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Estimated Time of Restoration (ETR) Guidance for Electric Distribution Networks

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Abstract:
Electric distribution utilities have an obligation to inform the public and government regulators about when they expect to complete service restoration after a major storm. In this study, we explore methods for calculating the estimated time of restoration (ETR) from weather impacts, defined as the time it will take for 99.5% of customers to be restored. Actual data from Storm Irene (2011), the October Nor'easter (2011) and Hurricane Sandy (2012) within the Eversource Energy-Connecticut service territory were used to calibrate and test the methods; data used included predicted outages, the peak number of customers affected, a ratio of how many outages a restoration crew can repair per day, and the count of crews working per day. Data known before a storm strikes (such as predicted outages and available crews) can be used to calculate ETR and support pre-storm allocation of crews and resources, while data available immediately after the storm passes (such as customers affected) can be used as motivation for securing or releasing crews to complete the restoration in a timely manner. Used together, the methods presented in this paper will help utilities provide a reasonable, data-driven ETR without relying solely on qualitative past experiences or instinct.

Keywords: electric reliability, ETR, outage, restoration, severe weather

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1 Introduction

The economic loss from power outages in the United States is estimated to be between $20 and $55 billion annually (Campbell 2013). Outages have direct and indirect consequences for businesses, government and social services (Sullivan 1996; Castillo 2014); all of which require a reliable estimated time of restoration (ETR) in order to mitigate loss and prepare to resume normal activities when power returns (Campbell 2013). In Connecticut, where we focus our study, the interaction of trees with the overhead lines during severe wind is a major cause of outages on the electric distribution network (Connecticut Light and Power 2014). Trees are especially problematic for power restoration activities because they can break poles and overhead equipment, become tangled in the conductors, and block roads (McGee et al. 2012). When restoring power, utilities must balance individual customer needs with the needs of the community at large. The typical priority of restoration activities by electric utilities is as follows: (i) "make safe" activities to support emergency services (i.e. police, fire, medical), (ii) power plants, transmission lines and substations are repaired in parallel, (iii) areas with large number of customers affected, and then (iv) individual customers (Edison Electric Institute 2014). More details on restoration activities following power failures, from restarting tripped generators to restoring unserved load, can be found in Castillo (2014) and Ancona (1995).

There have been many different approaches to ETR modeling, including by storm (Reed 2008), feeder (Brown et al. 1997) or individual outage location (Nateghi, Guikema, and Quiring 2014a; 2014b). As noted by Nateghi, Guikema, and Quiring (2014b), many existing ETR models have been designed in such a way that their predictive accuracy could not be tested including these studies (Brown et al. 1997; Davidson et al. 2003; Reed 2008). There has been much research into using public versus proprietary weather data for outage modeling (Nateghi, Guikema, and Quiring 2014a), as well as research into how weather conditions can influence outage duration (Davidson et al. 2003; Nateghi, Guikema, and Quiring 2011). While Davidson et al. (2003) found that wind and precipitation variables did not contribute to the duration of individual outages during hurricanes in the Carolinas, Nateghi, Guikema, and Quiring (2014b) showed that weather variables alone may explain the duration of individual outages in Gulf States. However, a main limitation of these previously mentioned studies is that the

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number of crews working were not considered when modeling the individual outage durations. Other studies, such as Ouyang and Dueñas-Osorio (2014), have incorporated the time-varying number of crews and restoration sequence into their ETR models, along with differing restoration strategies for various entities (i.e. power plants, critical facilities, regular customers).

In this study, we provide guidance on how to calculate ETR as a function of outage, customer and crew data. We first present an analysis of how a utility restored power during three major events: Storm Irene (2011), the October Nor'easter (2011) and Hurricane Sandy (2012). We then compare how an "outage-driven model" (e.g. using outage predictions or actual outage counts) and a "customer-driven model" (e.g. using affected customer meters to back-calculate potential outages) would predict ETR during these events for the Eversource service territory. While outage-driven models can be useful for pre-staging crews if they rely on outage prediction model (Guikema et al. 2014a; Guikema, Nateghi, and Quiring 2014b; He et al. 2016; Wanik et al. 2015), the customer-driven model serves an independent, complementary and near real-time method that can be used by any utility that tracks the peak customers affected during a storm event. The use of both the outage-driven and customer-driven ETR models allows Emergency Managers at electric utilities (defined as employees responsible for calculating required recourses, procuring, and managing crews during natural and man-made emergencies) to (a) stage crews and resources before a storm arrives by using the outage prediction model (if available), and (b) to make adjustments, if necessary, from the peak customer affected information. In addition to point estimates, we also present a method for calculating an upper and lower bound around the predicted ETR that is a function of past crew behavior.

