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Improving Emergency Storm Planning using Machine Learning

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Abstract—Extreme weather events pose significant challenges to power utilities as they require very rapid decision making regarding expected storm impact and necessary storm response efforts. In recent years National Grid has responded to a large number of events in its Massachusetts service territory including Tropical Storm Irene and Hurricane Sandy. National Grid, along with MIT, has built a statistical model which predicts localized interruption patterns based on weather forecasts, asset information, historical damage patterns, and geography. National Grid expects that this will become an important tool in its emergency response preparations. This paper will discuss the predictive model which will aid National Grid in its preventative emergency planning efforts. A machine learning predictive algorithm was built by considering physical properties of the network, historical weather data, and environmental information to predict outages, and ultimately damage, based on weather forecasts. The machine learning algorithm will continuously improve in granularity and accuracy through its continued use and the incorporation of additional information. As a data-driven model it provides an invaluable tool for decision making before a storm, which is currently motivated primarily by intuition from industry experience.

Index Terms—electric power distribution, decision making, emergency response, reliability, machine learning algorithms, power system restoration, weather.

I. INTRODUCTION

DUE to the unpredictable nature of severe weather events, emergency storm planning is a particularly challenging problem. The resulting damage to electrical networks may prompt over a week's worth of restoration work and even longer customer interruption times. In just the past two years New England was hit by both Hurricanes Sandy and Irene, coupled with ice storms and massive blizzards such as Nemo. The interruptions caused by these events were of such a large scale that in some regions of Massachusetts hundreds of thousands of customers were out of power, some for up to ten days. Though this is detrimental to both electricity providers and consumers, few analytical studies have been conducted

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with the intent of improving emergency planning. Much of the previous work has been done in either predicting damage or restoration times, but rarely both in conjunction. Our paper addresses this issue by introducing a tool that aids the decision making process of an electricity distributor ahead of a storm. By understanding the expected impact on power distribution assets, National Grid can take a much more data driven approach to aid its storm response planning. Furthermore, this creates opportunities for long term asset management and optimal crew allocation during storm situations.

II. DATA

In order to construct the predictive damage model, we built a database from several distinct sources. Since our goal is to forecast damage to the network based on the anticipated weather, we need to understand the network structure and its vulnerabilities during various types of storms. To accomplish this we collected data on the following three categories: physical network properties, historical weather logs and historical interruptions during different severe weather events.

A. Physical Network Data

To predict interruptions across an electrical network, we first needed to acquire data describing its structure. By using data from National Grid, an investor owned utility company in New England, we were able to construct an interactive mapping of their network across the state of Massachusetts. This included information on 1362 circuits and 60,000 devices, such as reclosers and fuses, which serve approximately 1.2M customers across the state.
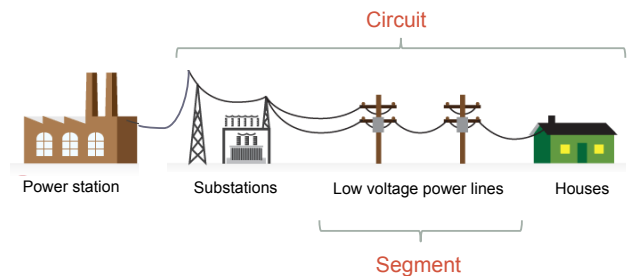

Fig. 1. A given segment in the electrical network.

We began this mapping by attaining a physical description of the 280,000 segments that make up the state-wide network. As shown in Fig. 1, a segment is a grouping of consecutive poles and wires that all share the same physical properties.

It may contain a device as described above, but does not necessarily need to. The provided list of physical properties included 35 parameters such as: wire insulation, above or below ground wiring, pole age, upstream and downstream segment coordinates, framing and length. By utilizing all of this information we were able to create a connected graph of all the segments for each given circuit.

