Data Analytics for Power Utility Storm Planning

Lan Lin[1], Aldo Dagnino[1], Derek Doran[2] and Swapna Gokhale[3]
[1]*ABB Corporate Research, Raleigh, NC, 27606, U.S.A.*
[2]*Department of Computer Science & Engineering, Kno.e.sis Research Center, Wright State University, Dayton, OH, 45431, U.S.A.*
[3]*Department of Computer Science and Engineering, University of Connecticut, Storrs, CT, 06269, U.S.A.*

Keywords: Machine Learning, Storm Damage Projection, Smart Grid, Data Analytics, On-line Social Media.

Abstract: As the world population grows, recent climatic changes seem to bring powerful storms to populated areas. The impact of these storms on utility services is devastating. Hurricane Sandy is a recent example of the enormous damages that storms can inflict on infrastructure, society, and the economy. Quick response to these emergencies represents a big challenge to electric power utilities. Traditionally utilities develop preparedness plans for storm emergency situations based on the experience of utility experts and with limited use of historical data. With the advent of the Smart Grid, utilities are incorporating automation and sensing technologies in their grids and operation systems. This greatly increases the amount of data collected during normal and storm conditions. These data, when complemented with data from weather stations, storm forecasting systems, and online social media, can be used in analyses for enhancing storm preparedness for utilities. This paper presents a data analytics approach that uses real-world historical data to help utilities in storm damage projection. Preliminary results from the analysis are also included.

1 INTRODUCTION

A 2012 Edison Electric Institute reliability report (Wang, 2012) shows that bad weather contributed to 67% of power outages time and that most damage after a big storm is in the power distribution lines and equipment. Hurricanes, tropical storms, and summer storms cause the majority of power outages. The report identifies that winter storms tend to have durations equal or greater than many of the summer storm events. Overhead power lines are typically the most vulnerable to storms. Although it seems that underground facilities may be less prone to major outage events, many underground facilities are also affected by major storms, since most existing underground facilities are supplied from overhead sections of the grid. Therefore, any event causing an overhead outage will also cause outages on sections of underground facilities. In the case of flooding, underground facilities are prone to severe damages.

Power utilities in the US face enormous challenges when responding to storms. Utilities have storm planning procedures that address different stages of storm preparedness. These stages include cyclic storm planning, storm damage projection, in-storm analysis, post-storm assessment, post-storm restoration, and grid hardening. Utilities have outage management personnel who often have worked for years in these areas. Decisions on storms are typically made based on experts' heuristic knowledge. Although utilities are using technologies such as outage management systems (OMS), geographic information systems (GIS), supervisory control data acquisition (SCADA) systems, and automated metering reading systems, there is still a wealth of data generated by these systems and other sources that utilities can use to be more proactive in addressing each of the stages of storm damage preparedness. This paper presents two examples of how data analytics can be used by utilities to become more proactive in the storm damage projection and in-storm analysis stages. The examples presented here represent just a "foretaste" of what is possible to achieve in this field. Section 2 discusses some of the data sources available today that can be used to develop models for storm planning. Section 3 and 4 present data sources and a machine learning approach and initial results that address the storm damage projection. Section 5 presents initial results and a machine learning approach that utilizes on-line social media to follow the evolution of a storm.

Lin L., Dagnino A., Doran D. and Gokhale S..
Data Analytics for Power Utility Storm Planning.
DOI: 10.5220/0005128203080314
In *Proceedings of the International Conference on Knowledge Discovery and Information Retrieval* (KDIR-2014), pages 308-314
ISBN: 978-989-758-048-2

Section 6 presents conclusions and future work that authors are pursuing in this field.

2 DATA ANALYSIS APPROACH

Utilities face difficult challenges regarding how to use available data for storm planning. First, the current available data are used primarily for tracking purposes and not for proactive storm planning. Second, the sources of data and data are heterogeneous in nature. Third, relying on data collected on past storms is challenging as no two storms are the same. These present a challenge when comparing storm-restoration performance of the past and present (Johnson, 2004). Another major data challenge is that utilities do not have a standardized method for collecting data on storm-restoration.

