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ARTICLE

Power Restoration Prediction Following Extreme Events and Disasters

Romney B. Duffey[1]

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Abstract This article examines electric power restoration following catastrophic damage in modern cities and regions due to extreme events and disasters. Recovery time and non-restoration probability are derived using new data from a comprehensive range of recent massive hurricanes, extensive wildfires, severe snowstorms, and damaging cyclones. Despite their totally disparate origins, over three orders of magnitude severe wildfires and hurricanes have the same non-restoration probability trends, which are of simple exponential form. The results fall into categories that are dependent on and grouped by the degree of damage and social disruption. The implications are discussed for emergency response planning. These new results demonstrate that the scientific laws of probability and human learning, which dominate risk in modern technologies and societies are also applicable to a wide range of disasters and extreme events.

Keywords Damage categories · Hurricanes · Restoration probability · Storms · Wildfires

1 Introduction

This research provides a new technical and realistic basis for determining the likelihood of when electric power will be restored after damage due to extreme events and disasters. The recovery time and non-restoration probability are derived by using new power outage data from a wide range of recent hurricanes, storms, snowstorms, cyclones, and extensive wildfires. The result is a new method for making outage time predictions in repairable power systems following disasters that is independent of the specific electrical system and its protocols.

Recent extreme events have highlighted the fragility of the power system in major cities, urban complexes, and industries that have been built totally dependent on electricity. There were 52 extreme events recorded in 19 countries causing power outages in 2013 alone (Klinger et al. 2014). "In the light of increasing demand and reliance, power outages will continue to have far-reaching impacts upon the health of vulnerable populations who are increasingly reliant on electrically powered technology" (Klinger et al. 2014, §7). The Great North-East Blackout also highlighted how failures can cascade throughout an internationally coupled transmission system (U.S.-Canada 2004). Just the economic impacts of outages due to extreme weather events was estimated to cost up to USD 30 billion per year for the United States alone (U.S. Office of the President 2013), and total disaster relief funding is an even larger amount.[1]

The ideal is for "perfect restoration" to all disconnected customers. There are hundreds of technical papers on the subject of retaining grid stability, automated control, emergency planning, and system dynamics (Adibi and Milanicz 1999; IEEE 2013). Small or even area-wide blackouts due to blown transformers, faulty switchgear, or

✉ Romney B. Duffey
duffeyrb@gmail.com

[1] Idaho Falls, ID 83404, USA

[1] See for example U.S. Public Law 113-2 (Pub.L. 113–2, H.R. 152, 127 Stat. 4, enacted 29 January 2013), containing Division A: Disaster Relief Appropriations Act, 2013 and Division B: Sandy Recovery Improvement Act of 2013; https://riskcenter.wharton.upenn.edu/disaster-aid/federal-disaster-rebuilding-spending-look-numbers/, 22 February 2018, Brett Lingle, Carolyn Kousky, and Leonard Shabman, U. Penn. Wharton Risk Management and Decision Processes Center.

power line failures on average take a few hours to restore power using emergency repair crews (EIA 2016). But people also live where major flood and other natural hazards are known but largely ignored, and low-income groups are particularly risk exposed (Masozera et al. 2007; Crowell et al. 2010). Despite being in a designated flood zone, many areas do not even have adequate sea walls or effective flood prevention and control.

There are regional mutual assistance groups where emergency help is mobilized to restore power with repair crews literally borrowed or contracted from unaffected systems. But as a recent report notes (EEI 2016, p. 6): "Our current mutual assistance program works well for regional events, but was not designed to be scalable for national events." Following Hurricane Irma, the President and CEO of FPL (Florida Power & Light) was quoted in a 2017 FPL news report as part of a lengthier statement expressing a commitment that highlights this need: "For example, we understand that what our customers want to know more than anything else is when will their power be restored. Unfortunately we were not able to accurately and consistently provide the kind of useful and detailed restoration estimates that our customers have come to expect from us during normal operations. We are going to get better at this and we're already working on it" (FPL 2017, §3). In order to make such predictions, the probability of failure to restore power (or the chance of non-restoration) must be determined or estimated as a function of time, so new data and outage prediction methods are clearly needed. Previous estimates have only been made for the average outage duration times following hurricanes using statistically-based geographic models, not the time-varying outage number (Nateghi et al. 2014).

