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Research Article

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Application of Hybrid Geo-Spatially Granular Fragility Curves to Improve Power Outage Predictions

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Abstract

Fragility curves depict the relationship between a weather variable (wind speed, gust speed, ice accumulation, precipitation rate) and the observed outages for a targeted infrastructure network. This paper describes an empirical study of the county by county distribution of power outages and one minute weather variables during Hurricane Irene with the objective of comparing 1) 'as built' fragility curves (statistical approach) to engineering 'as designed' (bottom up) fragility curves for skill in forecasting outages during future hurricanes; 2) county specific fragility curves to find examples of significant deviation from average behavior; and 3) the engineering practices of outlier counties to suggest future engineering studies of robustness. Outages in more than 90% of the impacted counties could be anticipated through an average or 'generic' fragility curve. The remaining counties could be identified and handled as exceptions through geographic data sets. The counties with increased or decreased robustness were characterized by terrain more or less susceptible to persistent flooding in areas where above ground poles located their foundations. Land use characteristics of the area served by the power distribution system can suggest trends in the "as built" power grid vulnerabilities to extreme weather events that would be subjects for site specific studies.

Keywords: Power outage; Infrastructure vulnerability; Extreme weather; Hurricane Irene, Classification of impacted areas

Introduction

Hurricanes, snowstorms, and other adverse weather events continuously inflict damage to the electric grid that costs between $20 billion and $55 billion annually [1]. The loss of electricity from adverse weather events also generates social consequences. Given these consequences, different methods can be implemented to ensure *persistent availability* of electricity supply, including strategic investments in more robust grid infrastructure, active management of grid components, real-time grid condition monitoring and control as well as preemptive placement of repair crews before adverse weather events. In addition to these hands-on strategies, other approaches include the statistical analysis of past power outage data during adverse weather events. This top down statistical analysis offers a powerful way to identify recurrent patterns in the power outage data, which would then allow for a better understanding of the vulnerability of the 'as built' power grid.

However, top down statistical methods require extensive data validation and risk over-fitting the data thereby explaining past events well but not predicting outages in future storms well. Bottom-up models such as failure analysis of individual engineered components require detailed proprietary information about the distribution topology and structure and can be computationally intensive. In this work, we explore a hybrid technique that combines county by county outage data with statistical outage information to provide spatially granular outage estimates in time to support emergency response activities. We identify those counties not explained by the statistical methods and apply a data driven, empirical approach for those counties. We discuss these counties as aggregates, however, to avoid identifying specific vulnerabilities.

Background

Fragility curves provide a powerful approach for understanding the relationship between a weather variable as a proxy for total environmental damage potential and the level of outages observed for a particular area during an extreme weather event. Liu et al., [2] first used a statistical model to provide predictions of where power would be lost for how many customers under hurricane conditions. In this early work, outages were defined as the non-transitory activation of a protective device, not as customers actually losing power. Liu [3] also recognized that different storms had different damages for similar wind or precipitation rates. Liu [3] followed the earlier National Infrastructure Simulation and Analysis Center lead of using analog storms from a built library of storm scenarios to predict outages by instituting a system of storm indicator variables [4]. Han et al., [5] attempted to remove the indicator variables by using a bigger set of measurements before a hurricane made landfall. However, Han discovered a geo-spatial bias; overestimating the damage in rural areas and underestimating the damage in urban areas with little increase in skill over the use of the indicator variables. Guikema et al., [6] used a method combining statistical and data mining approaches to forecast damage to distribution poles. However, the State of Maryland's resiliency study indicated that customers losing power was only indirectly correlated with physical damage to the distribution system and instead found that 80% of the outage was caused by distribution substations losing above ground connectivity to the wider grid [7].

National Infrastructure Simulation and Analysis Center researchers combined engineered fragility curves with spatially specific data sets of population, equipment, and interdependencies to build bottom-up fragility curves beginning in 2003 [4] and extending through Hurricane Sandy. Deviations of the total predicted outages from what was observed differed only along the storm edges and provided exceedingly close correlations for storms causing more than 1 million customers outaged.