In spite of these challenges the authors believe it is possible to demonstrate the potential predictive capabilities that machine learning models can provide with current data sources, imperfect as they may be. These data originates from heterogeneous sources and geographically dispersed environments. Primary data types available can be classified as static structured and unstructured historical data and dynamic real-time structured and unstructured data. Static data can be used to develop machine learning models while dynamic data can be used by trained models to analyse storm situations in near real-time. Static structured historical data includes GIS and grid topology, storm data, grid damage, OMS data, work management systems, work flow management with power restoration actions, grid intelligent electronic device (IED) data, vegetation and terrain, and transmission and generation data. Static unstructured historical data includes on-line social networks historical data, historical multi-media storm damage data, and unstructured damage reports. Dynamic real-time structured data includes weather feeds, grid sensor feeds, real-time OMS data, emergency response data, SCADA data, phasor measurement unit data, 61850 GOOSE data, network management and fault data, meter data, and IED data. Dynamic real-time unstructured data includes real-time OMS data, drones or robotic systems data, multi-media data, and repair crew report.

3 THE DATA

Storm damage projection refers to the use of prediction methods to project the severity and locations of damages, resource needs and time for power restoration after a storm has hit the power grid. Storm damage measurements include peak number of customers without power, outage duration, peak number of line restoration personnel, and equipment damage. Based on the projection, plans are made for positioning restoration resources, prioritizing repairs, and minimizing disruptions.

3.1 Data Sources

To develop machine learning models for storm damage projection we looked into several data sources public, proprietary, structured, unstructured, and acquired historical data related from an electrical Utility in the US, referred as *Public Utility* due to proprietary constraints. The sections below provide some details on the data used.

3.1.1 Weather Data

As a big source of public data, National Weather Service (NWS) has a large collection of historical weather data that can be downloaded through its website. The following two weather data sets are used in this study.

Severe weather event database for the United States from 1950 to 2011. A severe weather event is identified by timestamps of event type, begin date and time and end date time, begin and end locations of latitude and longitude, and a magnitude of severity. Typical events for the selected region include hail, thunderstorm wind, flash flood, and tornado. The database contains over 900,000 records with a total of 1.1 GB. This data is used to identify severe storms in this study.

Hourly weather data from over 10,000 weather stations all over the world from 2000 to 2012. The hourly weather include location of observing weather station in latitude and longitude, observation time, wind direction, wind speed, air temperature, sea level pressure, precipitation time and accumulation, etc. The total amount of data is over 220 GB. In this study we used some of the weather conditions as inputs to the predictive models. The weather stations are selected within half a degree from the boundaries of a *Public Utility*. Although the number of stations is increased over the years, it is still very small if we want to have one station every few square miles. In this project we relied on data interpolation to derive weather condition for locations at fine granularity.

3.1.2 Power Outage Data

The *Public Utility* has a total of 24,000 miles of distribution lines, 18,000 miles of which are overhead. It serves 830,000 customers, 600,000 of which are urban. OMS data related to historical storms in the geographic region of the *Public Utility* is over 2 GB and contains: (1) outage events identified by start time and end time, location in latitude and longitude, and the particular asset caused the event; (2) asset information including asset location; (3) customer information and priority level; and (4) crew information containing the crew type and contact information.

3.1.3 Social Media Data

Social media plays an increasingly important role in many aspects of our society. Data generated by utility's customers using social media provides more insights into outages and their locations faster. We explored social media data as unstructured public data from Twitter. Sample data of 10,000 tweets was downloaded using the Twitter API. An important consideration is that over 90% of messages do not contain geo-location information. Hence, our research is focused on determining the geo-location based on the contents of the message.