Within this network we now define a new term, known as an asset. An asset is a collection of segments originating at a given device and includes all of the segments downstream until the next device. To clarify, should that asset's device open due to a short circuit, all customers serviced by the network beyond this point would be out of power. Our problem then becomes predicting the probability of an outage on each asset. As explained in the next subsection, this new definition is necessary to allow modeling between historical interruption logs and the physical electrical network. We aggregated assets for a prediction on a 2 by 2 square mile area, as represented by Fig.2.
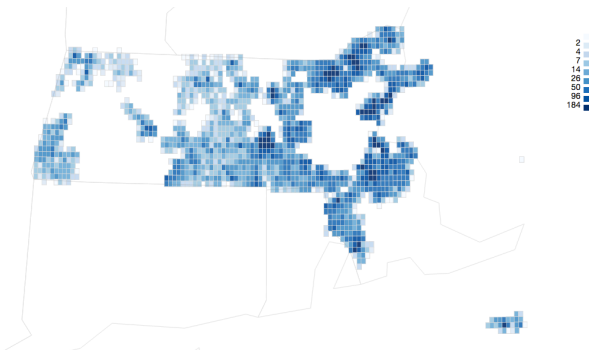

Fig. 2. This mapping displays the concentration of assets across Massachusetts. The darker blocks represent a higher number of assets in a 2 by 2 square mile area.

In order to also encompass external properties surrounding the network we overlaid a geographical land cover mapping that added tree coverage, elevation and population density information to each asset. These factors were crucial to capture as they are very likely to influence customer interruptions, given severe weather factors such as high wind speeds or heavy precipitation.

B. Historical Weather Data

Our primary objective is to identify future damage based on weather reports before a storm. However, obtaining historical weather forecast data proved to be a challenge, so we initially used historical weather data at the actual time of the storm. This allowed us to identify significant factors and test the model's predictive accuracy when it was given ideal retrospective information. The historical weather data contained approximately 5.2M hourly logs over the course of severe weather events between 2008 to 2012. These logs came from 234 stations across Massachusetts and contained records of 20 weather parameters including: time, wind speed, temperature, pressure and humidity. We used a triangulation algorithm to assign the weather to a given asset. This algorithm created

a weather vector for each asset by averaging the numerical hourly factors from all the weather stations within a 5 mile radius.

However, this data was not sufficient for our desired prediction, as weather typically deviates a great deal from forecasts. We therefore acquired historical weather forecast data that was comprehensive, but of less granular quality. Instead of hourly logs, the model incorporating forecasts used daily logs. There are only 20 stations from which we obtained forecast information, decreasing our geographical coverage by a factor of 10. Furthermore, there was a great deal of forecasting error depending on how many days before the event the data was collected. The greatest discrepancy between the two data sources is the lack of key weather features in the forecast logs. Of the five most significant factors (as identified by the model during the training on the historical weather logs), four were not available in the forecasting logs.

C. Historical Customer Interruption Data

The final piece in building our database consisted of interruption logs from the weather events of interest. These were records from 6 major storms and two years' worth of minor weather incidents. The large storms resulted in about 6,000 outages and 1.1M customers out of power (see Table I), and this information was supplemented by approximately another 25,000 outages from the minor events. This indicates that only approximately 2% of assets failed during severe weather, emphasizing the challenge of predicting due to such a small scale.

TABLE I
STORM DATA

Storm Name	First Interruption	Days	Interruptions	Customers Out
Winter Storm Dec 2008	12/12/08	10	1,784	504,495
Wind Storm Feb 2010	02/24/10	6	615	174,848
Winter Storm Dec 2010	12/26/10	4	444	124,073
Tropical Storm Irene 2011	08/28/11	8	1,715	501,767
Winter Storm Oct 2011	10/29/11	11	2,746	523,552
Hurricane Sandy 2012	10/29/12	7	1,466	296,735

III. PREDICTIVE DAMAGE MODEL

Our tool consists of a model which is a machine learning algorithm that predicts the damage expected on a network based on the weather forecast. This model was trained on historical interruption data and requires the following two inputs: asset features and weather factors. Using this information, our model then outputs the probability that a given asset has failed, in other words that a particular device has opened. This corresponds to a customer interruption, as provided by the historical logs. However, an interruption does not equate to a damaging event because an asset failure may be caused by one broken pole or three fallen trees. Therefore, our model also predicts the number of damaging events for a given segment, which is aggregated on an asset level.