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However, estimates along the edges of the meteorological storm track were more uncertain. Although the edges of the storm constitute less than 10% of the customers outaged, questions such as how close can supplies be pre-positioned or maintaining power to fuel stations on evacuation routes are critical to an effective response. This research examines whether county by county fragility curves can be developed statistically from the power grid's reaction to major storm events, such as Hurricane Irene and combined with engineered curves to provide skill in the run up to a major hurricane landfall.

Approach

Hurricane Irene provided a case study for the development of county by county fragility curves. Irene was a large and very destructive tropical cyclone that affected more than 500 counties on the East Coast of the U.S. (see Figure 1). In addition, the time and intensity of many of the outages or service interruptions were documented in official utility press releases and media reports. Hurricane Irene first made landfall in the United States (specifically, on the Outer Banks of North Carolina) on August 27, 2011 as a Category 1 hurricane. Although Irene remained at hurricane strength over land, it weakened to a tropical storm and made yet another landfall in the Little Egg Inlet in southeastern New Jersey on August 28. These intensity variations afforded a range of wind speeds to which the studied infrastructures were exposed. A few hours later, Irene made its final landfall in Brooklyn, New York City. Early on August 29, Irene transitioned into an extra-tropical cyclone near Vermont/New Hampshire border, after remaining inland as a tropical cyclone for less than 12 hours [8]. The path of Irene between August 20 and 28, 2011 is shown in Figure 1.

Description of datasets and their sources

The two principal datasets, their sources, and the preprocessing steps needed to develop the fragility curves were collected using the ORNL VERDE System [9]. Number of customers outaged in each of the more than 500 counties was acquired through the National Outage Map (NOM) system within VERDE maintained at the Oak Ridge National Laboratory (ORNL). The NOM is a near real-time system that collects power outage information at the utility service area level in the U.S., and reports the aggregated data at the county level as a web streaming service. The NOM system collects outage information every 15 minutes from disparate utility websites across the country. The NOM system is part of the real-time visualization and monitoring platform VERDE (Visualizing Energy Resources Dynamically on Earth) developed in 2008 at ORNL [10]. A screenshot of NOM and wind speed/direction as seen on VERDE is shown in Figure 2.

A data archive of temporally sequenced NOM data within the Eastern Interconnection was preserved and outage data extracted between August 21st 2011 and August 30th 2011-the dates Irene was over land in the U.S. The extracted data were processed by applying inclusion thresholds of a minimum one minute gusts of >2 knots and customer outages per county of >1%. This maximum observed outage value was matched with the maximum wind speed observed at the closest METAR station to the reporting county seat [11].

The date and time corresponding to each county's peak outage was then correlated to the recorded one minute wind gust speeds at the closest METAR station to provide a 'customers outage/one minute gust' fragility curve for each county under Hurricane Irene-like conditions. To quality check the METAR data, we correlated wind speeds observed at METAR stations with wind fields collected by the Warning Decision Support System – Integrated Information (WDSS-II) data as recorded through the VERDE system. An example of wind speed visualization within the VERDE system is shown in Figure 3.