3.2 Data Preparation

We use several software tools in this project for data processing, modelling, and visualization. These tools include: (a) *R* is chosen as the main data analytics tool for data pre-processing and data mining algorithms. Visualization is also conducted using *R*'s map and plot functions; (b) Google Earth is used for visualizing weather information as shown in Figure 1; (c) *Visual Studio* is used to write C++ program for processing the weather data; (d) *Oracle SQL Developer* is used to write queries for extracting data from the OMS system into files.

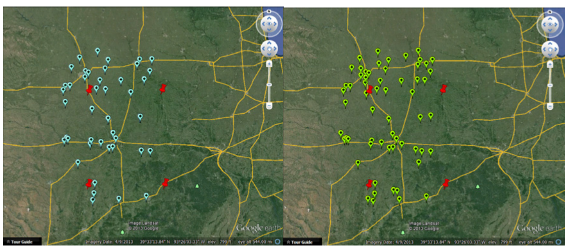


Figure 1: Weather station locations in Google Earth.

3.3 Data Selection

We use the tools described above to select the datasets for building machine learning models. Our selection criteria are largely based on the availability and quality of the data.

The OMS dataset contains outage data from March 2003 to September 2010. The plot in *R* of all outages between 2003 and 2010 overlaying on the total equipment in the *Public Utility* service territory is shown in Figure 2. The blue points denote equipment and the red points denote outages. According to a *Public Utility* expert, the three months of June, July, and August each year are the summer storm season, when utilities need to be ready for storm restoration activities.

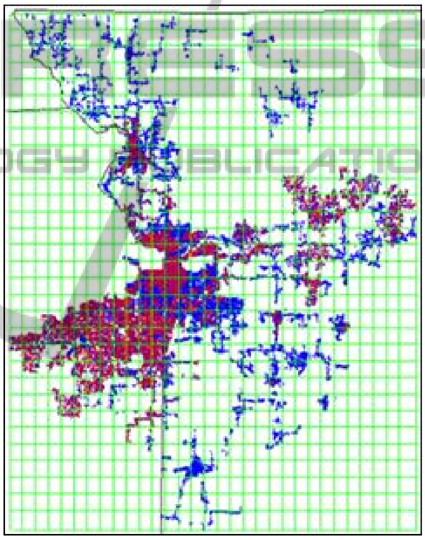


Figure 2: Locations of outages from 2003 to 2010 in the *Public Utility* service territory.

In the storm database, the number of weather events per month confirms that summer months are usually the time where severe weather events occur in the *Public Utility* territory. Storms include hail, thunderstorm wind, flash flood, flood, and tornado, where thunderstorms are the top event although hail occurs more frequently.

3.4 Data Pre-Processing

OMS data is processed in Oracle database using SQL queries and working with domain experts.

The pre-processing of the hourly weather data from NWS is built from scratch. The original hourly weather data is formatted as flat files of records in ASCII characters. We parse the files to extract weather measurements into columns and save as comma-separated values. We also collect the associated weather station locations in latitude and longitude. Then we select weather stations within at most 0.5 degree in latitude and longitude away from the boundaries of the *Public Utility*'s service territory. Only the weather measurements from those stations are selected for further use. There were 20-40 weather stations from 2003 to 2012 that meet this criterion, varied by year.

The bounding box of the *Public Utility*'s territory is roughly 220 by 160 square miles. We divide it into a grid of 1.5 by 1 mile cells which give us 160 by 160 cells. The cell size is small enough to be useful for location identification of outages. We also need weather measurements for each cell but since there are more cells than weather stations, we need to extrapolate weather information for the cells.