2 Data Description

Our study area (Figure 1) was the Eversource Energy ("Eversource") service territory in Connecticut, which serves 149 of all 169 towns in the state. We focus our study on three major events that impacted this region: (1) Storm Irene ("Irene", 2011) which had >15,000 outages, 671,000 peak customers affected, and a 10 days restoration; (2) the October Nor'easter ("the Nor'easter", 2011) which had >26,000 outages, 807,000 peak customers affected, and an 11 days restoration; and (3) Hurricane Sandy ("Sandy", 2012) which had >16,000 outages, 496,000 peak customers affected and a 9 days restoration. Note that peak customers affected are the customer electric meters themselves, and not the people they serve (e.g. an individual meter can serve many members of a single household or business).

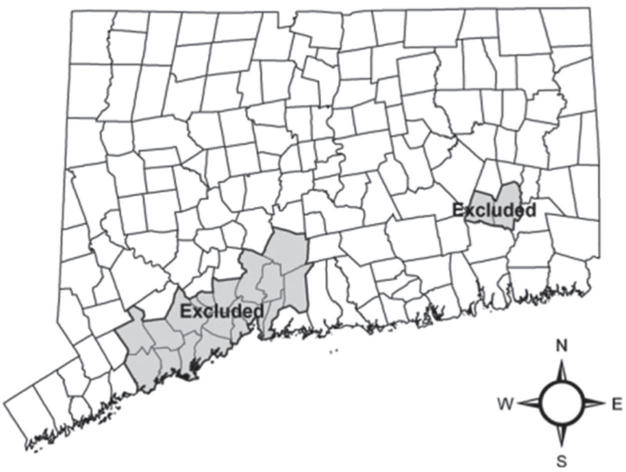

Figure 1: Eversource Energy Connecticut Service Territory (white); Shaded Areas are Other Service Territories that were Excluded from the Analysis.
The large, coastal area is part of United Illuminating, and the eastern Connecticut towns are served by a municipal utility.

2.1 Outage Variables

Outages are defined as locations that require a two-man restoration crew to manually intervene and restore power (Connecticut Light and Power 2014), which are recorded at the nearest upstream isolating device to the fault (i.e. snapped conductor, broken pole). It is essential to have an accurate estimate of the outages needing repair following a storm in order to calculate the ETR for a service territory. However, a considerable problem that Emergency Managers face is that the total number of outages during storm is not known until all outages have been repaired, as outages may be recorded over multiple days as they are discovered by crews or called in by the public. Figure 2A shows the number of outages that were fixed per day during each of the three storms.

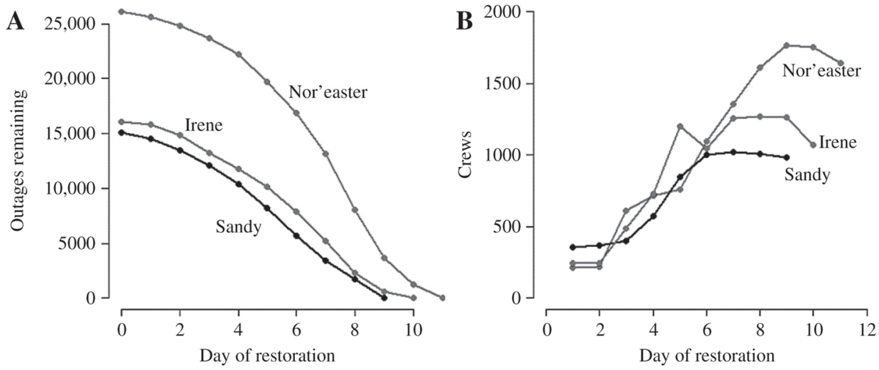

Figure 2: (A) Outages Remaining to be Fixed Per Day and (B) (A) Crews Working Per Day During Storm Irene, the October 2011 Nor'easter and Hurricane Sandy. Color versions of all plots in this manuscript are available from the corresponding author upon request.

