Predicting Hurricane Power Outages to Support Storm Response Planning

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ABSTRACT

Hurricanes regularly cause widespread and prolonged power outages along the U.S. coastline. These power outages have significant impacts on other infrastructure dependent on electric power and on the population living in the impacted area. Efficient and effective emergency response planning within power utilities, other utilities dependent on electric power, private companies, and local, state, and federal government agencies benefit from accurate estimates of the extent and spatial distribution of power outages in advance of an approaching hurricane. A number of models have been developed for predicting power outages in advance of a hurricane, but these have been specific to a given utility service area, limiting their use to support wider emergency response planning. In this paper, we describe the development of a hurricane power outage prediction model applicable along the full U.S. coastline using only publicly available data, we demonstrate the use of the model for Hurricane Sandy, and we use the model to estimate what the impacts of a number of historic storms, including Typhoon Haiyan, would be on current U.S. energy infrastructure.

INDEX TERMS

Hurricane, storm response planning, outage prediction, outage model.

I. INTRODUCTION

Hurricanes regularly cause widespread and prolonged power outages. Utilities must make decisions about crew and material requests and placement in the days before a storm that are critical to a rapid and cost-effective hurricane response. A number of public and private organizations dependent on electric power or responsible for populations potentially impacted by the approaching storm must simultaneously make a number of decisions about how to prepare for the approaching storm. Where should emergency shelters be opened? How much ice, water, and other emergency response supplies should be stockpiled? Should certain facilities be evacuated in advance of the storm in anticipation of prolonged power outages? Accurate estimates of the extent and spatial distribution of power outages has the potential to significantly improve storm preparation decision-making by allowing decision makers to request the appropriate amount of resources for the anticipated impact and locate them appropriately given the likely spatial distribution of the impacts.

We developed a model to predict the fraction of the population in each census tract that will lose power from an approaching hurricane, with the predictions provided beginning four to six days before landfall and updated approximately every six hours based on updated hurricane track and intensity forecasts. This provides a strong base of information to improve decision-making. Our model is a data analytic, statistical model that is trained with data about power outages during past hurricanes. We start from a utility-specific model we previously developed [1]–[3] and generalize that model to use only publicly available data, making it applicable along the entire U.S. coastline. The focus of this paper is on this spatially generalized hurricane outage prediction model.

The work in this paper builds from Liu et al. [4], [5], the first published statistical models for estimating power outages due to hurricanes. Liu et al. [4], [5] used generalized linear models and generalized linear mixed models and focused on model fit, not predictive accuracy. They also included explanatory variables that could not be directly estimated in advance of an approaching hurricane, limiting their practical use. Zhu et al. [6] also developed outage forecasting models for storms, but focused on short lead-time (one hour and five hour ahead) forecasts. Related work includes Reed [7]. While not specifically focused on hurricanes, this work utilized...
linear regression models to estimate power outages from high wind events in the Seattle area.

Our utility-specific model, also referred to as HOPM (Hurricane Outage Prediction Model), is the result of 8 years of research in collaboration with a large utility in the Gulf Coast region of the U.S. ([1]–[3], [8]–[11]). It has been used operationally by that utility for approximately 4 years. The focus of the HOPM, unlike [6], is longer lead-time forecasts for hurricanes, with outage forecasts beginning 4-6 days in advance of storm landfall, matching the time frame within which utilities must make preparatory decisions. The major advances in this utility-specific model over earlier work are: (1) our models focus explicitly on out-of-sample predictive accuracy and achieve higher predictive accuracy than previous models, (2) we leverage advanced ensemble data mining methods to improve predictive accuracy, and (3) we use a wider range of explanatory variables to capture more characteristics of storms and service areas while also using only input variables that can be reasonably estimated in advance of a hurricane. This modeling work thus builds from earlier work by substantially improving both the predictive accuracy and the practical usefulness of the model.