In contrast, dynamic restoration management and outage duration prediction require using data that are time varying and not time-averaged values. There are online catalogs and lists of past and present power outage events (Wirfs-Brock 2014; Klinger et al. 2014; U.S. DOE 2017; Bluefire Studios 2018), but there are no national or international centers that collect detailed or openly publish dynamically varying power outage duration data. This study examines cases of reparable damage, not requiring entire system reconstruction, or massive rebuilding of fragile power networks.[2] This study collected the publically reported dynamic power outage numbers for several large independent and disparate events, including:

- Superstorm Sandy flooding the U.S. East Coast;
- Hurricane Matthew impacting Florida after decimating Haiti;
- Hurricane Harvey inundating the U.S. Gulf Coast;
- Hurricane Irma ravaging the entire length of Florida;
- Wildfires destroying large areas of California;
- Winter storms Grayson and Riley sweeping the U.S. Northeast

For comparison, data were also collected for less severe events in other national regions, namely Hurricanes Nate and Ophelia and Cyclone Gita impacting, respectively, Georgia, the Irish Republic, and New Zealand as downgraded storms.

Each repair case has unique challenges to be resolved by the on-the-spot management and restoration teams that deal with both social disruption and system damage. The rate of restoration depends on the elapsed time or accumulated experience for effective action and learning opportunity. The physical restoration process relies on the ability, experience, knowledge, and situational awareness of the repair crews and emergency management staff being deployed, which naturally increase with increased restoration time. The integrated system response, management, and repair crew actions reflect the combination of this myriad of individual and collective human learning processes. This idea of applying human learning from experience to fault repair and/or error correction holds for multiple technological systems, and disasters are no exception (Duffey and Saull 2008; Thompson 2012). The same trends have been shown to apply even during the chaos and destruction of warfare on land (Duffey 2017a) and at sea (Duffey 2017b).

In an earlier study, Duffey and Ha (2013) showed that for both massive national grid and purely local outages the "normal" restoration probability or outage fraction followed exponential curves. Using limited extreme event data, Duffey (2014) showed that the probability of restoration was significantly lower, or restoration took much longer, for an unexpected storm (Superstorm Sandy) and a major earthquake-induced tsunami in Japan. This delayed recovery time and/or lower probability of restoration were attributable to the extensive damage, widespread social disruption, and overloaded emergency response capability.

The focus of this article is to provide extensive new data and analyses that confirm that these previous results and trends are common. The previous work and models are outlined and an expanded validation presented, which results in new predictive correlations for the dynamic restoration probability for extreme events.

2 The Physics and Probability of Power Restoration

The correction and/or repair of failures are part of a statistically varying but systematic professional, technical, and personal learning experience and opportunity. Any

[2] For example, the recent cases of Puerto Rico and Haiti required many months for essentially full replacement of major plants and fragile power grids.

new analysis must realistically include the variations that exist because of the inherent randomness and uncertainty (Chow et al. 1996; Billinton et al. 2001). Since we cannot describe the innumerable human decisions, actions, and processes, we reduced this complex outage restoration problem to an extremely simple model, both mathematically and physically, by adopting an emergent method for the external outcomes (Duffey and Saull 2008; Duffey and Ha 2013; Duffey 2014). This technique implicitly includes but does not need to explicitly describe all the detailed restoration processes, or the complexities of internal technological, organizational, managerial, and regional factors.

The restoration process can be measured in terms of the outage fraction representing the number of customers who are still without power. For overall emergency management of power system distribution, control, and restoration, it is not known beforehand when or where each of the numerous restorations in the entire service region may occur. Predicting the potential absolute number of outages, for example in hurricanes, remains highly uncertain, even using complex geographic computer models tuned to past events (Han 2008; Guikema et al. 2014).

The occurrence probability, $p(n)$, of the outage outcomes observed statistically constitutes a Poisson-like random process (Bulmer 1969) but with a varying or dynamic occurrence rate, $\lambda(h)$. For $n(h)$, non-repairs, the probability p_i of any non-restoration for the total number N_o is given by: $p_i \sim (n(h)/N_0)$. The measure of the overall state of repair (or order) H, in the system is described by the usual entropy definition, being the probability of the distributions, $H = N_0!\ \Pi\ (p_i/n(h)!)$. But only specific distributions can satisfy the applicable physical and hence mathematical restraints. Adapted and derived from statistical physics for a closed system (Wannier 1987; Jaynes 2003), the distribution and number of outcomes (outage faults detected and/or corrected) should obey the fundamental postulates of statistical learning (see Duffey and Saull 2008, §5 for the full derivation). Statistical learning is based on the precepts of human error correction and recall (Ohlsson 1996; Duffey 2017c) using probabilistic analysis (Bulmer 1969; Jaynes 2003), where the knowledge and experience accumulated from the past is adapted to and corrected in the evolving present, and the most likely outcome distribution is that actually observed. In the present new application of human learning to power outage correction, the outcomes are the individual restorations, where the event state space is the number of outage restorations progressively occurring in any given region or area as a function of the experience gained or existing at any restoration time. The restoration is treated as a systematic learning process occurring in real time subject to:

- Repair or restoration of any and all outages are equally likely, and hence can occur in any observation interval during the event duration;
- In any time interval, restorations occur and are observed stochastically but are a systematic function of the learning and/or experience of the management and repair crews during the event;
- For an entire event, there is a known maximum or nearly constant total number of initial outages to be restored;
- Total restoration experience of the management and repair crews accumulated during the entire outage event duration is finite and conserved;
- The outage repairs and restoration that occur with time are, on average, the most likely, being the ones that are actually observed;
- The most likely distribution is that which gives a maximum number of repairs/restorations (or minimum number of non-repairs), consistent with learning.

The validity of these assumptions, conditions, and approximations can and will be fully tested and demonstrated by the subsequent comparisons to the new event data reported here. Subject to these mathematical and physical constraints, and following standard statistical physics theory (Wannier 1987), the most likely outcome distribution in any observation sub-interval is exponential in form. Summing over all the discrete restoration outcomes gives the instantaneous number of outages, n_i, for any ith sample at any elapsed time, h, as (see also Duffey and Saull 2008),

$$n_i(h) = n_m + (N_{0i} - n_m)\mathrm{e}^{-\beta h} \tag{1}$$

Here, n_m is the residual or minimum attainable outage number remaining at very long times; β, is a constant for that sample; and N_{0i} the total or maximum outage number. The difficulty of outage correction determines whether the restoration is "perfect" in which case n_m=0. For comparison, the average number, $\bar{n}$, of outages that have lasted for a total of say, T hours, from integration of Eq. 1, is,

$$\bar{n} = -\frac{1}{T}\int_T^0 n_i(h)\mathrm{d}h = n_m + \left\{\frac{N_{0i} - n_m}{\beta T}\right\}\left(1 - \mathrm{e}^{-\beta T}\right)$$

From conventional reliability theory (Lewis 1994), at some elapsed time, h, the instantaneous repair or restoration rate, $\lambda_i(h)$, per unit time is

$$\lambda_i(h) = -\left\{\frac{1}{N_{0i}(h) - n_i(h)}\right\}\frac{\mathrm{d}n_i}{\mathrm{d}h} \tag{2}$$

The negative sign accounts for the fact that the number of outages is declining, with non-restoration being the opposite of restoration. The commonly used intensity or rate,

$I = \mathrm{d}n_i/\mathrm{d}h_i$, does not allow for the varying outage (sample) size, and applies only if or when $N_{oi} >>> n_i$.

The finite probability of non-restoration, $P_i(\mathrm{NR})$, is given by the classic Laplace ratio or fraction of the number of outages remaining, $n_i(h)$, or not repaired to the initial or maximum number, N_{0i}, initially observed in any ith area. Dividing Eq. 1 by N_{0i} gives the instantaneous non-restoration probability, $P(\mathrm{NR})$, or outage fraction variation,

$$P(\mathrm{NR}) = P_m + (1 - P_m)\mathrm{e}^{-\beta h} \tag{3}$$

with the lowest attainable non-restoration probability value, $P_m = n_m/N_{0i}$. The probability at any time or outage interval is therefore decreasing exponentially.