A. Model Setup

We may assume, without loss of generality, that events occur independently across the network because a tree falling across a wire in Worcester would not affect a pole breaking in Athol. We assume that events happen on each segment as a Poisson process of rate:

$$\lambda_{s,t} = l_s g^*_{c_s} w_t$$

Here $\lambda_{s,t}$ is the probability of a segment failure where s is the segment index and t is the point in time. Note that λ is a function of the segment length, l_s, a risk vector g of the segment type c_s, and a vector of weather features at a given point in time, w_t. Note that the probability of segment failure is proportional to the length of the segment, which is intuitively sound as a longer segment is more likely to be damaged than a shorter one. This construction further ensures that certain features will result in a higher probability of failure than others: for example, an underground segment will have a much lower risk factor than a segment with bare framing in a forested area. By aggregating the segments we can say that events happen on each asset with rate:

$$\begin{aligned} \lambda_{a,t} &= \sum_{s \in a} l_s g^*_{c_s} w_t \\ &= \sum_c l_{a,c} g^*_c w_t \\ &= l^*_a g w_t \end{aligned}$$

Now $\lambda_{a,t}$ is the probability of failure on an asset level. We can then rewrite this as:

$$\lambda_{a,t} = \gamma^* x_{a,t}$$

We use γ^* to represent the new risk vector, with $x_{a,t}$ defined as the combined vector of length per segment type (each asset contains different types of segments) and weather at an asset at a given time. We derive these new vectors by taking the outer product of l^*_a and w_t and collapsing this from a matrix into a vector. We see that γ^* is simply the same as g from before, but also collapsed into vector form. From now on, we will use the subscript i to represent the combination (a,t) of a given asset and a particular time. Since events follow a Poisson process, the total number Y_i of events that occur on each asset is a Poisson random variable with parameter:

$$Y_i \sim \mathcal{P}(\gamma^* x_i)$$

From here we can derive the probability distribution of an outage occurring on a given asset. Define Z_i as the indicator variable corresponding to an asset failure: $Z_i = 1$ if and only if an interruption occurs, i.e. $Z_i = \min(Y_i, 1)$. We are interested in predicting γ, which represents the risk factor for every combination of asset features and weather factors. We consider the case where only Z_i is observed, because this is precisely the level of granularity of our data.

In this case, our data points correspond to the tuple (z_i, x_i), where both are defined as above, giving the corresponding likelihood function:

$$\mathcal{L}(\gamma) = \mathbb{P}(\forall i, Z_i = z_i | \gamma)$$

As is commonly done in the literature, we will focus on the following loss function:

$$\begin{aligned} L(\gamma) &= -\ln \mathcal{L}(\gamma) + K \\ &= \sum_{z_i=0} \gamma^* x_i - \sum_{z_i=1} \ln(1 - e^{-\gamma^* x_i}) \end{aligned}$$

Proposition III.1. *The following maximum likelihood problem is strictly convex:*

$$\max_\gamma L(\gamma)$$

Therefore it admits a unique solution $\hat{\gamma}$.

Proof. Hessian is positive semi-definite:

$$\begin{aligned} H &= \left(\sum_i z_i \frac{x_{i,k} x_{i,l}}{(e^{\gamma^* x_i} - 1)^2} \right)_{(k,l)} \\ &= (Dx)^*(Dx) \end{aligned}$$

where D is a diagonal matrix with entries $D_{i,i} = \frac{z_i}{e^{\gamma^* x_i} - 1}$. If $rank(Dx) = J$, then the Hessian is positive definite and the optimization problem is strictly convex. $\square$

Proposition III.2. *The maximum likelihood estimator $\tilde{\gamma}$ is consistent under mild assumptions on the data.*

B. Significant Model Features

We initially chose significant weather features manually and then aggregated them by device. This ultimately resulted in the following significant parameters:

- Mean pole age
- Mean pole class
- Mean pole height
- Mean spacing
- Total customers
- Total number of poles
- Total segments
- Total length per framing type

With respect to the weather features, we first selected mean, 5th and 95th percentiles of:

- Average wind speed
- Hourly gust
- Daily rainfall
- Outdoor temperature
- Pressure
- Light
- Humidity
- Rainfall rate
- Light rate
- Total rainfall rate

C. Numerical Results Using Historical Weather Logs

We initially implemented our model using historical weather logs, in other words the weather data from the actual time of the severe weather events. Practically speaking, this information is not realistically available as an input. Although the prediction granularity is on a 2 by 2 square mile basis, we aggregated results on a platform level in order to produce a suitable output for National Grid in order to aid in the planning of crew allocation. A platform is a staging area where crews are positioned during a storm, from where they work on a daily basis during restoration times. In practice, approximately 6 platforms are opened during severe weather events, but there are about 30 total across Massachusetts. Each platform accounts for a subset of specific towns and cities, so this aggregation was convenient because each interruption log entry contained a device's location by town.