Outage prediction models (OPMs) at electric distribution utilities, which rely on weather and geographic data as inputs to predict outages, can provide estimated counts of outages in advance of a storm and can be used as justification for pre-storm allocation of crews and equipment (Guikema et al. 2014a; Guikema, Nateghi, and Quiring 2014b; He et al. 2016; Wanik et al. 2015; 2017a; 2017b). Some outage prediction models have been calibrated based on utility-specific data (Mensah and Duenas-Osorio 2014; Winkler et al. 2010), while others (Nateghi, Guikema, and Quiring 2014a) have used only publicly available data, which can be generalized over regions for which data are limited or do not exist (Guikema et al. 2014a; Guikema, Nateghi, and Quiring 2014b). We will later describe an additional source of publicly available data that is immediately available during a storm that Emergency Managers can use to inform their decision-making ("peak customers affected", Section 2.3).

2.2 Crew Variables

For each of the three storms, we were provided with data on daily maximum crews ("crews") that worked and the total number of outages that were fixed each day by all crews. The maximum number of crews differs from the total number of crews working per day, as crews can work at different times during the day, afternoon or night shifts. During catastrophic events, utility crews must be called in from around the country to help restore power (this is known as "mutual assistance"). Due to competition with other utilities for crews along with an individual utility's response strategy (e.g. proactively ordering crews in advance of a storm vs. reactively ordering crews after the storm has passed), there may be a lag before crews actually arriving and start working (Figure 2B). Late ordering of crews coupled with excessive travel times may prolong the restoration process. From the daily crew and outage data, we can readily calculate the daily crew fix rate ("Rate", Eqn. 1), which is defined as the number of outages fixed per day divided by the maximum number of crews that were working that day.

$$\text{Rate} = \frac{\text{Outages Fixed}}{\text{Crews}} \tag{1}$$

It is interesting to note that closer to the end of a storm, there was a decrease in the number of crews working (Figure 2B). The decision to release crews during a storm can vary for many reasons – including regulatory pressure, or deeming that there are excessive crews relative to the amount of outages that need to be repaired (Abrams and Lawsky 2013; Caron et al. 2013).

The rate for each storm and day of restoration is provided in Figure 3A. During major storms, repair rates will likely be lower at the onset due to road clearing and emergency "make safe" priorities. Towards the end of the storm, one may notice a decrease in crew fix rate. While outages still need to be repaired during the "tail" of the storm, there is also a great deal of non-outage work (i.e. tree branch leaning on a pole, sagging conductor, etc.) that needs to be completed and this was excluded from our current study. Another contributing factor to lower crew fix rates during the tail of the storm includes increased driving distances between outages, which may decrease the crew fix rate due to excessive driving times, but we ignore this aspect. We assume that each daily rate is independent and view the rates from the three storms individually and collectively (dashed line) as distribution (Figure 3B). From these distributions we can calculate probabilities of exceedance, such as the 25th percentile (P25), 50th percentile (P50) and 75th percentile (P75) of the rates. We will demonstrate how the rate is essential to calculating an ETR in Sections 3 and 4.

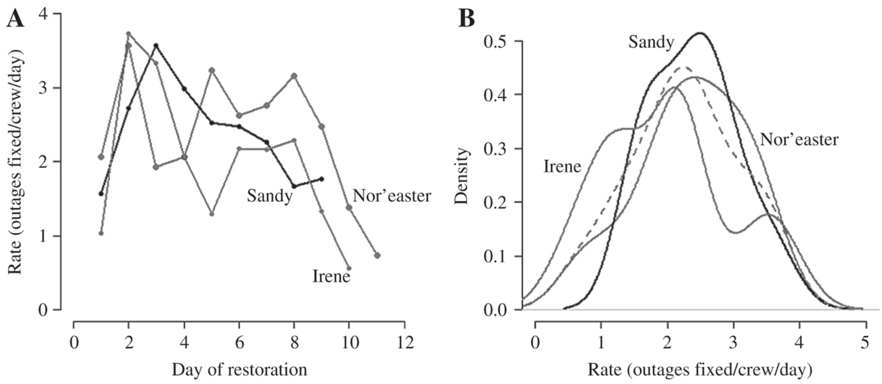

Figure 3: (A) Crew Fix Rate Per Day of Restoration During Each Storm; (B) Kernel Density Plot showing the Distributions of Rates During Each Storm, Dashed Line Represents the Density of all Three Storms Combined (n = 30).

