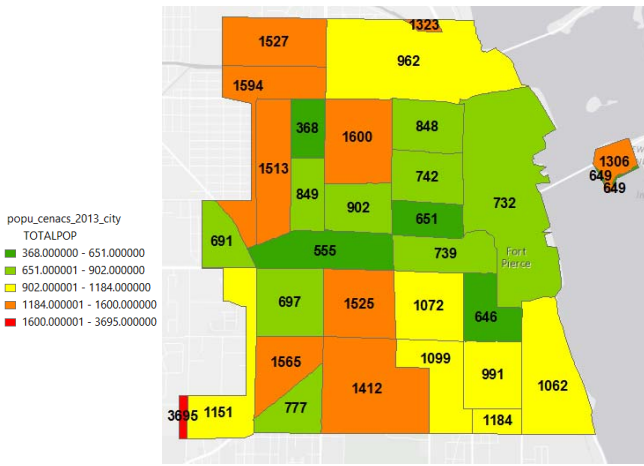


Fig. 6: Population Map

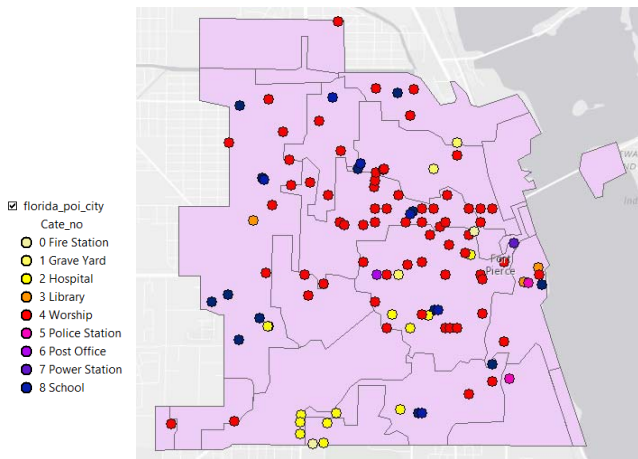


Fig. 7: Points of Interest Map

A. Studied Network

The distribution network data used in this study is part of the Storm Vulnerability Assessment tutorial from Esri [28]. Data layer for distribution network primary overhead feeders

was extracted. The layer is presented in Fig. 5. The network consists of 20 feeders containing single, double and three phase primary overhead lines. The network is located in Fort Pierce, Florida.

In Fig. 6 population count for different areas of the network is presented. Each area represents part of the distribution network connected to one feeder. In Fig. 7 locations of customer types of interest is presented. Different points of interest will affect risk factor differently, for example area with hospital will have higher risk factor compared to the area without a hospital that is experiencing same weather conditions.

B. Test Scenarios

Historical outage data is obtained for three years, starting from Jan.1st of 2012 and ending with Dec. 31st of 2014. Historical weather data is prepared to correlate with each historical outage event. The customer population data obtained from national census report and the location of facilities which also indicate the customer categories are demonstrated in map as Fig. 6 and Fig. 7. An example of a normal weather scenario and an upcoming bad weather scenario is assumed based on the historical weather conditions in Fort Pierce area. For each weather condition, the risk indices of all the feeder areas are calculated accordingly and shown in the map with successive colors indicating the severity of risk.

C. Study Results

For each feeder area, risk value was calculated, assigned, and presented on a map as shown in Fig. 8, with a) showing the results under normal weather scenario and b) showing the results under expected bad weather scenario. The values of risk indices are presented as a percentage, where 100% is assigned to the feeder area with highest risk for the severe weather scenario. It can also be defined according to utility's standard of risk acceptance. The severity of the customer impact risk increases from the areas with green color to the areas with red color. After viewing the result map,