Kriging is the most widely used technique in geo-statistics to interpolate data and it is a very good interpolation method that can capture the true spatial variability of temperature variation (Holdaway, 1996). Kriging can handle the situations inherent in a precipitation field and produce the best results for interpolating precipitation (Earls and Dixon, 2007). Kriging is a form of linear interpolation where the value of a field f_a in a position r_0 is interpolated from N neighboring values $f_0(r_i)$, i = 1 … N in its region of influence is given by

$$f_a(r_0) = \sum_{i=1}^{N} \lambda_i f(r_i)$$

where λ_i are a set of weights.

To determine the weights, we use a variogram to write the cost function in terms of the mean square error. The weights used in Kriging are the ones that minimize the cost function under certain constraints. We use a library provided in *R* that contains Kriging method. In this study we are only interested in severe storms that cause big damages to the utility. To identify severe storms, we manually go through all the outages in the three months of summer for years 2005 to 2010 and identify severe storms date and time based on the following criteria: (1) number of outages in the hour; (2) number of customers lost electricity in the hour; (3) average number of customers per outage in the hour; and (4) accumulated number of customers in the next 24 hours. The top 42 storms are selected. For each storm, we select the hour that is the peak for most of the criteria.

4 DATA ANALYTICS MODEL

Figure 3 shows the storm damage projection data analytic model developed in this research. We use historical weather, outage data, and asset data as primary inputs to the machine learning engine. The outage projection model created by the machine learning engine takes in weather forecast and generates outage projections as output. In the future, other environmental data may be incorporated as inputs to the model.

4.1 Models and Model Variables

The target of the outage projection model is to predict outage locations in terms of the grid cells and outage scale in terms of the number of outages occurred in the next 24 hours for each cell.

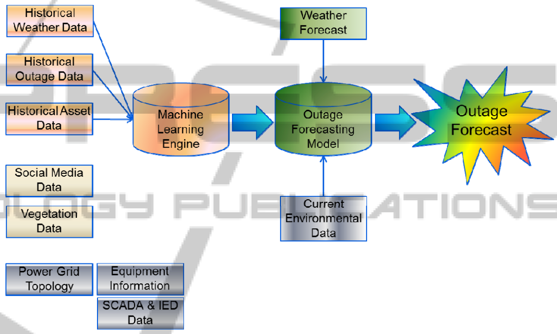


Figure 3: Outage forecasting framework.

The selection of variables for the model is to find the subset of all the input variables to build the model that will perform with the best accuracy against the test data. The four variables used as inputs to the model are: (1) wind speed; (2) wind direction; (3) precipitation amount; and (4) air temperature. To model the nonlinearities in the data, we add the 20th, 40th, 60th, and 80th quintiles of measurements of wind speed, precipitation amount, and air temperature. For this, we use a B-spline function called *ns* in *R*.

For each of the 42 severe storms selected, we build analytical models to predict number of outages for each grid cell. We use data from 2005 to 2010 to build the models. First, we partition the data into two sets, one for training, the other one for test. Data used for training are records from 2005 to 2009; data for test is the 2010 data. Test data is dedicated to test alone and not used in any way for fine-tuning the trained models. We build models using generalized linear models (GLM) and neural networks (NN). Neural network models outperform generalized linear models in accuracy of predicting the location and scale.

4.2 Results

The performance and accuracy/precision of the GLM and NN models are presented and compared in this section. NN models outperform the GLM models in all the error metrics, but the computing time of the NN is greater than GLM. We use the following metrics to evaluate the performance. For the outage locations, we use the Absolute Error (AE) of all the cells, defined as the following.

$$AE = \sum_{i=1}^{n} | TrueOutage_i - PredictedOutage_i |$$

where $TrueOutage_i$ is the number of outages occurred in cell i, $PredictedOutage_i$ is the number of predicted outages in cell i, and n is the number of cells.

For the outage scale, we use the Root Mean Square Error (RMSE) for all the cells, defined as the following.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (TrueOutage_i - PredictedOutage_i)^2}{n}}$$

where $TrueOutage_i$, $PredictedOutage_i$, and n are the same as defined above.