As discussed above, we also developed a more general version of HOPM for the entire Eastern Seaboard and Gulf Coast, and we used this model for predicting outages caused by Hurricane Sandy\(^1\) (2012). This work is first reported in this paper, and it is the focus of this paper. The main advance of the spatially generalized model, referred to as SGHOPM (Spatially-Generalized Hurricane Outage Prediction Model) in this paper, is the use of only publicly available data as inputs. This eliminates the reliance on privately held utility data, allowing the model to be used over a wider area served by multiple utilities. This is particularly important for supporting multi-utility coordination and emergency response planning by private and government organizations. There is a trade-off though, as will be discussed below. The utility-specific model, HOPM, is more accurate because it can rely on a richer dataset. However, the spatially generalized model, SGHOPM, provides useful information over a much wider geographic area while still maintaining strong overall predictive accuracy and using only publicly available data.

In this paper, we describe the data needed for model development for both the HOPM and SGHOPM, we then describe the model development and validation process before discussing how the model is used in practice and summarizing model use to date. We then present the results of using the model for “what-if” analysis to evaluate the impacts of past and hypothetical hurricanes on various tracks in the U.S. Finally, we describe the potential for generalizing the modeling approach to other types of weather events and close with a discussion of the potential benefits of this type of model for hurricane preparation decision-making.

\(^1\)Note that we will refer to Sandy as “Hurricane Sandy” throughout its track. It did merge with a non-tropical system, and the correct name to apply to the storm after that point is subject to debate. We will refer to the storm as a Hurricane throughout its track.

II. DATA USED

Past research has suggested that a large number of factors are useful in accurately predicting power outages during hurricanes [1]–[3], [8]–[11]. In our HOPM model, we included a number of explanatory factors, including the customer density, the number of poles, switches, and transformers and miles of overhead and underground line in each area, a number of local geographic characteristics including topographical factors and land use, climate-related factors including pre-storm soil moisture levels and long-term precipitation, and local characteristics of the hurricane winds estimated from a hurricane wind field model. The development of SGHOPM started from the development of HOPM. HOPM was based on data provided by a utility company serving the Gulf Coast region of the United States and on publicly available data. Their service area was divided into 12,000-foot (3.66 km) by 8,000-foot (2.44 km) grid cells, and the data was collected at the level of these grid cells. The SGHOPM relies on a significantly reduced set of the publicly available covariates used in HOPM, and census tracts are used as the unit of analysis. We generalized the HOPM to other areas by iteratively removing utility data, using cross-validation to ensure strong predictive accuracy [1]–[3], [9]–[11]. Below we provide a brief overview of the data used in HOPM because this forms the starting point for SGHOPM. Additional details of these variables are available in our earlier work [1]–[3], [9]–[11].

A. RESPONSE VARIABLE

The response variable for HOPM is the number of customer meters without power in each grid cell. For our partner utility, this data comes from a combination of customer call-in data a model of the electric power system that estimates which customers will be without power given the activated protective devices. The SGHOPM is developed and trained using this response data as well, though it is scaled to a census tract level. We also had spatially-detailed outage data, also from a combination of customer call-in data and a utility-run model of the power system, for adjacent states which was used to validate our models. Similarly, we collected outage data during and immediately following Hurricane Sandy from Department of Energy situation reports and the web sites of a subset of the affected utilities.

B. HURRICANE VARIABLES

To estimate hurricane wind speeds for both the HOPM and SGHOPM, we used a parametric wind field model, the same model used in previous work [1]–[3]. This model was validated against actual time-varying wind speeds in the Gulf Coast region. Our model used the maximum 3-second wind gust and the duration of time with wind exceeding 20 ms\(^{-1}\) for each grid cell. 20 ms\(^{-1}\) was chosen as the cutoff because it is approximately the design wind speed for wooden poles [12].
C. LAND COVER
To allow for the possibility of different outage rates for different types of land use and land cover, we used National Land Cover Database (NLCD) land use/land cover data [13]. We aggregated the NLCD data into eight land use classes (water, developed, barren, forest, shrub, grassland, planted/cultivated, and wetland), and the fraction of each grid cell that is associated with each land use class was used in the model.