2.3 Customer Variables

Like many electric distribution utilities, Eversource relies on their customers to call, text or use a website to alert the utility that they are without power. Eversource tracks these calls and uses predictive algorithms to estimate the number of customers without power at any one time. The peak customers affected (PCA) is defined as the maximum number of customers (meters) without power during a major storm, and usually occurs within the first 24 h of the storm. The PCA is different from the total number of customers affected during the entire storm event, as some customers may lose power multiple times during the storm event and be double-counted (Guikema et al. 2014a; Guikema, Nateghi, and Quiring 2014b). We were provided with a historic database from Eversource that included the total number of outages and PCA per storm across 55 storms that impacted the Eversource territory between 2007 and 2013 including Irene, the 2011 Nor'easter and Sandy. From these data, we calculated the ratio of PCA to outages, resulting in the ratio of peak customers affected per outage (PCAO, Eqn. 2).

$$\text{PCAO} = \frac{\text{PCA}}{\text{Total Outages}} \tag{2}$$

Figure 4A shows that the total outages and PCA are highly correlated and linearly related. Figure 4B shows that while there may be PCAO variability for storms less than 500 outages, the locally weighted regression line shows no discernable trend between PCAO and total storm outages. Figure 4C shows the kernel density of PCAO from all storms with the P25, P50 and P75, and these will be subsequently used to convert PCA into outage estimates, which can then be used for ETR modeling (see Eqn. 4).

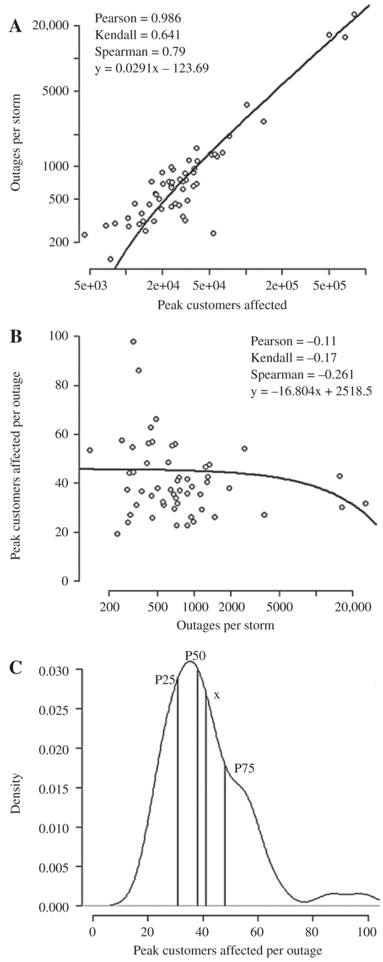

Figure 4: (A) Scatter Plot of Peak Customers Affected During a Storm vs. the Total Storm Outages; (B) Scatter Plot of Peak Customers Affected Per Outage (PCAO) vs. Total Storm Outages; (C) Kernel Density Plot of PCAO with Plotted Statistics for the 55 Storms (2007–2013, Including Irene, the Nor'easter and Sandy).

3 Point Estimates

An ideal scenario would be that outages are predicted perfectly before a storm arrives and that crews work at a constant rate. One could then create a model that would relate the number of outages to average number of crews working per day and the crew fix rate (Eqn. 3).

$$\text{Predicted ETR} = \frac{\text{Total Outages}}{(\text{Avg. Daily Crews} \times \text{Rate})} \tag{3}$$

The results from this model are presented in Figure 5 using the P25, P50 and P75 of the rates from Figure 3 for specific outage thresholds (e.g. 5000–40,000 outages). Note how wide the contours are for the left panel (P25) relative to the right panel (P75) as the faster rates translate into steeper contours and shorter restoration times. In this way, if a utility knows the desired ETR (i.e. 7 days or 10 days), it can assume a certain crew fix rate and estimate the number of average daily crews that must work per day to achieve a restoration goal.

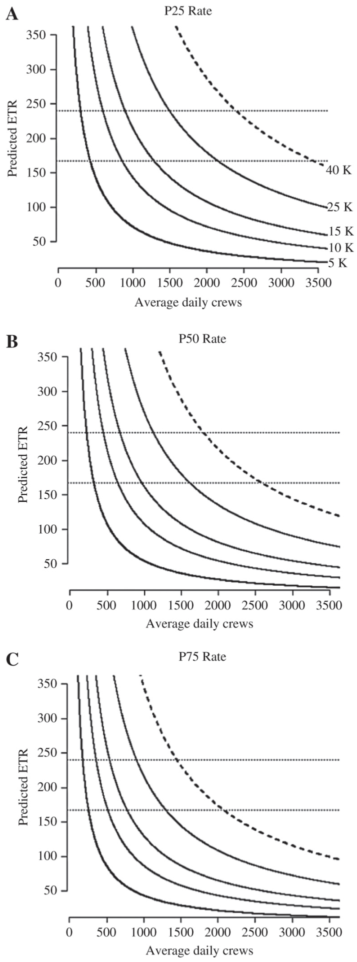

Figure 5: Changes in Predicted ETR (y-axis units are hours) as a Function of Average Daily Crews and Outage Thresholds Using the (left) 25th Percentile, (center) 50th Percentile, and (right) 75th Percentile of All Daily Fix Rates (Figure 3). Dashed, horizontal black lines represent a 7 days (168 h) and 10 days (240 h) restoration goal. Ordering and labeling of outage contours is consistent between all three panels (e.g. the thick, dashed contour always represents 40K outages and the bottom contour always represents 5K outages on each panel).