D. Initial Prediction Accuracy

To test the predictive accuracy, we trained the model on 5 severe weather incidents (as well as two consecutive years of daily outages), and then tested it on the remaining storm. As shown in Table II, the correlation represents the ratio between the predicted number of outages at a platform and the actual number of outages that occurred.

TABLE II
OUT OF SAMPLE CORRELATION FOR OUTAGE PREDICTION

Storm name	Correlation
Winter Storm December 2008	**0.55**
Wind Storm February 2010	**0.50**
Winter Storm December 2010	**0.48**
Tropical Storm Irene 2011	**0.79**
Winter Storm October 2011	**0.67**
Hurricane Sandy 2012	**0.85**
Average	**0.64**

Graphically, this is represented by the circles in Fig. 3, where an orange ring that is larger than the blue circle indicates the model's over-prediction of interruptions, and vice versa.
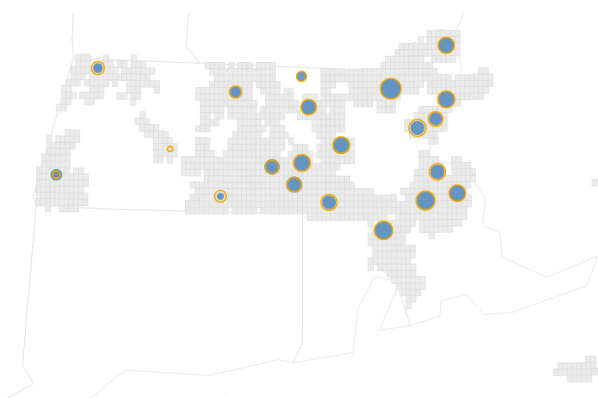

Fig. 3. The orange rings represent our model's prediction of interruptions and the blue circles represent the actual number of interruptions that occurred during the out of sample storm.

E. Using Historical Weather Forecast Data

As described under the data subsection in Section 2, we were limited by number of available weather stations that could provide historical forecast logs. Specifically, we had less than 10% of the previously available number of stations, as depicted by the map in Fig. 4.
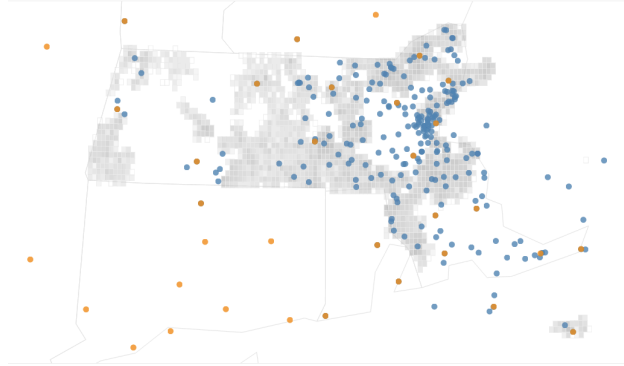

Fig. 4. The stations in blue are those that provided *hourly* historical weather logs and the stations in orange provided *daily* historical weather forecasts.

The weather forecast logs also severely limited how much information we can input in terms of available factors that were available in the historical weather logs. The list of the available forecast factors includes: temperature high and low, probability of precipitation, average wind speed and direction, presence of haze or fog, extreme heat or cold indicators, wind category, chances of rain, snow or thunderstorms and the sky condition. However, we are missing precipitation rates, hourly gusts and several other factors, found significant by the model, that were available in the historical logs. Additionally, we found that as the number of days before the storm increases, the forecast data demonstrates increasing discrepancies with actual data. As an example, consider the figures below. Fig. 5 demonstrates the error in the forecast of wind speed first 3 days, then 7 days and finally 14 days before the actually measured amount, which is indicated by the grey bar in the center. If we then consider Fig. 6, we see the mean of the forecast error and the standard deviation of the error, which increases drastically with time.
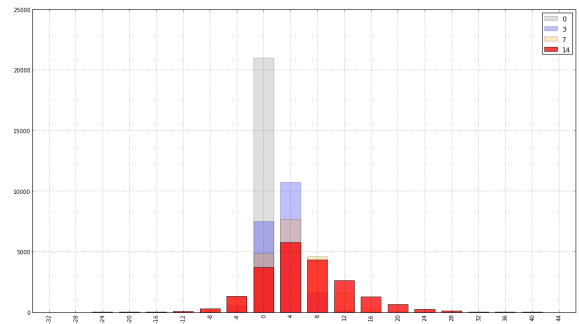

Fig. 5. A plot of the forecast error in predicting wind speed as the time horizon extends to 3, 7 and 14 days before the actual measured speed, which is shown in grey.