D. SOIL AND PRECIPITATION VARIABLES
As discussed in Han et al. [1], [2], we included measures of soil moisture, long-term drought, and mean annual precipitation, each at the grid cell level. Soil moisture levels were thought to impact tree and pole stability. We simulated soil moisture at 1/2 degree (latitude/longitude) resolution with the Variable Infiltration Capacity (VIC) model [14], [15]. Soil characteristics were extracted from the State Soil Geographic (STATSGO) database. Additional details are available from [1], [2]. Vegetation type near power lines can have an impact on outages during storms, but vegetation type is difficult to measure at that local scale across an entire multi-state area. As a proxy, we included mean annual precipitation, one of the drivers of differences in vegetation type [16]. Mean annual precipitation (mm) was calculated at a grid cell level based on daily precipitation data from 1915 through 2004 from the National Oceanic and Atmospheric Administration (NOAA) Cooperative Observer (COOP) network. Finally, we used the Standardized Precipitation Index (SPI), a statistical measure of precipitation compared to normal conditions as a measure of local drought or wetness pre-storm to capture the potential for drought conditions that lead to stress in trees, potentially making them more prone to failure. Additional details on these variables are available from Han et al. [1], [2].

E. TOPOGRAPHIC VARIABLES
We collected a number of topological characteristics, including the mean, standard deviation, minimum, and maximum of elevation, aspect ratio, and compound topographic index. Again, details are available in Han et al. [1], [2].

III. MODEL DEVELOPMENT
Both HOPM and SGHOPM are trained to power outage data from 10 past hurricanes. These are ensemble predictive models, discussed in more detail below. Developing statistically complex models such as these requires selecting the type of model, the appropriate set of predictor variables, and validating the model. This process was iterative in nature, with different models and sets of predictor variables compared based on holdout validation analysis. A critical distinction here is model fit versus model predictive accuracy. A measure of model fit such as $R^2$ for a linear regression model or mean square error on a training data set, measures how well a model can match patterns in a past data set. This does not guarantee strong predictive accuracy for events not in the training set [17]. Achieving strong predictive accuracy requires careful out-of-sample validation to balance the bias-variance trade-off. Measures of model fit generally do not do this well [17]. In this section we describe the type of statistical model we use. We then discuss our model validation approach in detail.

A. STATISTICAL MODEL
We used a Random Forest as our predictive model based on the results of Nateghi et al. [3] where we found that model yielded substantially lower out of sample prediction errors for HOPM than other models such as generalized linear models [1], [4], generalized additive models [2], and the hybrid data mining-regression approach we previously developed [11]. A Random Forest is a flexible non-parametric ensemble data-mining approach developed by Breiman [18]. A Random Forest consists of a large number of regression trees, each developed through recursive binary partitioning of the data. Bootstrap resamples are drawn from the data. For each sample, a regression tree is grown, randomly selecting a subset of the possible explanatory factors to use as a splitting variable at each branch in the tree. The trees in the forest are then approximately uncorrelated and unbiased [17]. The prediction from the forest is the average of the predictions from the individual trees in the forest, leveraging model averaging with approximately uncorrelated, unbiased ensemble members to achieve variance reduction for the overall prediction. Further details of this approach are available from Nateghi et al. [3], [19].

We couple the Random Forest prediction model with a Bayesian mass-balance multiscale model to post-process the statistical model predictions. This model, developed by Reilly and Guikema [20], is an explicit probabilistic approach for scaling count data across different spatial levels, and it is used for two main purposes. The first is to provide outage estimates at different spatial resolutions. The native resolution of the Random Forest outage prediction model is either the utility grid cells for HOPM or census tracts for SGHOPM. In many cases, decision-makers and the public would be interested in predictions at coarser scales such as metropolitan areas or even larger regions. The Bayesian multiscale model accomplishes this in a way that accounts for the underlying spatial patterns by placing explicit but non-informative prior distributions on counts at each level and then updating these with the predicted outages. The second reason for using the multiscale model is to spatially smooth the SGHOPM predictions in a way that is consistent with the underlying data. This is important for the SGHOPM because it contains less spatial information than the original HOPM model and hence the predictions are less spatially coherent than might be expected. The multiscale model smooths the predictions at a given spatial resolution while maintaining mass-balance (i.e., not changing the total number of predicted people without power).
B. MODEL VALIDATION PROCESS