Similarly, updating Eqn. 3 to use PCA and PCAO instead of outages (Eqn. 4), we see that a lower PCAO will increase the estimated outages and the number of crews required to achieve a restoration goal.

$$\text{PredictedETR} = \frac{(\text{PCA}/\text{PCAO})}{(\text{Avg. Daily Crews} \times \text{Rate})} \tag{4}$$

While useful, these relationships do not fully account for the uncertainty associated with the restoration process. The total number of outages is not known to Emergency Managers until the storm is complete, which means that utilities need to rely on outage prediction models or customer data to estimate the total outage impacts. In addition, we previously showed that crews do not work at a constant rate during storms (Figure 3), which can be a function of outage severity (i.e. broken poles take longer to fix than snapped conductors), storm footprint (i.e. damage due to a tornado will limit the number of crews that can work in the affected area), and crew management issues (i.e. external crews are unfamiliar with the service territory; and the utility may not have work orders ready when crews arrive, resulting in crews waiting instead of working; or roads may be blocked, preventing crews from traveling). To account for these uncertainties, we demonstrate how outage and customer data can be used to create ETR prediction intervals.

4 Prediction Intervals

4.1 Outage-Driven ETR Model

As previously mentioned, some utilities may have an outage prediction model to estimate the number of outages before a storm hits (Guikema, Han, and Quiring 2008; Guikema et al. 2014a; Guikema, Nateghi, and Quiring 2014b; He et al. 2016; Wanik et al. 2015). During operational use of these models, error from a weather forecast can propagate error into the outage predictions. For the purpose of proving the concept, we ignore any outage prediction model uncertainties and assume that these models can accurately predict outage impacts. To illustrate how the fix rate uncertainty affected ETR estimates, we show how using the actual crew staffing per day coupled with three fix rates can provide an upper, lower and likely restoration curve. We first present in-sample results that use the P25, P50 and P75 rates from all three storms (Figure 5), and then present out-of-sample results (Figure 6) that use the rates from the two other storms to predict the storm of interest (e.g. Irene is predicted from the Nor'easter and Sandy rates; the Nor'easter is predicted from Irene and Sandy rates; Sandy is predicted from Irene and the Nor'easter rates). In these plots, the dashed center line represents the P50 of the predicted ETR distribution, and the solid lines represent upper and lower predictions from the P25 and P75 of rate distribution, and the dots represent the actual outages that are remaining each day. Results (Figure 7) show the P50 fix rate is a reasonable predictor of the final ETR for the Nor'easter and Sandy, while Irene's outages are encapsulated by the P50 and upper bound. The out-of-sample results (Figure 8) show that the Nor'easter was encapsulated by the lower and P50 bounds, while Irene was outside the upper prediction bounds.

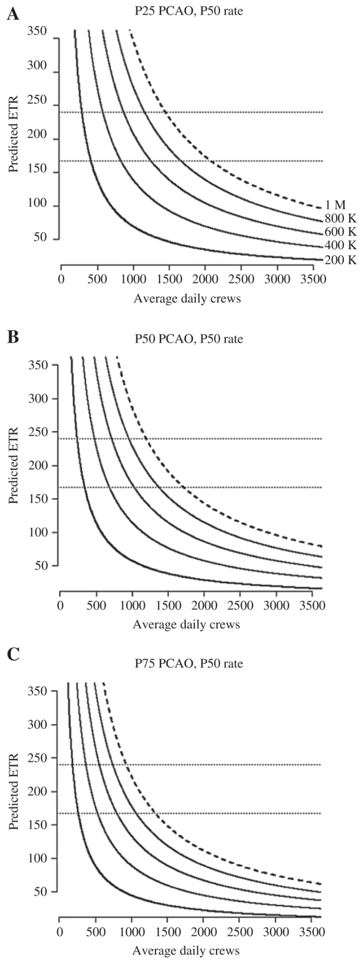

Figure 6: Changes in Predicted ETR (y-axis units are hours) as a Function of Average Daily Crews for Specific Outage Thresholds Using P50 Rate and the (left) P25, (center) P50, and (right) P75 PCAO Values from the 55 Storms (2007–2013, Including Irene, the Nor'easter and Sandy).
Dashed, horizontal black lines represent a 7 days (168 h) and 10 days (240 h) restoration goal. Ordering and labeling of customer affected contours is consistent between all three panels (e.g. the thick, dashed contour always represents 1M customers affected and the bottom contour always represents 200K outages on each panel).