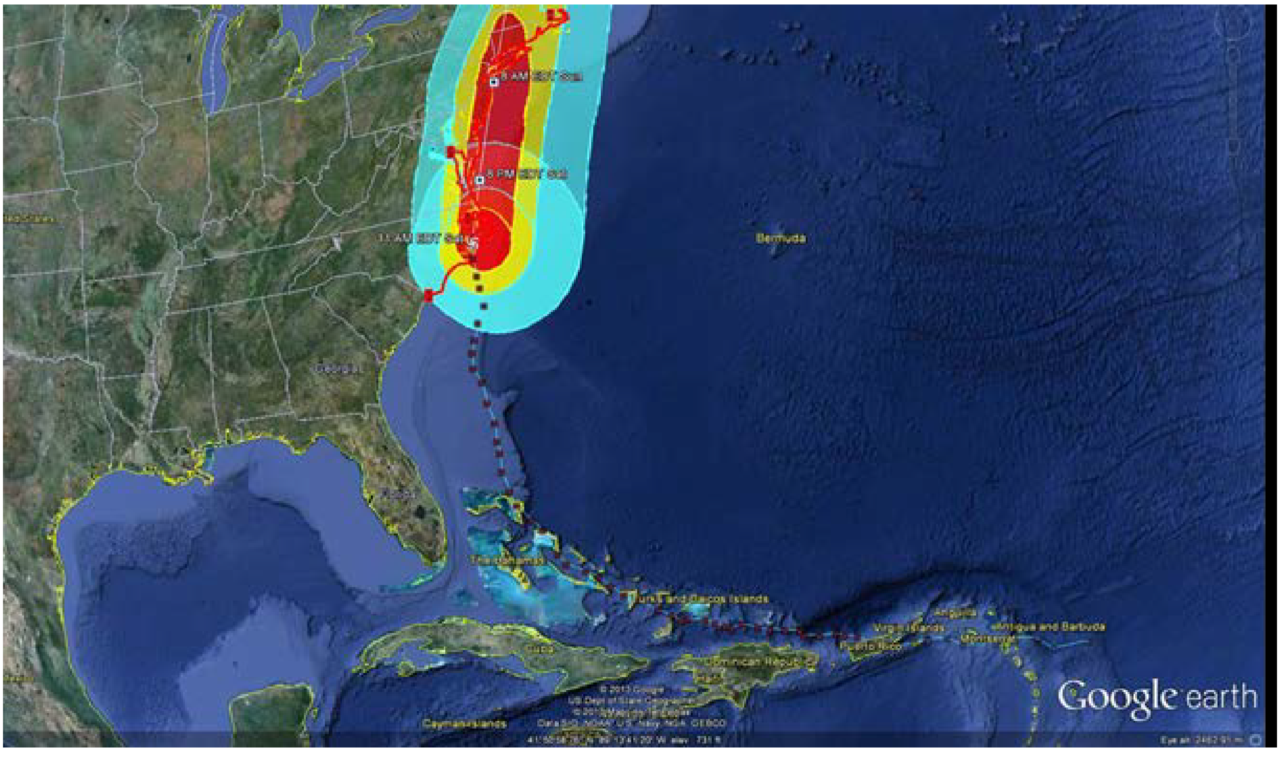

Figure 1: The path of Hurricane Irene between August 20 and 28, 2011 with current location in North Carolina.

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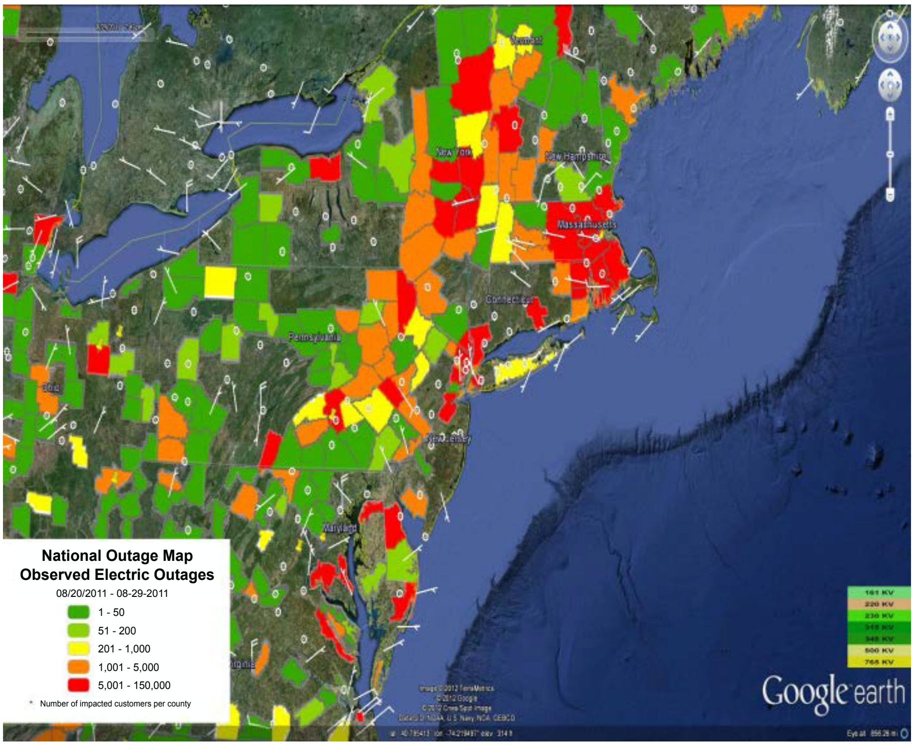

Figure 2: National Outage Map (NOM) data from the VERDE system.