Hence, after the maximum or initial total outages, N_{0i}, the probability of recovery $P(R)$ is the standard result (Lewis 1994),

$$P(R) = 1 - P(\mathrm{NR}) = 1 - \frac{n_i(h)}{N_{0i}} = 1 - \mathrm{e}^{-\int \lambda_i(h)\mathrm{d}h} \tag{4}$$

For an entire service region, the total outage number is the summation of the recovery over all the i-areas, $n(h) = \Sigma_i n_i(h)$, with total or maximum outages, $N_0 = \sum_i N_{0i}$ at initial time, h_0. The probability of non-restoration at time, h, after the peak, for an average repair rate, $< \lambda >$, is,

$$P(\mathrm{NR}) = \frac{\sum_i n_i(h)}{\sum_i N_{0i}} = \frac{n(h)}{N_0} = \mathrm{e}^{-\int \lambda \mathrm{d}h} = \mathrm{e}^{-\lambda(h-h_0)} \tag{5}$$

With few remaining outages, $P_m \ll 1$, and $h \gg h_0$, then Eq. 5 becomes identically Eq. 3 implying physically that $\beta \approx < \lambda >$. The expected outage duration for any expected or future outage number, inverting Eqs. 3 and 5 for incomplete and complete restoration respectively, is,

$$h = \frac{1}{\beta}\ln\left\{\frac{N_0 - n_m}{n(h) - n_m}\right\} \text{ or } h_{n_m=0} = \frac{1}{\beta}\ln\left\{\frac{N_0}{n(h)}\right\} \tag{6}$$

Note that both the average number of outages, $\bar{n}$, and the expected duration depend not only on the outage number, N_0, but also on the two key parameters, the characteristic e-folding rate, β and the residual number of outages, n_m.

The existence of a minimum attainable probability, P_m, only arises from the potential for incomplete restoration, implying an imperfect learning response with a residual non-restoration rate, λ_m. To estimate its value, from Duffey (2015) the minimum is,

$$P_m \sim (\lambda_m/k)^{1/2} \tag{7}$$

So, as an estimate, the lowest attainable outage correction rate becomes,

$$\lambda_m = k(n_m/N_0)^2 \tag{8}$$

This minimum rate value scales with the inverse square of the initial outage number, N_0, as more outages lead to better ultimate repair performance. Substituting Eq. 8 into Eq. 3 and reasonably assuming $P_m \ll 1$ yields the working approximation,

$$P(\mathrm{NR}) \sim \left(\frac{\lambda_m}{k}\right)^{1/2} + \mathrm{e}^{-\beta h} \tag{9}$$

Numerical values are available from previous work (Duffey and Saull 2008; Duffey 2015). For the rate, $\lambda_m \sim 5 \cdot 10^{-6}$ per risk exposure (accumulated outage) hour has been derived from the lowest attainable error (fatal crash) rate achieved in any modern technology, namely by commercial airlines with over 200 million flights for 1977–2000; and $k \sim 0.1$ has been implied by the Superstorm Sandy data (see below). Hence, as an order of magnitude estimate,

$$P_m = (\lambda_m/k)^{1/2} \sim (5 \cdot 10^{-6}/0.1)^{1/2} = 0.007$$

In summary, we expect the outage fraction or non-restoration probability to decrease exponentially towards some small but perhaps finite minimum.

3 Outages Remaining at Long Times: Defining the End

There is a risk of extended outage times and "imperfect" restoration, but there is no standard for what constitutes sufficient completion in time, number, or probability. Ideally everyone eventually has power restored but, in reality, some outages may be delayed or even completely irrecoverable due to damage and access problems. The theoretical minimum probability, P_m, corresponds to a slightly less than 1% chance of non-restoration even after a very long time.[3]

When an outage emergency has ended or can be declared "over" is a potentially controversial determination. The wide publication and use of a 99.9% overall reliability for power systems shows the general public does understand the concept of probability. But the end point is clearly not the common phraseologies currently being used like: a "vast majority" with power restored; or, say, "99.99% have power" when that percentage incudes all those who did not even lose power during the event; or the intriguing "close to the finishing line"; or the general statement "restored to essentially all" while thousands may still remain blacked out. One apparently accepted practice is declaring completion of restoration when the total outage number for some overall region or total customer number is

[3] Instead of unreliability of non-restoration, some experts, media, and electric utilities prefer to quote the complementary "reliability" for the restored and still-connected number. The oft-published fraction $\{(1-(n/(N + N_P))\} \times 100\%$, is the "odds" of outage if it includes all those customers who did not even lose power, N_P, but is a larger and more impressive number than the unrestored fraction still left without power.

back to "near normal." This definition is not applicable when this estimate includes large unaffected parts of the region and/or customers who were never disconnected by the event. The sample for measuring restoration probability and declaring "success" should be limited to those restored and directly impacted by having outages.

Formal risk/safety/reliability assessments require precise limits or uncertainty ranges for the smallest possible probability of non-restoration or extended outage times. The presence of stubborn or difficult outages requires extensive data collection (even beyond 500 h) to properly establish the end point or the correct asymptotic probability, P_m, of non-recovery.