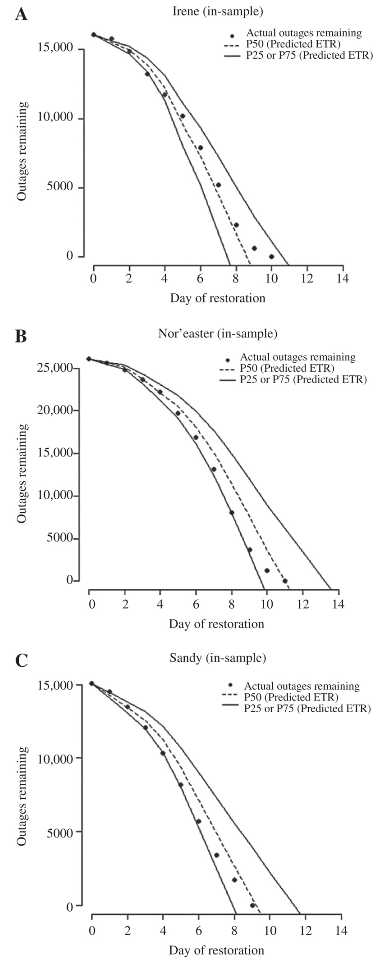

Figure 7: In-Sample Restoration Curve Results Using the P25, P50 and P75 Rates from Distribution of All Rates and Actual Daily Crews (i.e. Irene is Predicted from the Irene, Nor'easter and Sandy Fix Rates with Irene's Daily Actual Crews).

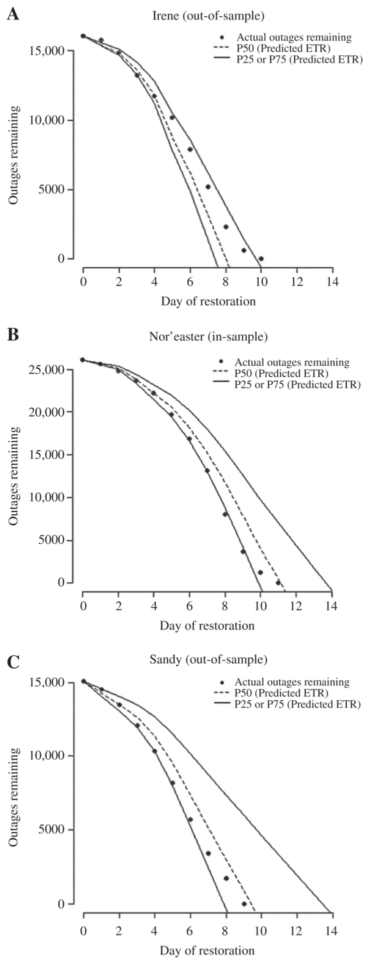

Figure 8: Out-of-Sample Restoration Curve Results Using the P25, P50 and P75 Rates from the Two other Storms to Predict the Validation Storm (i.e. Irene is Predicted from the Nor'easter and Sandy Fix Rates with Irene's Actual Daily Crews).

4.2 Customer-Driven ETR Model

We now explore how PCA and PCAO can be used to estimate outage impacts which can then be used for calculating ETR (Eqn. 4). We first present in-sample results, where the rate is assumed to be the P50 rate of the three storms, the upper and lower bounds are calculated from the P25 and P75 of the PCAO distribution, and the actual number of crews working per day during each storm are used. Figure 9 shows that the actual outages remaining per day were generally encapsulated for each day and each storm using this method. The P50 PCAO gives estimated outages that were close for Irene, while the P25 PCAO (upper bound, more conservative) gave better predicted outages for the Nor'easter and Sandy. We also present out-of-sample results, where the rates from the two remaining storms are used to predict the storm of interest. To evaluate the sensitivity to different rates and outage predictions, we present out-of-sample results where the P25 PCAO is coupled with the P25 of the fix rate to calculate the upper bound, and the P25 PCAO is coupled with the P75 of the rate to calculate the lower bound. In this way, the highest predicted outages (upper bound) had the slowest crew fix rate and the lowest predicted outages (lower bound) had the fastest crew fix rate. Figure 10 shows the P50 rate and outages still provides an accurate snapshot of the predicted ETR, even when the rates from other storms are left to predict the remaining storm.