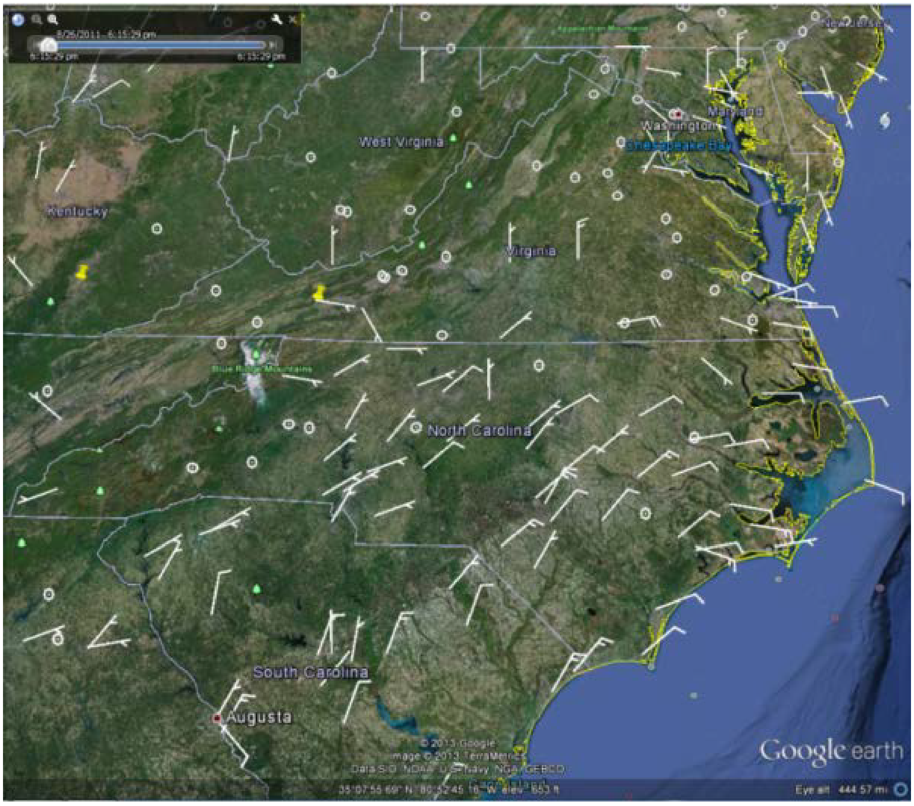

Figure 3: Example of WDSS-II data within the VERDE system.

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Similar to the NOM data, data preprocessing was required to extract the WDSS-II surface observation data and compare it to data in the METAR format. The surface observation data were available in Keyhole Markup Language (KML) file and uses a METAR format to summarize the weather information (a specialized coded format for reporting weather information). We extracted the relevant wind information from the METAR format using a parsing process provided in Microsoft Excel.

Methodology

The methodology used in the creation of fragility curves involves three basic steps: the acquisition of relevant datasets, the preprocessing of these datasets into a spatial format, and the analysis of the county level fragility curves. In this section, we discuss the methodology for constructing the fragility curves.

In this work it was assumed that fragility curves can be expressed in terms of two fragility parameters, wind gusts and customers outaged. Fragility curves have been developed to represent failure as a function of ice accumulation, precipitation, or multiple combinations of these events. NOAA has published power outage likelihoods based on sustained wind speeds, ice accumulation, [12] and flooding. Based on studies by the State of Maryland during Snowmegedden and Hurricane Irene, more than 82% of the power outages were caused by wind acting on substations' above ground connectivity [7].