What is needed is an objective and technically defined end state, and some options include:

1. Limit the maximum elapsed time to when all outages that can be physically restored have been, so $n(h) \rightarrow n_m$, as $h \rightarrow h_m$ and any residual or non-restorable outages do not then count;
2. Define the non-restoration probability as referenced to the total that can possibly be restored, that is $P(\mathrm{NR}) = (n(h) - n_m)/(N_0 - n_m)$, so $P(\mathrm{NR}) \rightarrow 0$ as $n(h) \rightarrow n_m$, which then requires actually knowing or defining the lowest average value;
3. Utilize the purely theoretical relation, $n_m \sim N_0(\lambda_m/k)^{1/2}$ as a "best" estimate minimum, and hence infer the rate value from the observations, for example, $n_m \sim 0.007 N_0$, where the maximum outage number is known.[4]

4 Initial Test with Superstorm Sandy Data

The first scoping test of the prediction model to outage restoration described in Sect. 2 was for Superstorm Sandy (Category 2) in 2012 (Duffey 2014) and is briefly summarized again here. Officially listed as the largest hurricane ever to have formed in the Atlantic Basin, Sandy reached 1000 miles in diameter and record wave heights impacted New York City and New Jersey. The storm outage numbers, $n(h)$, were accessed at the Consolidated Edison Company website, which at that time constituted the most complete reporting of the three affected power companies (Duffey 2014). Data were recorded at approximately daily intervals from 31 October to 14 November, when some 16,300 customers ($\sim$ 1%) were still without power. The probability of non-restoration was calculated from $P(\mathrm{NR}) = n(h)/N_0$, with N_0 being the maximum number of outages observed.

[4] For fire, earthquake, or war damage, some outages may not be restorable until damaged property is physically rebuilt, which number should strictly be subtracted from the maximum possible.

Figure 1 shows two curves given by fitting the prediction model to the Sandy data, using an effective learning rate constant, $k = 0.1$ (Duffey 2014), and from Eq. 3 the best fit line, with an $R^2 = 0.89$,

$$P(\mathrm{NR}) = 0.007 + 0.956\mathrm{e}^{-0.012h} \quad (10)$$

This lowest or minimum probability, $P_m \sim 0.007$, is consistent with the theoretical minimum expected restoration probability (Eq. 7). Although encouraging, there were insufficient data then available for determining a more definitive correlation. So new data were collected in the present study to generalize the analysis by encompassing wider outage scales, more extreme event types, and multiple power suppliers/restorers.

5 New Extreme Event Power Outage Restoration Data

To validate the prediction model and the learning trend predictions, extreme event outage data for diverse modern cities, regions, and populations for hurricanes, storms, fires, and floods were collected. Data were accessed at regular intervals on public "power tracker" or "outage map" websites that update the status, location, and number of customer outages and give general possible restoration timescales for those "without lights." The websites were usually very complete and only occasionally were not accessible presumably due to reporting overload, update intervals intermittently changing, or reporting delays and gaps of many hours.

5.1 Severe Event Chronology and Data Sources

The data selected were for disparate natural severe events causing massive damage and societal disruption[5]:

- Hurricane Harvey (Category 4) in Texas had rapid initial restoration after landfall at Rockport, Texas, with the worst rainstorm in U.S. history at a rate of 10" (254 mm) per day causing massive concomitant flash flooding of rivers, creeks, and bayous that entirely swamped the surrounding suburban areas and the city.[6] During the storm from 25 August to 28 September 2017, outage numbers were collected from the local

[5] More details on individual events can be found by name searches at https://en.wikipedia.org/wiki/ and lists at https://www.ncdc.noaa.gov/billions/events/US/1980-2018, http://cdfdata.fire.ca.gov/incidents/incidents_statsevents.

[6] We also collected public Flood Warning System (FWS) rainfall and water level data for selected stations in Harris County to analyze the predictions for such an extreme event (accessed and available at https://www.harriscountyfws.org/GageDetail/Index/).