The purpose of models such as HOPM and SGHOPM is prediction for future events, making predictive accuracy, often termed generalization performance, the critical factor in model selection and development. The standard approach for estimating generalization performance, more formally defined as the expected prediction error for an event not in the training data, is cross-validation, and this is the approach we used.

We first iteratively trained and validated SGHOPM for the state in which our partner utility is located and for which we had detailed training data using random holdout cross validation. Because the utility wishes to remain anonymous, we will term this state “State A.” We did 30 replications of holding out a randomly selected 20% of the training data, trained the model to the remaining 80%, and then predicted the power outages for the withheld 20%. We used this approach to compare predictive models with different combinations of explanatory variables. This reproduced the results of the Nateghi et al. [3] Random Forest outage model, but with the detailed information about the power system and power system maintenance practices used by Nateghi et al. [3] dropped from the analysis so that only publicly available covariates were used. The random holdout testing evaluated the predictive accuracy of the model in out-of-sample test cases within the service area for which the model was developed but without the private utility-specific data. During this process we also developed multiple models, differing in the input variables used, and used the cross-validation to choose the simplest model with acceptable cross-validation estimated prediction error. In the end, the simplest model that produced adequate prediction error used only the 3-second gust wind speed, duration of strong winds, and customers per area as inputs.

We then trained the SGHOPM with the combination of explanatory factors giving the lowest prediction error using all training data from State A and used this trained model to predict the outcomes (fraction of population without power at the census tract level) for specific storms in two nearby states where we also had spatially detailed outage data. We refer to these states as State B and State C.

As a final test of the model, we then predicted outages in real time as Hurricane Sandy was approaching the U.S. and compared these forecasts with estimated realized outages after the event. Figure 1 summarizes this process, emphasizing the important roles that validation has in this modeling. Each of these steps is described below.

Table 1 shows the results of the SGHOPM validation testing for both random holdout cross-validation and storm-state pair cross-validation. We see that the predictive accuracy is strong for the random holdout validation; the model offers strong predictive accuracy for State A. The total error in predicted fraction of customers without power (i.e., |predicted fraction out – actual fraction out|) was < 0.001. When the model was trained with all data from State A and then used to predict the impacts of specific storms in neighboring states A and B, the results were also strong, with errors less than 0.02 (2%), except for three cases. For Hurricane Ivan impacting State C, the model predicted 41% of customers would be without power, but the actual fraction without power was 13%. In this case, only the edges of Hurricane Ivan impacted State C, exposing that state to only the weaker, more uncertain outer bands of the storm. Similarly, for Hurricane Dennis, which had a similar track to Hurricane Ivan, impacting State C, the model predicted 39% without power, but the realized outage rate was 24%. Again, this storm impacted State C only with its weaker edges. The best comparison for these cases are the predictions for Hurricane Katrina in States B and C and Hurricane Ivan in State B. In these cases, the model accuracy was strong (error < 2%). These were all cases of a strong hurricane tracking more directly over the area being modeled. There is less localized variability of the wind impacts in these cases – the impacts are significant across the area. For State C for Hurricanes Ivan and Dennis, the area modeled was on the outer edges of the storm, leading to more localized variability in wind impacts. Our results suggest that the model does well for strong hurricanes impacting an area but loses some accuracy on the outer edges of the storm.

For Hurricane Frances impacting State C, the model predicted 1% of customers would be without power whereas the realized outage rate was 30%. In this case, the hurricane
TABLE 1. Validation results for the SGHOPM model, both within-state random holdout validation and cross-state comparative validation.