Fragility curves should be site-specific (i.e., region specific). We chose each region as a county because emergency supplies and responses are organized according to county response plans. For Hurricane Irene, 529 counties were included in the study area. For Hurricane Isaac, nine parishes were included as independent regions. Each county would have specific fragility curves depending upon the state of maintenance, land use features within the county, and local building projects to protect the grid. Therefore, identifying those localities whose robustness can be approximated by a default curve and those with enhanced or degraded robustness is of particular value to emergency planners.

For our purposes, fragility curves will display the bivariate relationship between wind speeds and number of observed power outages at a particular time period and for a given area. To create this relationship, each county in the NOM data layer is joined with the corresponding county in the WDSS-II and METAR data layer using the ESRI ArcGIS software packages. The resulting data product consisted of a county-level vector file with wind speed one minute gust values and maximum observed outages during the nine day study time frame. The generic (bottom-up) electric grid fragility curves based on engineering robustness relationships developed by EPRI is shown in Figure 4. Counties with more robust grids than called for in engineering designs will be found to the right of the design curve. Those counties found significantly to the left of the design curve will sustain more outages than the design basis curve.

Indicated in Figure 4 are the generic thresholds found in the EPRI design defined as the expected percent of customers without power for the corresponding one minute gust wind speed [13]. A polynomial function of different degrees can be fitted to these points to estimate the deviation of the observed data from this curve.

Results

A scatter plot was generated of the data when the wind gust threshold of 2 knots and the outage threshold of 1% of county customers outaged were exceeded. This scatter plot is shown in Figure 5. The engineering design curve was constructed by fitting an exponential to the engineering standards for 25%, 50%, and 100% failure. This engineering correlation followed the exponential function of $y=4.732\ e^{0.0487x}$ where

y=percent of county customers without power

x=one minute maximum wind gusts at nearest METAR station in knots.

The observed correlation followed the form of $y=e^{0.0982x}$ which does not significantly diverge from the engineering curve until more than 30% of the customers are outaged. At high outage levels the statistical approach provides higher outage estimates than the engineering curve.

Through analysis of the QQ plot shown in Figure 6 it was apparent that the population of data points consist of at least two populations. Of the 262 data points composing the data set, all but fifteen counties fall within the 95% confidence interval of the engineered equation, or $y=4.732\ e^{0.0487x}$. For these 15 counties, the counties share common characteristics of low altitude, containing waterways that exceeded

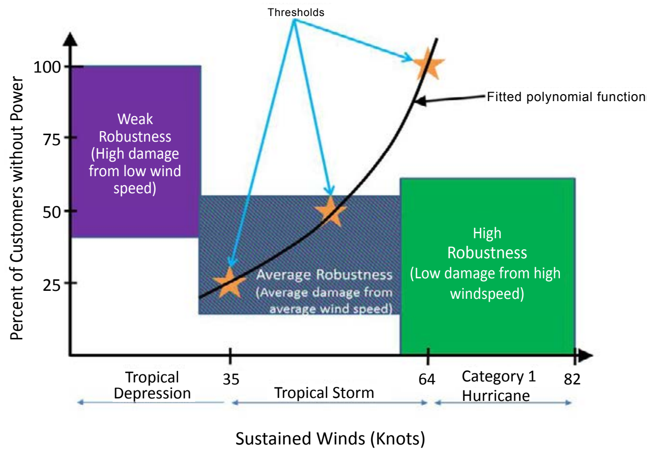

Figure 4: A hypothetical fragility curves. The green box indicates areas with robust power grid; the blue box indicates areas having power grid with average robustness; and the purple box indicates areas with weak power grid.