The outputs of the models are predicted number of outages for all the cells. We plot them in R on a map of the *Public Utility* territory. An example is shown in Figure 4. The color associated with each cell denotes the number of outages in the following way: Black=1, Red=2, Green=3, Blue=4, Cyan=5, Magenta=6, Yellow=7, and Gray=8. The showed results are from an NN model.

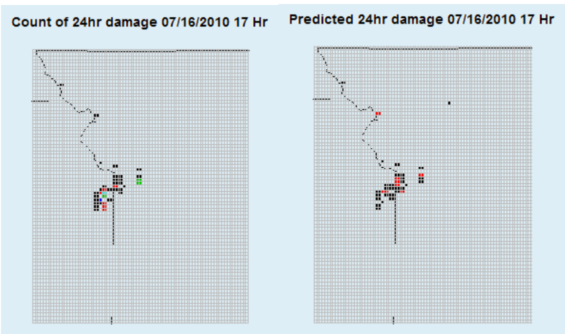


Figure 4: Plots of true and predicted outages.

The results of GLM and NN are shown in Tables 1 and 2 respectively. For the NN models, the predicted numbers better resembled the true outages. The models captured the characteristics of individual storms better.

The columns in the tables include: Storm Date; Num outages (occurred in time period); Num Pred Outages; Num Outage Locs (the total number of predicted outages); Num Pred Locs (the total number of cells predicted to have outage > 0); Num Pred Locs>0.5 (the total number of cells predicted to have outage > 0.5); Num True|Pred Locs: (total number of cells that outages occurred or were predicted); Num True&Pred Locs (total number of cells that outages both occurred and were predicted); RMSE of True Locations (measures how the prediction deviates from the true); RMSE of True&Pred Locs (measures how the models perform for the cells that are predicted and happened).

Comparison of the performance of GLM and NN shows that NN outperform GLM in all metrics. This agrees with what we have discussed previously, that NN tends to have better accuracy than other regression models.

Table 1: Prediction results of GLM.

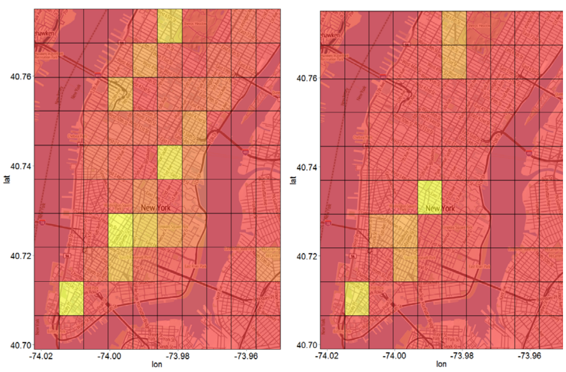
Storm Date	Num Outages	Num Pred Outages	Num Outage Locs	Num Pred Locs	Num Pred Locs>0.5	Num True|Pred Locs	Num True&Pred Locs	RMSE of True Locations	RMSE of True&Pred Locs
06-02-2010_5hr	121	157.659	107	652	98	668	91	1.19482	0.4781964
06-08-2010_7hr	90	148.3046	77	649	94	660	66	1.341822	0.4583193
06-12-2010_9hr	127	162.8983	112	732	102	736	108	0.9677328	0.3775075
06-13-2010_23h	262	185.5746	193	715	122	731	177	1.226589	0.6302588
06-16-2010_18h	133	176.9472	114	754	113	759	109	1.092211	0.4232899
06-18-2010_20h	271	168.5292	193	672	99	719	146	1.449487	0.7509803
06-19-2010_11h	308	153.1811	213	680	87	721	172	1.559368	0.8475605
06-20-2010_23h	145	166.6354	111	692	95	709	94	1.51938	0.6011804
06-23-2010_16h	63	161.1181	59	663	94	671	51	1.34572	0.3990428
07-11-2010_9hr	325	166.4136	161	701	101	715	147	3.169998	1.504246
07-14-2010_22h	134	164.476	104	676	101	702	78	1.469797	0.5657253
07-16-2010_17h	151	160.0669	112	697	96	709	100	1.489612	0.592051
07-20-2010_4hr	164	183.739	129	762	108	774	117	1.181355	0.4822863
07-24-2010_17h	120	149.4541	97	617	101	636	78	1.404506	0.5485054
08-13-2010_19h	196	173.0979	151	707	109	729	129	1.282013	0.583468
08-20-2010_13h	451	175.9459	305	776	111	817	264	1.490663	0.91079
08-31-2010_19h	164	167.0613	135	661	105	689	107	1.292527	0.5721327