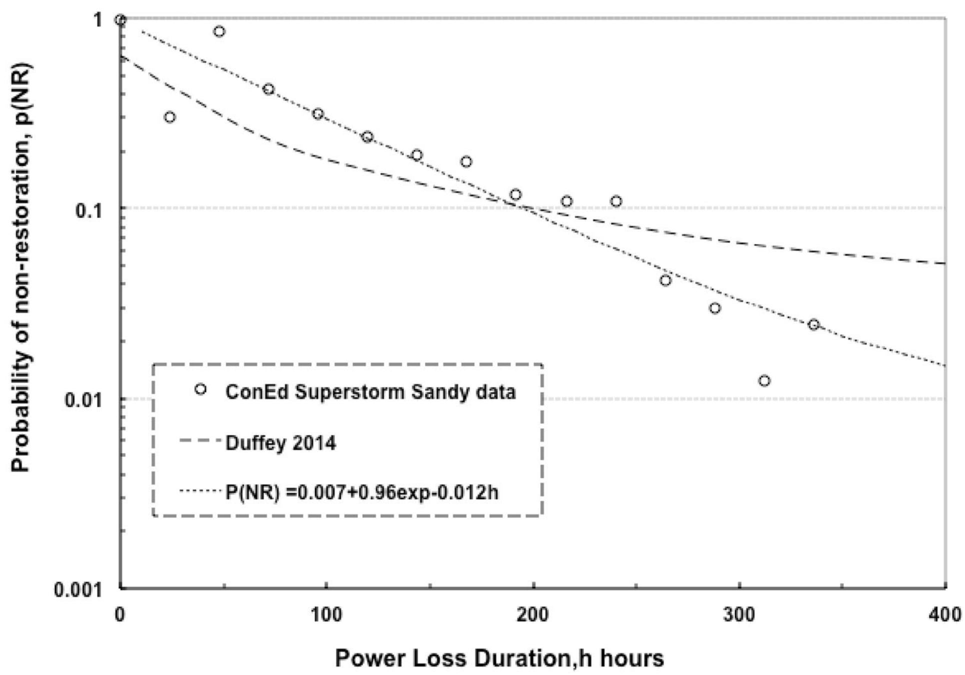

Fig. 1 Comparison of the initial scoping test of outage restoration prediction models (dashed lines) and Superstorm Sandy data (circles)

electric power distribution company website for Houston's CenterPoint Energy.[7] Outage data for the Corpus Christi area, including nearby Rockport from American Electric Power[8] with 1,000,000 customers covering the effects of coastal landfall, were collected.

- Hurricane Irma (Category 4) arrived just 2 weeks later in 2017, the largest ever hurricane to strike the United States, and raged over the entire length and width of Florida. The impact was much wider due to the storm's size, and, as Irma progressed northwards, it flooded the ocean shores and battered everything with over 100 mph winds and heavy rain. Therefore, during the storm data were collected for Florida's five major urban conurbations of Miami, Naples, Fort Lauderdale, Tampa, and St Petersburg, as well as northwestern Florida, an area containing a total of about 7,425,000 customers. From 9 to 28 September, the public websites of the local electric power distribution companies were monitored: Florida Power and Light[9] with 4,900,000 customers; Duke Energy Florida[10] with 1,800,000 customers; and the adjacent Tampa Electric Company[11] with 725,000 customers. As examples of a more remote region, from 300 h onwards the data from the two small power companies that supplied a string of resort enclaves along the Florida Keys (Florida Power Electric Cooperative and Keys Energy Services) were also monitored. Whenever possible, the numbers were checked against the overall Florida Disaster Organization (FDO) county-by-county reports.[12] This official state site was also the source of the limited United States data that we had collected in 2016 for Hurricane Matthew (Category 5), which had mainly ravaged Haiti, Grand Bahamas, and Cuba.
- A week or so later in 2017, Hurricane Nate (Category 1) impacted the Gulf Coast near the Alabama/Georgia border and quickly downgraded to a tropical storm (winds less than 75 mph). This event is of interest as a case where damage and outages were more limited, so it is an effective baseline to compare against more severe events. Some 150,000 Alabama Power Company (APC) customers lost power, and in the absence of an outage map the data were accessed at APC's online social media feed.[13]
- Almost immediately Hurricane Ophelia (Category 1), the "biggest and most destructive storm" to form in the Eastern Atlantic,[14] was downgraded to a cyclonic storm but then swept across the Irish Republic, causing over 200,000 outages or power cuts. From 15 to 27 October, data from the Electricity Supply Board's (ESB) two sources were collected: 30 selected local areas[15]; and

[7] http://gis.centerpointenergy.com/outagetracker/.