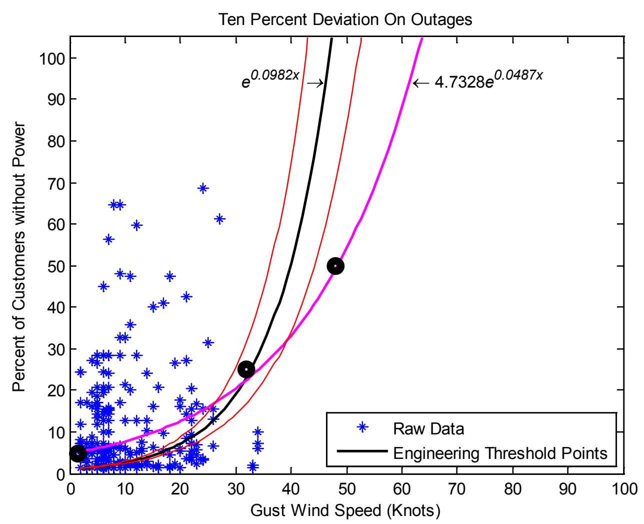

Figure 5: A scatter plot of Hurricane Irene outage vs. wind speed data.

flood stage during the storm and have not employed underground runs of either the distribution system or the transmission system.

For each of these counties, outages were estimated through individual county fragility curves. In aggregate, these counties followed a fragility curve described by the equation $y=5.1519e^{0.0546x}$. For these counties, we recommend a hybrid approach of using utility reported outages where available or the county by county fragility curve.

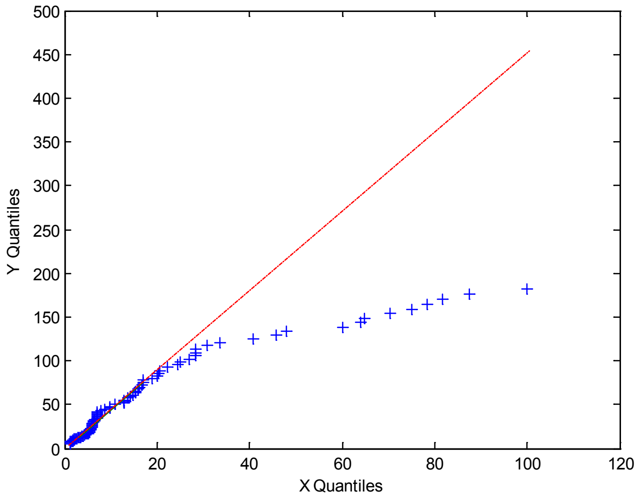

Figure 6: QQ plot for all county aggregated data.

We applied both the engineering fragility curves to Hurricane Isaac as shown in Figure 7. By applying the top down and engineering fragility curves to the observed METAR measured gusts on a customer averaged basis, we forecasted that 35% of Louisiana Entergy customers would lose power at some time during the storm using the top down engineering curve and 48% would be outaged using the engineering curve as the one minute maximum gusts. County by county data ranged from 49 knots (resulting in 80% outaged) to 34 knots (25% outaged). Both estimates compare closely with the Entergy estimate of 43% of their customers outaged during Hurricane Isaac [14].

To further validate the wind based fragility curves we aggregated the observed Hurricane Isaac parishes outage information with the gust velocities observed during the landfall depicted in Figure 7. The comparison of the Isaac curve (blue) did not differ significantly from the Irene curve (orange). This slight displacement upward from Irene is in line with expectations given the 35% average outage based on Irene data and the Entergy estimate of 43%.

These results lend support to the generalized approach of predicting potential outages during cyclone events, but argue for a generalized fragility curve intermediate between the two results. Further research is required to further define the uncertainty factors important to these forecasts.

Conclusions

This work supports the wide geo-spatial application of fragility curves using an indicator weather variable such as one minute wind gust speed. Depicting the relationship between a weather variable