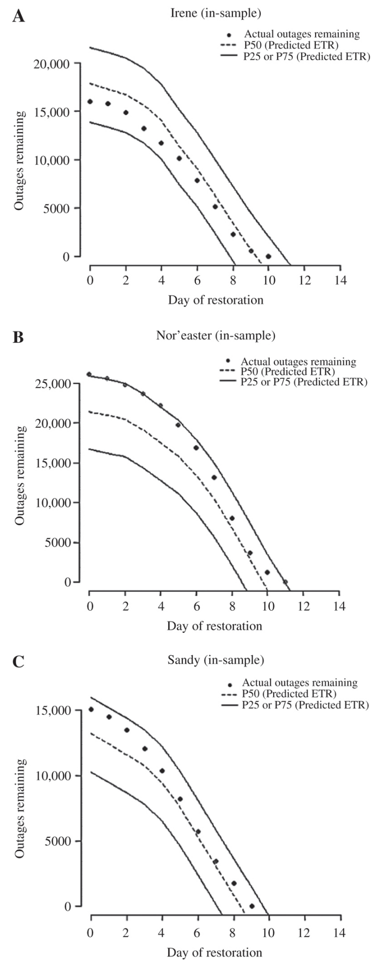

Figure 9: In-Sample Restoration Curve Results Using the P25, P50 and P75 of PCAO Distribution from Three Major Storms (i.e. Irene is Predicted from the Irene, Nor'easter and Sandy Distribution of PCAO).
P50 fix rate is assumed for each predicted outage. Actual crews for each storm are used. Last days of actual crews held constant when extrapolating beyond actual restoration day.

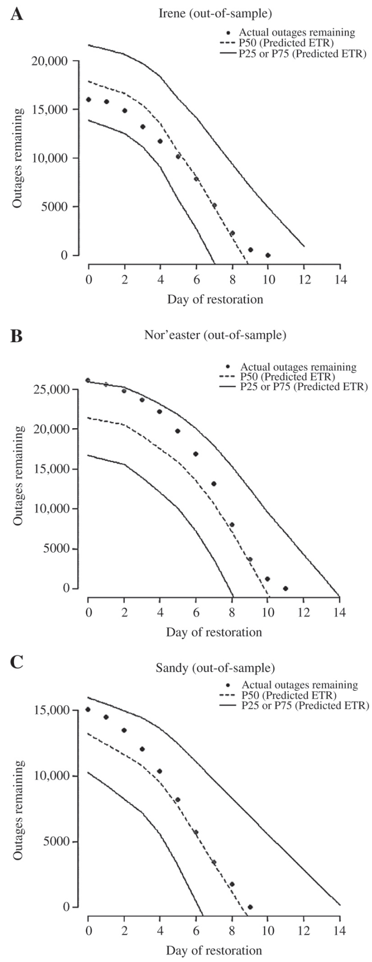

Figure 10: Out-of-Sample Restoration Curve Results Using the P25, P50 and P75 of PCAO Distribution from Three Major Storms (i.e. Irene is Predicted from the Nor'easter and Sandy Distribution of PCAO).
The P75 fix rate is used with the P75 PCAO such that the lowest predicted outages have the smallest ETR, similarly, the P25 fix rate (slow) is used with the P25 PCAO such that the highest predicted outages has the largest ETR. Actual crews for each storm are used. Last days of actual crews held constant when extrapolating beyond actual restoration day.

5 Discussion

We have presented guidance on how to predict ETR at service territory resolution as a function of predicted number of outages, peak customers affected, and crews working per day. Both in-sample and out-of-sample models exhibited satisfactory results when outages (Figure 5 and Figure 6) or PCA (Figure 7 and Figure 8) were used. Irene exceeded the upper ETR projection when using actual outage data, but was encapsulated by the middle and upper bounds using the PCAO method. The out-of-sample results using P50 ETR proved to be within 1 day of the actual restoration time for Sandy and the Nor'easter using both the outage-driven and customer-driven methods. It is important to note that the restorations for Irene and the Nor'easter (McGee et al. 2012), as well as Sandy (Caron et al. 2013) were all within the Department of Energy's (DOE) industry standards at the time.