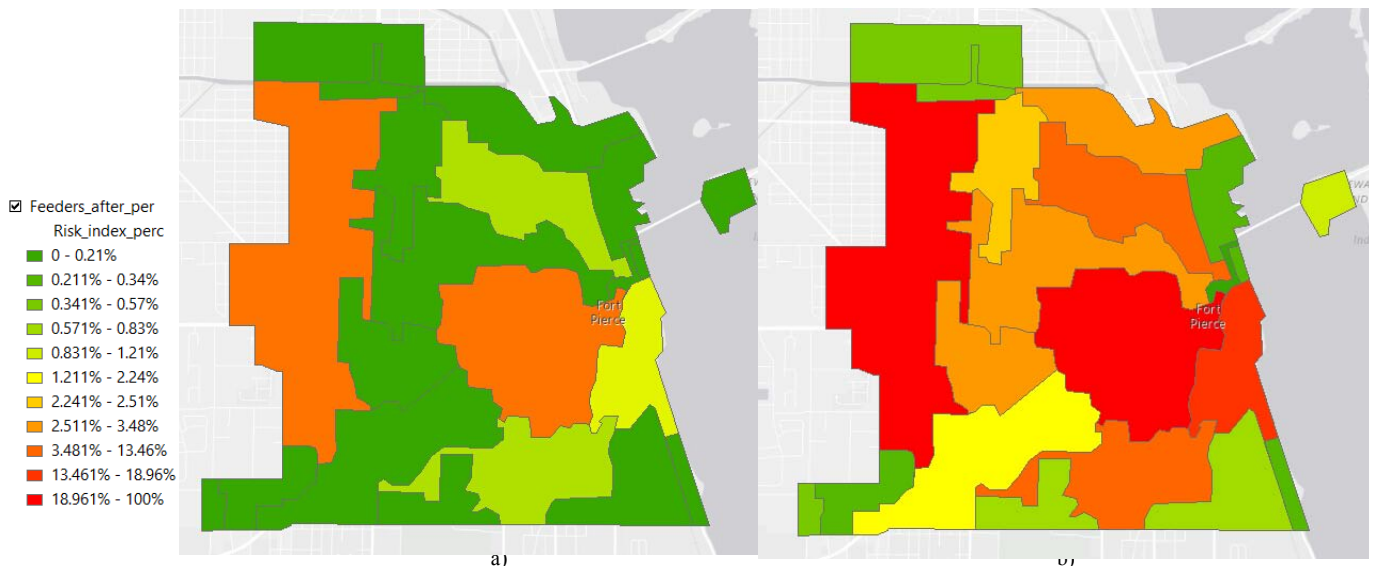


Fig. 8: Predicted risk for two weather scenarios: a) normal weather conditions; b) expected severe weather conditions

utilities can judge whether to send pre-warning notifications to their serving customers or to take some actions to avoid such customer loss. Compared with a sudden unexpected power outage, a pre-notified power outage may significantly decrease the customer loss.

V. CONCLUSION

The contribution of this study is in an ability to provide risk assessment of weather driven customer impacts. More specifically:

- Customer interruption cost model that incorporates weather impacts is established and assigned for each customer category, which allows assessment of weather impacts on customer interruption cost.
- The probability of outage in each location is determined based on the historical outage events and prevailing weather condition, which allows formulation of customer risk indices based on weather-caused outages.
- The customer risk assessment methodology can be used by distribution system operators to make preventive measures to minimize the potential losses.
- Customers can get the pre-warning information about the possible outages that could happen in their local area from distribution system operators and make plans to mitigate losses by actions from their side.