<table>
<thead>
<tr>
<th>Model Validation Scenario</th>
<th>Fraction Without Power</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training state 30-fold cross-validation</td>
<td>Predicted</td>
</tr>
<tr>
<td>Trained in training state on all storms, predicted Katrina in State B</td>
<td>0.51</td>
</tr>
<tr>
<td>Trained in training state on all storms, predicted Katrina in State C</td>
<td>0.02</td>
</tr>
<tr>
<td>Trained in training state on all storms, predicted Ivan in State B</td>
<td>0.39</td>
</tr>
<tr>
<td>Trained in training state on all storms, predicted Ivan in State C</td>
<td>0.41</td>
</tr>
<tr>
<td>Trained in training state on all storms, predicted Dennis in State C</td>
<td>0.39</td>
</tr>
<tr>
<td>Trained in training state on all storms, predicted Hanna in State C</td>
<td>0.06</td>
</tr>
<tr>
<td>Trained in training state on all storms, predicted Jeanne in State C</td>
<td>0.03</td>
</tr>
<tr>
<td>Trained in training state on all storms, predicted Isidore (2002) in State C</td>
<td>0.02</td>
</tr>
<tr>
<td>Trained in training state on all storms, predicted Cindy in State C</td>
<td>0.01</td>
</tr>
<tr>
<td>Trained in training state on all storms, predicted Frances in State C</td>
<td>0.01</td>
</tr>
</tbody>
</table>

*These values are the mean across the 30 random holdouts. That is, the predicted and actual fractions without power are the means of the 30 realizations. The error reported in the table is the mean of the 30 calculated errors, one per holdout.

was not particularly strong as it impacted this state, but it was slow-moving and produced high amounts of rainfall. SGHOPM does not explicitly model outages due to rainfall, instead, focusing on primarily the wind hazards associated with hurricanes. The best cases for comparison here are Hurricanes Jeanne, Isidore, and Cindy in State C. In all of these cases, the storms moved more quickly through State C, producing less prolonged, intense rainfall. These results suggest that SGHOPM will not be as accurate for storms that move slowly through an area producing heavy rainfall. In an ongoing study we have found that total precipitation is a valuable predictor variable for slow-moving events in areas with heavy rainfall but relatively low gust wind speeds [26]. The slow-moving, heavy rainfall nature of Hurricane Frances in this state likely explains the difference in predictive accuracy, and incorporating rainfall into SGHOPM is an active area of research.

IV. RESULTS FOR HURRICANE SANDY

The trained SGHOPM was used to estimate the fraction of the population without power for each census tract in the area potentially impacted by Hurricane Sandy. This was done in real time for Hurricane Sandy as the storm progressed up the coast, with the estimates being updated for each of the 6 hourly track and intensity updates. For each forecast update, the official track and intensity estimates from the National Hurricane Center (NHC) [21] were used to run our hurricane wind field model. The maximum 3-second gust wind speed and duration of winds above 20 ms\(^{-1}\) at the centroid of each census tract estimated by our model was used together with census tract population as a proxy for number of customers as the input for the statistical outage models. The outage model then yielded an estimate of the fraction of the population without power for each census tract.

We assessed the accuracy of SGHOPM for Hurricane Sandy on the basis of a combination of U.S. Department of Energy (DOE) data and outage data reported directly on utility web pages. We gathered information on the peak number of outages and the number of customers in different areas from DOE Situation Reports and directly from utility public web pages in those cases where enough information was reported. There is an important distinction to note here. Our model estimates the cumulative population without power, i.e., total number of people without power during a storm. Most utilities and the DOE report peak outages. That is, they report the most that they thought were without power at any given point in time during the storm or its restoration process. In working with utilities, it has become clear this is an underrepresentation of the total number that will ultimately be recorded as being without power. This occurs for several reasons. First, restoration efforts in the early part of the storm before it becomes too dangerous for repair crews to operate do lead to some customers being restored early in the storm in many events. These customer outages then do not count in a peak outage estimate. Second, some customers lose power several times during a storm as their power is restored, lost, and then restored again. These customers count only if they were out when the peak number of outages...
FIGURE 2. Power outage forecasts for Hurricane Sandy at 84, 60, 36, 12, and 0 hours before landfall. Outage forecasts are at the census tract level.