Table 2: Prediction results of NN.

Storm Date	Num Outages	Num Pred Outages	Num Outage Locs	Num Pred Locs	Num Pred Locs>0.5	Num True|Pred Locs	Num True&Pred Locs	RMSE of True Locations	RMSE of True&Pred Locs
06-02-2010_5hr	121	136.5601	107	609	96	614	102	0.6609009	0.2758951
06-08-2010_7hr	90	113.75	77	633	70	636	74	0.7681333	0.267272
06-12-2010_9hr	127	148.5843	112	628	107	630	110	0.5620699	0.2369895
06-13-2010_23hr	262	285.1845	193	742	188	747	188	0.8584513	0.436349
06-16-2010_18hr	133	185.6865	114	640	111	642	112	1.074938	0.4529689
06-18-2010_20hr	271	255.0522	193	645	178	647	191	0.9646558	0.5268644
06-19-2010_11hr	308	206.2307	213	553	184	554	212	1.018775	0.6317031
06-20-2010_23hr	145	146.7086	111	621	90	630	102	1.107528	0.4648856
06-23-2010_16hr	63	81.94394	59	505	57	506	58	0.6240312	0.213087
07-11-2010_9hr	325	195.1761	161	676	152	680	157	2.853286	1.388365
07-14-2010_22hr	134	141.7851	104	606	86	613	97	1.055211	0.434636
07-16-2010_17hr	151	166.6915	112	649	109	651	110	1.160479	0.4813444
07-20-2010_4hr	164	155.2223	129	592	115	598	123	0.8200834	0.3808924
07-24-2010_17hr	120	93.92097	97	443	86	447	93	0.8842315	0.411906
08-13-2010_19hr	196	182.8227	151	629	137	636	144	0.873698	0.4257172
08-20-2010_13hr	451	279.8458	305	620	242	646	279	1.166685	0.8016547
08-31-2010_19hr	164	173.6378	135	657	117	668	124	0.916504	0.412015

5 ANALYSING SOCIAL MEDIA

This section presents preliminary results on the development of machine learning algorithms that can be used to analyse social media postings as a storm hits a geographic region of interest. People's perceptions about events they encounter are often embodied in words, terms, and phrases that form their spoken language as the ones found in social media posts. These perceptions may be influenced by inherent regional characteristics and they are further modulated by specific local features or a situation surrounding a person. Doran et al. (2013) developed a methodology, based on a probabilistic language model that extracts perceptions from online social media postings that may be relevant to assist utilities in near real-time identifying specific locations where power outages have occurred. Authors suggest that the analyses of these perceptions will be a useful add-on to physical sensors deployed in the smart grid and current analytic methods that utilities have at their disposition. On-the-ground perceptions from humans as they experience a storm can provide insights which may allow utilities to quickly evolve their response plan. New York City faced two major storms during our data collection period: hurricane force winds during a January rain storm, and a snow storm that piled on over a foot of heavy, wet snow. Both these storms caused scattered citywide power outages due to heavy winds (Johnson, 2004) and the weight of melting snow on trees and power lines over subsequent days. Since outage maps during these events are unavailable, regions with the perception "power outage" are identified utilizing the data analytics method presented in Doran et al. (2013) in Figure 5a. The locations of these perceptions reflect the scattered nature of the reported outages. Physical sensors in the smart grid can identify locations of outages, but they cannot explain their cause. A possible hypothesis is that heavy winds and wet snow led to downed trees and branches causing power outages. To confirm this hypothesis, the language models developed in Doran et al. (2013) were queried with the phrase "damaged tree". The heat map in Figure 5b shows that people discuss damaged trees in sub-regions that either