[8] http://outagemap.aeptexas.com.s3.amazonaws.com/external.

[9] https://www.fpl.com/storm/customer-outages.

[10] https://www.duke-energy.com/outages/current-outages.

[11] https://www.tampaelectric.com/residential/outages/outagemap.

[12] https://www.floridadisaster.org/info/outage_reports.

[13] https://twitter.com/alabamapower.

[14] https://www.rte.ie/news/2017/1017/912796-ophelia-aftermath/.

[15] https://www.esb.ie/esb-networks/powercheck/.

the periodically reported overall numbers[16] with the associated occasional "heat maps" of the geographic distribution of outages.

- Soon afterwards in 2017, driven by high winds, the largest ever wildfires occurred in California, and are a major test of the applicability of the prediction model for a totally different severe event type. The first fire spread across the northern Napa Valley wine region, burning about 9000 structures and over 200,000 acres, and causing more than 300,000 outages and USD 9 billion in property damage. From 10 to 28 October we collected data twice daily from the Pacific Gas and Electric outage lists for 15 cities in the fire[17] and also from the occasional News releases.[18] The second fire in the south burned over 230,000 acres in Ventura County's Thomas fire and threatened major power lines. From 5 to 21 December we collected data as reported a few times daily by Southern California Edison's news releases[19] and occasionally by its Customer Support Team, which was created on December 19 after the onset of the emergency to provide information, wildfire and mudslide support, and financial advice to customers impacted by the disaster.[20]
- Storm Emma was called the worst storm to hit the U.K. in 50 years with high winds and record heavy snowfalls in Eire/Republic of Ireland, so ESB outage data were again collected from 1 to 5 March 2018.
- For the Southern Hemisphere, a downgraded Cyclone Gita struck New Zealand with high winds and rain, and limited outage data were available online from Powerco from 19 to 26 February 2018.[21]
- Early 2018 provided baseline data for completely different event types with heavy snowfall, high winds, and very cold conditions. Successive and almost identical "bomb cyclones" or late winter storms Riley, Grayson, and Quinn blasted the Northeast United States, providing a further test of the reproducibility and generality of restoration trends. Relevant outage data for the Eversource service areas in Connecticut, Massachusetts, and New Hampshire were downloaded from 3 to 11 January and for 2 to 6 March.[22] Immediately after Riley, Storm Quinn occurred in this same region and service area with almost identical outage numbers and type, so data were also collected from 7 to 11 March, as well as from United Illuminating.[23]

The affected regions and their events cover widely different communities and multiple (14) power companies (Table 1) with diverse power systems. The differing events also provide tests of the generality of the prediction model and insights into the underlying common features governing restoration trends. Therefore, this comprehensive data set also constitutes a new benchmark for testing outage restoration predictions for severe events.

5.2 Summary of the Data Set

Table 1 lists the dynamic data sets for these 13 extreme events occurring between 2012 and 2018, which were entered into Excel worksheets. Totaling 2900 data points and covering 5500 h for 17 million outage occurrences, this is believed to be currently the most comprehensive database anywhere for such diverse extreme events and ranges of outage extent.[24]

One of the lessons learned is the estimated times of restoration reported on the websites or published in corporate news bulletins were occasionally incorrect, inconsistent in style, and/or usually overly optimistic. The precise causes of these problems are unknown, but they underscore the need for a verified or independent outage predictor for extreme events. They illustrate beautifully the impacts of stress in adversely affecting overall emergency management response and the increased uncertainties in planning for, communicating about, and executing recovery during extreme and unexpected circumstances.

6 Comparisons of Reported Data and Model Predictions

Using the additional detailed outage records from 2016 to 2018 listed in Table 1, the probability of non-restoration, $P(\mathrm{NR}) = n(h)/N_0$, was calculated. The data fell naturally into distinct main groupings (Sect. 7) depending on the severity and extent of the extreme event.

16 www.esbnetworks.ie/power-outages-updates/latest-updates.

17 https://m.pge.com/#outages.

18 https://www.pge.com/en_US/about-pge/media-newsroom/media-newsroom.page.

19 https://www.sce.com/wps/portal/home/outage-center/check-outage-status.

20 https://www.sce.com/wps/portal/home/safety/family/emergency-tips/CrisisSupport.

21 https://www.powerco.co.nz/about-us/power-cuts-page/ and www.powerco.co.nz/news.

22 https://www.eversource.com/clp/outage/outagemap.