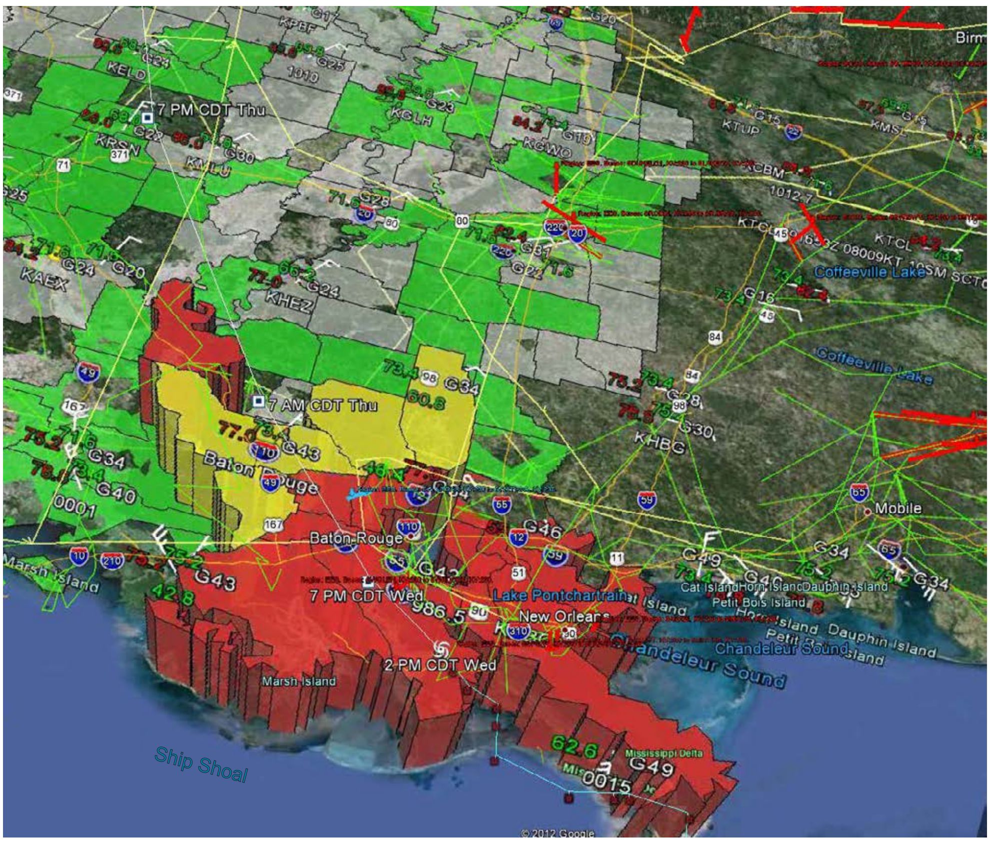

Figure 7: Hurricane Isaac data capture within the VERDE System.

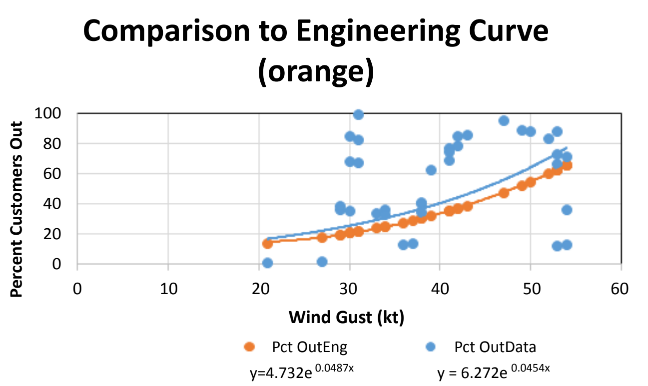

Figure 8: Comparison of Irene aggregated curve (orange) to Isaac fragility curve (blue).

(such as wind speed, gust speed, ice accumulation, precipitation rate) and the observed outages allows emergency response personnel to anticipate recovery resources. This empirical study of the county by county distribution of power outages and one minute wind gust speed during Hurricane Irene supports 'as built' fragility curves (statistical approach) and shows similar skill as engineering 'as designed' (bottom up) fragility curves for forecasting outages during future hurricanes (Figure 8). County specific fragility curves found a population of about 5% of counties that deviated significantly from average behavior. The engineering practices of outlier counties suggest future engineering studies of robustness. Outages in more than 90% of the impacted counties could be anticipated through engineering based fragility curves. The remaining counties could be identified and handled as exceptions through geographic data sets. The counties with increased or decreased robustness were characterized by terrain more or less susceptible to persistent flooding in areas where above ground poles located their foundations. Land use characteristics of the area served by the power distribution system can suggest trends in the 'as built' power grid vulnerabilities to extreme weather events that would be subjects for site specific studies.

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