Using the methods presented in our study, an Emergency Manager retrospectively would have been able to forecast that there likely were not enough crews to accomplish a 7 days restoration for any of the three storms we investigated. We can use the October 2011 Nor'easter as an example to further this point. As demonstrated in Figure 6C and Section 3, we see that even if the crews were working at the P75 rate during each day of the Nor'easter, an estimated 1345 crews would be needed to restore power in 7 days compared to the 1068 crews that were actually working. Using the outage-driven model as described in Figure 8 and Section 4.1, combining the actual outages (26,132 outages) with the actual daily crew data and the P75 rate would have resulted in an estimated 10 days restoration (Figure 8). Using the customer-driven model as described Figure 10 and Section 4.2, using the actual peak customers affected (831,000 customers) and P25 PCAO to derive the lower bound of predicted outages (17,312 outages) and using the fastest P75 rate, the projected ETR would have resulted in an estimated 8 days restoration (Figure 10).

Expedited restorations are desired, but utilities must be aware about how fast and efficaciously crews can repair outages when calculating ETR. The arrival of contractor and mutual aid crews from surrounding regions during severe weather can result logistical challenges to utilities that can prolong a restoration (Edison Electric Institute 2014). If the number of predicted outages and/or ordered crews are insufficient (e.g. underestimated) for an upcoming storm, the delayed crew arrival can contribute to prolonged ETRs. During major events like hurricanes it may take a crew one to 5 days to arrive at the service territory, which is a function of how far crews need to travel and when a contracting utility will release their crews for someone else to use. The use of both the outage-driven and customer-driven ETR models can help provide actionable information to Emergency Managers who must decide how many crews are needed, when they should arrive, and how quickly they can repair the grid. In the future, other technologies to monitor and assess power outages in near-real time such as remotely-sensed images of nighttime light measurements may also prove as useful inputs to future ETR models (Cao and Bai 2014; Cole et al. 2017).

This research is complementary to previous models that investigate ETR at higher spatial and temporal resolution than our study (Liu, Davidson, and Apanasovich 2007; Nateghi, Guikema, and Quiring 2011; 2014b). Recent work by Nateghi, Guikema, and Quiring (2014a), which used weather-related variables to predict ETR for individual outage locations (not the entire service territory), found that areas with the most severe weather conditions had the longest outage durations. Although weather was not directly included in our study, weather data is a critical component of outage prediction models , which feed downstream ETR models. A limitation of Nateghi, Guikema, and Quiring (2014a) was that crews were not used as a predictive variable in the model, such that an influx or decrease in the number of crews would not affect the individual outage prediction during an active storm event. In comparison, in this paper we demonstrate how the number of crews along with the rates influence ETR. As more granular crew data for storms becomes available, we envision that our ETR models can be built for geographic subunits of a service territory instead of the entire region.

6 Conclusion

We have presented methods for utilities to predict ETR during storms using a variety of data sources that utilities likely have on-hand, including crews, outages fixed and rates. We believe this is paper one of the first to use actual crew-related variables to predict ETR during recent storm events. Relationships between average daily crews and outage thresholds can provide early guidance to Emergency Managers who must decide whether or not enough crews have been ordered. Initial models inputted with outage predictions and a distribution of crew fix rates can be used to predict ETR, which can be later updated in an operational context as the peak number of customers become known. Utilities that want to be optimistic about ETR can use faster fix rates, while utilities who want to be more conservative can use the median or upper fix rate. Both approaches help utilities provide a reasonable, data-driven ETR without relying solely on qualitative past experiences or instinct. Although we have shown methods to predict a range of ETR, individual utilities need to decide how best to communicate uncertainty to the general public, government officials and regulators. An ETR that is too early or too late will result in over or under-preparation, which both have their advantages and disadvantages.

Finally, grid resilience improvements (e.g. structural and electric hardening) and vegetation management play a key role in the occurrence of outages and the time it takes to fix outages by changing the way the grid fails during storm events. Not all trees that are proximal to overhead lines are "risk trees", but given that the majority of storm outages in Connecticut are tree-related (Connecticut Light and Power 2014), we expect there would be a decrease in tree-related outages if a utility could have less risk trees interacting with the overhead lines. If altering the tree conditions is not a viable option, some have suggested the way that outages occur could be altered such that repair times are decreased. The concept of "design for repair", as described by (Reed 2008), suggests that if overhead lines were to snap rather than bring down a pole, crews would be able to fix outages faster, thereby decreasing ETR. These are interesting aspects that we hope to incorporate into future research works.

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