To capture the entirety of the assets across the state, we had to expand the minimum distance between devices and weather
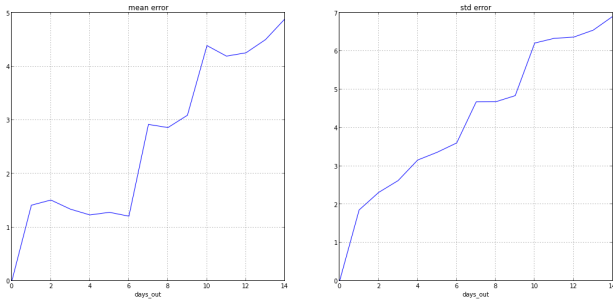
Fig. 6. The left graph displays the mean of the wind speed forecasting error and the right plot represents the standard deviation of the error.

stations. If we use the previous 5 mile radius around a given asset, we capture information for only 17.5% of the devices (10,814 out of 61,704). Thus we enlarged this to a 20 mile radius and were able to cover 97.7% of all devices (60,289). Although this represents 98.6% of customers (953,656 out of 966,750), there is a significant decrease in prediction accuracy and granularity because the weather features may be taken from a location up to 20 miles away from the actual asset.

We then found numerical results using the same methodology and out of sample testing, but now using forecast data from the day of the weather event as input. These results are shown in Table III.

TABLE III
OUT OF SAMPLE CORRELATION FOR OUTAGE PREDICTION USING "DAY OF" FORECAST DATA

Storm name	Correlation
Winter Storm December 2008	**0.32**
Wind Storm February 2010	**0.20**
Winter Storm December 2010	**0.24**
Tropical Storm Irene 2011	**0.53**
Winter Storm October 2011	**0.31**
Hurricane Sandy 2012	**0.67**
Average	**0.38**

Addressing the practical purposes of our tool, the "day-of" weather forecast is not sufficient for a prediction because a distributor contracts crews up to five days ahead and places them at platforms as least a day in advance. Therefore, we obtained numerical results using the forecast data each day for up to a week before the storm. The results are presented in Table IV.

TABLE IV
OUT OF SAMPLE CORRELATION FOR INTERRUPTION PREDICTION AT THE PLATFORM LEVEL USING FORECAST DATA FROM SEVERAL DAYS AHEAD

Storm name	Days ahead							
	0	1	2	3	4	5	6	7
Dec 2008	**0.35**	0.34	0.34	0.30	0.30	0.32	0.29	0.26
Feb 2010	**0.25**	0.24	0.24	0.23	0.20	0.20	0.18	0.20
Dec 2010	**0.26**	0.24	0.24	0.25	0.25	0.24	0.23	0.22
Irene 2011	**0.63**	0.56	0.58	0.51	0.51	0.53	0.52	0.51
Oct 2011	**0.47**	0.47	0.40	0.34	0.32	0.31	0.31	0.29
Sandy 2012	**0.68**	0.67	0.66	0.68	0.66	0.67	0.63	0.64
Average	**0.44**	0.42	0.41	0.39	0.37	0.38	0.36	0.35

Surprisingly, note that the model's prediction based on weather forecasts does not deteriorate drastically as the num-

ber of days before the storm increases up to a week. This demonstrates that the model is fairly robust and identifies the appropriate key influential factors in its analysis.

IV. CONCLUSION

Due to the large impact of severe weather events on power utility assets, proper planning for storm events is critical to ensuring that costs remain low while distribution reliability is maintained for consumers. The predictive model presented in this paper will aid National Grid in understanding the effects of incoming extreme weather events and allow for a more optimal response plan. The machine learning approach presented here not only adds a data-driven method for understanding the impact of an upcoming storm, but also builds a model that continuously improves as more granular and rich data sets become available from future storms in Massachusetts. Understanding the effects of various types of storms on assets has tremendous value to National Grid, as well as other utilities, because it also creates an opportunity for significant development in other areas of their business. Optimizing crew allocation both before and during a storm will ensure that costs are reduced and power delivery is returned to customers as soon as possible. In addition, the predictive model provides an avenue for understanding the network vulnerabilities and how they may be improved upon to increase durability during storms by employing methods such as vegetation trimming and asset management.

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