occurred, and they only count once. Third, many utilities have an imperfect estimate of whether or not a meter is without power. Without smart meters, many utilities use a combination of customers calling in to report outages and, in some cases, predictive algorithms based on system topology to determine if a customer is likely without power. In some cases, this leads to a significant difference between peak and cumulative totals because some customers are marked as having their power restored when, in reality they have not had their power restored. This leads to a second entry (“outage”) in the outage database for this customer, leading to a difference between peak and cumulative outage totals. We chose to report cumulative outages, as this is the measure of most interest to the public and public planners. That is, we seek to answer the question “how many people will lose power as the result of this storm?” and not “what is the most that will be without power at any one point in time as a result of this storm?” This does, however, make direct comparison with DOE-provided numbers difficult.

Figure 2 shows the results of running our outage forecast model 84, 60, 36, 12, and 0 hours before landfall. At 84 hours prior to landfall, the storm was forecast to take a more southerly track than was later realized, and this is reflected in the map of forecast outages. There were significant outages forecast for the northern edges of Virginia and relatively few forecast for Long Island. At 60 hours, the storm intensified and began to move more quickly, leading to a track that would penetrate much further inland while maintaining high wind speeds. This is reflected in the model output with some areas along the northern edge of New York State having forecasts of 25% or more of customers without power. At 36 hours the forecast track began to converge towards the ultimately experienced track. Although the forecast track did gradually shift further north in subsequent forecasts, the changes were not as dramatic. By the time of landfall, the model forecasts suggested widespread impacts from Long Island through the Mid-Atlantic region and well inland in Pennsylvania.

Our final best estimate as Hurricane Sandy transited the mid-Atlantic region of the U.S. was that there would be 10 million customers without power. We compared our outage totals by state to those from the DOE Situation Reports. Our model estimates were within 8% for New York, Pennsylvania, Massachusetts, Rhode Island, and Virginia. However, our model substantially overestimated outages in Maryland and Delaware and underestimated outages in Connecticut. Based on post-storm analysis of the wind data, the overestimate for Maryland and Delaware is expected. Hurricane Sandy was forecast to have high wind gusts in this area, even shortly before landfall. It was a substantial storm, but it had a more asymmetric wind field than most hurricanes, with substantially weaker winds on the south side of the storm than would have been expected for a more typical wind field. Because our wind model did not account for this, it overestimated outages on the south side of the storm. The situation in Connecticut is somewhat less clear. The wind field was stronger on the
north side than we would have expected prior to the storm, but the model estimated the number of customer meters without power reasonably accurately for two neighboring states, Rhode Island and Massachusetts. The difference may be the high level of surge damage in coastal Connecticut, but this is a hypothesis that requires further investigation. Overall, the model yielded a reasonably accurate estimate of the total number of outages approximately 4 days in advance, and the estimated spatial pattern was reasonably accurate as well except at the edges of the storm. This is consistent with the performance seen in the holdout analysis where the model estimated outages well in the most heavily impacted areas but struggled a bit more on the edges of the storm.