Figures 5a and 5b: Storm response perceptions.

overlap or are adjacent to those where power has been lost. For example, the perceptions of power outage and damaged trees are strongly exhibited near SoHo and close to Sara Roosevelt Park. With this supplementary information at hand, a city can adjust its storm response to position workers and machines to clear branches and other debris caused by damaged trees.

6 CONCLUSIONS

As power transmission and distribution grids expand, a larger number of equipment and power lines are exposed to strong storm conditions and potentially to catastrophic damages. Utilities have limited tools to proactively address the damages that storms such as hurricanes and ice storms can cause to the grid. With the advent of the smart grid, predictive storm damage models can be developed using a rich variety and quantity of data generated by cheap and accurate sensing technologies, geo-spatial databases, and on-line social media. This paper presents a data analytics framework and two experiments on how utilities can use these data to become more proactive in storm planning.

REFERENCES

Bahl, L. R., Jelinek, F., and Mercer, R. L. 1983. A maximum likelihood approach to continuous speech recognition. In *IEEE Transactions on Pattern Analysis and Machine Intelligence*. pp. 179–190.

Batty, M., K. Axhausen, F. Giannotti, A. Pozdnoukhov, Bazzani, A., Wachowicz, M., Ouzounis, G., and Portugali, Y. 2012. Smart cities of the future. *The European Physical Journal*, vol. 214, pp. 481–518.

Caragliu, A., Bo, C. D., and Nijkamp, P. 2009. Smart cities in Europe. Vrije Universiteit, Faculty of Economics and Business Administration.

Cerruti B. and Decker S. 2012. A Statistical Forecast Model of Weather-Related Damage to a Major Electric Utility. *Journal of Applied Meteorology and Climatology*, Vol. 51. (February 2012).

Doran, D., Gokhale, S., and Dagnino, A. 2013. Human Sensors for Smart Cities. *Workshop on Social Network Analysis in Applications* (SNAA 2013), co–located with the *2013 International Conference on Advances in Social Networks Analysis and Mining*, August 25-28, Niagara Falls, Canada.

Johnson, B. 2004. Utility storm restoration response. *Edison Electric Institute* (January 2004).

Klein, K. Springer, P., and W. Black, W. 2010. Real-Time Ampacity and Ground Clearance Software for Integration Into Smart Grid Technology. In *IEEE*

Transactions on Power Delivery.
Holdaway, M.R. 1996. Spatial modelling and interpolation of monthly temperature using kriging. *Climate Research*, 6, 215–225.
Earls, J. and Dixon B. 2007. Spatial Interpolation of Rainfall Data Using ArcGIS: A Comparitive Study. *http://gis.esri.com/library/userconf/proc07/papers/papers/pap_1451.pdf*.
IBM whitepaper. 2010. Electric Utility gets ahead of the weather with new forecasting models. *IBM*.
Porter, C., Baranowsky, B. C., Clarke, B., and Shaw B. 2012. The Polarimetric Radar Identification System (POLARIS): Leveraging Dual Polarized Radar data for real Time Operational Applications. Extended Abstracts, *28th Conference on Interactive Information Processing Systems* (IIPS), American Meteorological Society.
McManus, G. et al. 2008. Development and Testing of an Ice Accumulation Algorithm. Extended Abstracts, *17th Conference on Applied Meteorology*, American Meteorological Society.
Wang, U.2012. A New Weapon for Storm Responders: Send in the Drones. *EPRI Journal*. Summer issue.