REFERENCES

- [1] Blackout Tracker, Eaton corporation. [Online] Available: <http://powerquality.eaton.com/blackouttracker>
- [2] R. Billinton et al., "Methods to consider customer interruption costs in power system analysis," CIGRE, TF 38.06.01, 2001
- [3] D. Cheng, B. Venkatesh, "Literature survey and comparison of consumer interruption costs in North America and Europe," Electrical and Computer Engineering (CCECE), 2014 IEEE 27th Canadian Conference on, vol., no., pp.1, 7, 4-7 May 2014
- [4] Leahy E., Tol R. S. J., "An estimate of the value of lost load for Ireland." *Energy Policy*, 39 (3), 1514-1520.
- [5] Linares P., Rey L., "The costs of electricity interruptions in Spain. Are we sending the right signals?" Working Paper WP FA5/2012, Economics for Energy Research Centre, University of Vigo, Spain
- [6] Nooij M., Koopmans C., Bijvoet C., "The value of supply security: the costs of power interruptions: economic input for damage reduction and investment in networks." *Energy Economics* 29, 277-295
- [7] M. Lehtonen, B. Lemstrom, "Comparison of the methods for assessing the customers' outage costs," *Energy Management and Power Delivery*, 1995. Proceedings of EMPD '95. 1995 International Conference on, vol.1, no., pp.1, 6 vol.1, 21-23 Nov 1995
- [8] Kjølle G., Samdal K., Singh B., Kvitastein O., "Customer Costs Related to Interruptions and Voltage Problems: Methodology and Results", *IEEE Trans. Power Systems*, Vol. 23, No. 3, August 2008
- [9] Bertazzi A., Fumagalli E., Schiavo L. L., "The use of customer outage cost surveys in policy decision-making: The Italian experience in regulating quality of electricity supply." Proceedings of 18th CIRED, Turin, Italy, June 2005.
- [10] Bliem M., "Economic Valuation of Electrical Service Reliability - Experiences from Austria", The Council of European Energy Regulators (CEER) Workshop on Continuity of Supply Regulation by Incentives - Willingness to Pay and Accept, September 2008, Lisbon
- [11] Sullivan M., Perry M., Schellenberg J., Burwen J., Holmberg S., and Woehleke S., "Pacific Gas & Electric Company's 2012 Value of Service Study", Report prepared for Pacific Gas & Electric Company by the Freeman, Sullivan & Co.
- [12] Subramaniam R.K., Billinton R. and Wacker G. (1993), "Understanding Commercial Losses Resulting from Electric Service Interruptions", *IEEE Trans. Industry Applications*, Vol. 29, No. 1, January-February 1993
- [13] Sullivan M. J., Mercurio M. G., Schellenberg J. A. (2009) "Estimated Value of Service Reliability for Electric Utility Customers in the United States", Report No. LBNL-2132E, Lawrence Berkeley National Laboratory, June 2009, Berkeley, California, USA
- [14] Balducci P.J., Roop J. M., Schienbein L. A., Desteese J. G., Weimar M. R., "Electrical power interruption cost estimates for individual industries, sectors and U.S. economy." Report No. PNNL-13797, Pacific Northwest National Laboratory, Richland, Washington, USA
- [15] Systems Control, Inc. "Impact Assessment of the 1977 New York City Blackout." Prepared for United States Department of Energy by Systems Control Inc., Palo Alto, California
- [16] L. Goel, R. Billinton, "Prediction of Customer Load Point Service Reliability Worth Estimates in an Electric Power System," *IEEE Proc.-Gener, Tans, Dist*, Vol.141, No. 4, July 1994.
- [17] M. Sullivan, D. Keane, "Outage Cost Estimation Guidebook", TR-106082, Electric Power Research Institute, Palo Alto, CA: December, 1995.
- [18] T. Dokic, P. Dehghanian, P.-C. Chen, M. Kezunovic, Z. Medina-Cetina, J. Stojanovic, Z. Obradovic "Risk Assessment of a Transmission Line Insulation Breakdown due to Lightning and Severe Weather," HICCS – Hawaii International Conference on System Science, Kauai, Hawaii, January 2016.
- [19] Z. Medina-Cetina and F. Nadim F, "Stochastic Design of an Early Warning System", *Georisk: Assessment and Management of Risk for Engineered Systems and Geohazards*, vol. 2, no. 4, pp. 223 – 236, 2008.
- [20] National Centers for Environmental Information – National Oceanic and Atmospheric Administration, "Data Access," [Online] Available: <https://www.ncdc.noaa.gov/data-access>
- [21] 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
- [22] National Centers for Environmental Information – National Oceanic and Atmospheric Administration, "Numerical Weather Prediction," [Online] Available: <https://www.ncdc.noaa.gov/data-access/model-data/model-datasets/numerical-weather-prediction>
- [23] Weather Research and Forecast Model, [Online] Available: <http://www.wrf-model.org/index.php>
- [24] Vaisala, "National Lightning Detection Network – Technical Specification," [Online] Available: <http://www.vaisala.com/en/products/thunderstormandlightningdetectionsystems/Pages/NLDN.aspx>
- [25] M. Kezunovic, et al., "The role of big data in improving power system operation and protection," *Int. Inst. for Research and Education in Power Syst. Dynamics Symp. (IREP)*, Aug. 2013.
- [26] ArcGIS, Esri. [Online] Available: <https://www.arcgis.com>
- [27] Karin A., Impact of Dependencies in Risk Assessments of Power Distribution Systems, Licentiate Thesis, KTH, Stockholm, Sweden, 2008
- [28] Storm Vulnerability Assessment, ArcGIS for Utilities, Esri. <http://solutions.arcgis.com/utilities/electric/help/storm-vulnerability/>