V. USE FOR ‘WHAT IF’ ANALYSIS FOR HISTORIC STORMS AND POTENTIAL FUTURE STORMS

The SGHOPM also offers a strong “what if” capability; it can be run for past storms with current population distributions or for hypothetical future storms on specified paths with specified intensities to estimate what the impacts of these storms would be. This can help utilities, government agencies, and private organizations better understand and plan for outages they may face in the future. To demonstrate this capability and to examine the potential impacts of past storms if they were to occur today, we ran the SGHOPM model for 9 historic hurricanes using the best track and intensity estimates from the National Hurricane Center: the Galveston storm of 1900, Camille (1969), Andrew (1992), Isabel (2003), Ivan (2004), Katrina (2005), Rita (2005), Ike (2008), and Irene (2011). We also included Sandy (2012) for comparison. For each, we used the best estimate of track and intensity (NCDC) together with 2010 population and estimated outages with the model. To examine the potential outages from a substantially stronger storm, arguably the strongest on record, we also used preliminary estimates of the track and intensity of Typhoon Haiyan, superimposed over four historic tracks in the U.S., the tracks of Hurricanes Andrew, Katrina, Ike, and Irene, and estimated outages for each of these with the model. In doing this, we maintained the same forward speed of the storm as the historic track. That is, the storm was assumed to cover the same distance between each 6-hour location, but the distance was imposed on top of the historic track. Note that this is likely not realistic due to differences in surface roughness and sea surface temperatures between the U.S. and the islands of the Philippines. However, it does serve to demonstrate the what-if use of the model, and it gives an estimate of what a particularly bad hurricane could do if it were to occur.

Table 2 summarizes the outage estimates for each of the historic storms as well as for Typhoon Haiyan on each of the four historic tracks. The results are expressed relative to the predicted outages for Hurricane Irene, for which the model estimates approximately 6.5 million people without power. For example, the model suggests that Hurricane Isabel occurring with the 2010 population distribution would lead to approximately one third as many outages as Hurricane Irene.

Table 2. Predicted number of people without power for historic storms as well as for Typhoon Haiyan on four historic tracks in the U.S. Outages are expressed relative to the number of outages predicted for Hurricane Irene.

<table>
<thead>
<tr>
<th>Storm</th>
<th>Predicted Population Without Power Relative to Hurricane Irene</th>
</tr>
</thead>
<tbody>
<tr>
<td>Isabel</td>
<td>0.35</td>
</tr>
<tr>
<td>Rita</td>
<td>0.60</td>
</tr>
<tr>
<td>Ivan</td>
<td>0.67</td>
</tr>
<tr>
<td>Camille</td>
<td>0.72</td>
</tr>
<tr>
<td>Ike</td>
<td>0.82</td>
</tr>
<tr>
<td>Irene</td>
<td>1.00</td>
</tr>
<tr>
<td>Katrina</td>
<td>1.04</td>
</tr>
<tr>
<td>Andrew</td>
<td>1.21</td>
</tr>
<tr>
<td>Galveston</td>
<td>1.27</td>
</tr>
<tr>
<td>Haiyan-Andrew track</td>
<td>1.64</td>
</tr>
<tr>
<td>Haiyan-Katrina track</td>
<td>2.73</td>
</tr>
<tr>
<td>Sandy</td>
<td>2.92</td>
</tr>
<tr>
<td>Haiyan-Ike track</td>
<td>3.83</td>
</tr>
<tr>
<td>Haiyan-Irene track</td>
<td>6.91</td>
</tr>
</tbody>
</table>

The worst case of those tested was Typhoon Haiyan on the track of Hurricane Irene, with nearly 7 times as many outages predicted as were predicted for Hurricane Irene.

Figures 3 and 4 show maps of the predicted fraction without power for each of the storms shown in Table 2. Together with Table 2, we see that while Hurricanes Irene and Sandy were very destructive storms and led to large numbers of outages, a storm such as Haiyan would be predicted to cause substantially more widespread outages, up to 7 times as many outages as in Hurricane Irene. That a storm this strong would be worse is not surprising, but the model allows us to estimate how much worse outages might be if it happened. The ratio of predicted outages from Typhoon Haiyan on a given track to the predicted outages of the actual storm on that track varies: 1.37 for Hurricane Andrew, 1.86 for Hurricane Katrina, 2.64 for Hurricane Ike, and 6.92 for Hurricane Irene. These ratios follow the original storm intensities, with the increment from the original storm to the Haiyan estimates being greatest for the weakest historic storm (Irene) and smallest for the strongest of the historic storms (Andrew). Having damage estimates for potential future storms can help emergency response planners and elected officials by offering scenarios to consider in their long-term planning and to provide scenarios for use in training exercises.

VI. MODEL LIMITATIONS

The model (SGHOPM) discussed above worked well for Hurricane Sandy, and the utility-specific model (HOPM) has been strongly validated for a number of hurricanes (see [1]–[3]). However, there are several limitations of the models that could be addressed in future research. First, relative to HOPM, SGHOPM uses a substantially reduced set of input variables. For example, it does not include utility-specific data, and it does not include soil moisture data.
Adding variables such as soil moisture conditions could help to improve the predictive accuracy of SGHOPM, though at the cost of increased complexity. Additionally, neither HOPM nor SGHOPM explicitly considers estimates of hurricane surge inundation. We have a version of HOPM that does contain estimates of surge inundation as an input variable [22], but we found that adding surge did not improve the predictive accuracy in a statistically meaningful way. Surge inundation is correlated with other inputs such as wind speed and duration of strong winds, and adding it did not improve the model given that the other storm parameters were already accounted for, at least for the Gulf Coast region. It remains to be seen if this is the case for other portions of the coast where surge inundation is complicated by the presence of more complex coastlines and bays (e.g., mid-Atlantic and Northeast of the U.S.). Finally, the focus of both HOPM and SGHOPM is on power outage forecasts several days before a storm makes landfall. This contrasts with [6], where the focus is on short lead-time forecasts. Because of this, information such as radar-derived rainfall just before landfall are not included in SGHOPM or HOPM. For short lead-time forecasts this information may help to improve the outage estimates.

VII. POTENTIAL FOR MODELING OTHER TYPES OF STORMS

We have so far used our model only for tropical cyclones. However, the modeling approach could be used to develop predictive models for other types of weather events impacting power systems including ice storms, snowstorms, and straight-line wind events. Some work has been done on ice storms [23] and straight-line wind events [24]. However, previous work in this area uses statistical models (e.g., generalized linear regression) that we have found to have lower predictive accuracy in the hurricane setting than more flexible, ensemble predictive models [2], [3], [25]. There has also been less exploration of a wide range of potential predictor variables in these settings than in our recent work on hurricane outage prediction, particularly our work with the HOPM model. We hypothesize that some of the variables used in HOPM, particularly those related to pre-storm soil moisture and soil type, may substantially improve predictive accuracy. However, the main challenge for many types of weather events beyond hurricanes is the uncertainty in the weather predictions at lead times long enough to make outage forecasts useful for improving decision making. Consider ice storms for example. Small meteorological changes can
lead to substantial changes in ice loads on overhead power lines, and these lines are very sensitive to small changes in ice loads. This amplifies the uncertainty in ice load forecasting, leading to the potential for wide uncertainty bands in power-outage forecasts for icing events. For straight-line wind events it may not be possible to form spatially strong predictions with enough lead time for some types of events and locations within the U.S. If an outage forecasting model is to have value, the weather event needs to be forecasted with enough lead time to allow decision makers to make use of the forecasts to improve decision making. While there is significant potential to use this approach for other types of weather events impacting power systems, more research is needed, particularly on incorporating uncertainty into long lead-time forecasts for weather events such as thunderstorms and ice storms.

VIII. SUMMARY

Hurricanes can cause significant, wide-spread power outages in the U.S., effecting population both through direct loss of power and loss of other services and infrastructure dependent on electric power. Power system emergency response managers, operators of power-dependent utilities, government and private sector emergency responses, and individuals in the potentially impacted area make a number of preparedness decisions in the days before the storm that would benefit from having accurate estimates of the total number and spatial distribution of power outages. In this paper we have summarized the development and results from a power outage forecasting model appropriate for use along the entire U.S. Eastern Seaboard, the Spatially Generalized Hurricane Outage Prediction Model (SGHOPM). The model has been shown to provide accurate estimates of power outages in the days before a storm makes landfall, particularly for large, strong storms impacting an area. As a result, this model offers the possibility of an improved information source to support emergency preparedness decision-making by power utilities, other utilities dependent on electric power, and public and private emergency response organizations.

REFERENCES


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