23 http://www.uinet.com/outageinfo/outages/outagemap.html.

24 Subsequent to the paper being submitted and reviewed, Hurricane Florence occurred in the United States and further data were collected.

Table 1 Extreme event outage data summary

City and/or region	Data source (event)	Data #	Span h	Minimum outages n_m/days	Maximum outages N_0
New York, NY	ConEd (SS)	14	336	16,300/14	1,345,000
Florida	FDO (M)	10	240	5650/10	10,234,174
Houston, TX	CPE (H)	500	800	1000/30	109,244
Corpus Christi	AEP (H)	500	800	100/30	201,635
Florida South	FPL (I)	1020	400	3000/15	1,810,290
Florida NW	Duke-FL (I)	270	400	1500/15	1,610,280
Tampa, FL	TECO (I)	270	400	100/15	330,103
Florida Keys	FKEPC/KES(I)	120	400	1500/15	60,000
Alabama	APC-SCS (N)	20	60	80/9	156,000
Eire, EU	ESB (O)	30	240	1000/10	385,000
Eire, EU	ESB (E)	14	60	203/4	127,000
NE, USA	Eversource (S)	20	50	320/2	25,796
NE, USA	Eversource (R)	22	90	3500/4	220,378
NE, USA	Eversource (Q)	34	120	400/5	209,706
Taranaki, NZ	Powerco (G)	10	160	135/7	26,000
Napa, CA	PGE (F)	40	450	200/15	359,000
Ventura, CA	SCE (F)	44	450	32/18	8400
Total		2938	5458		17,218,006

Event key: SS = Sandy, E = Storm Emma, F = Wildfires, G = Cyclone Gita, H = Harvey, I = Irma, M = Matthew, N = Nate, O = Ophelia, Q = Storm Quinn, R = Storm Riley, S = Snowstorm Grayson

6.1 Extended Restoration: Wildfires and Hurricanes Harvey, Irma, and Sandy

Figure 2 shows that the six different most severe events and longest lasting outages (up to about 600 h), with many billion dollars in consequential costs, follow the same restoration trajectories. This comparison of P(NR) for Hurricane Harvey and the California wildfires to Superstorm Sandy demonstrates that the overall macrotrends are remarkably similar over three orders of magnitude, and that all these new restoration data are also exponential in form. In addition, changing the initial number of outages or type of event does not markedly change the response, so these variables are not the key factors. This is confirmed by the factor of 10 smaller outages for the Ventura (Thomas) fire whose data were collected after the other events but still followed the same trends.

By comparing these many and varied disparate events, we have now shown that common learning and statistical effects (discussed in Sect. 2) dominate all such extreme event data. This result is entirely new, and indicates that non-restoration timescale and probability are essentially independent of location, size, and type of disaster.

Each series of data for an event can be individually fitted by its own exponential curve without the minimum, n_m, all with $R^2 > 0.9$, as illustrated by the solid line $P(\mathrm{NR}) = 0.96$ exp–0.012 h example. The dotted line in Fig. 2 is the fitted curve Eq. 10 from Fig. 1 for Superstorm Sandy but extrapolated to 600 h from the original 350-h span since the minimum probability is reached after 600 h. The finite minimum, $P_m = 0.007$, is remarkably close to the prior inferred value for Superstorm Sandy from the initial scoping test (Duffey 2014). The two fitted curves then bracket the diverging minimum data points of the larger "tail" for Houston with persistent flooding effects lasting longer than for Corpus Christi, which suffered mainly direct landfall damage.[25]

To compare the hurricane data with differing times of peak outage, where necessary the time scales for the six events in Fig. 2 were made relative to the shifted time origin, h_0, for the maximum outage, N_0. The result is given by the established commercial statistical routine TableCurve2D,[26] with an $R^2 = 0.94$:

$$P(\mathrm{NR}) = 0.003 + 1.06\mathrm{e}^{-0.011(h-h_0)} \tag{11}$$

This recommended fit, with $\beta = 0.011$, is very close to the independently derived original Superstorm Sandy estimate from only 15 data points in Eq. 10, proving that pooling the

[25] Note that standard numerical curve-fit routines find it difficult to capture such statistical distributions that include the "tail" values, simply because they are so small, except by using completely arbitrary high-order polynomials.

[26] http://www.sigmaplot.co.uk/products/tablecurve2d/tablecurve2d.php.

totally different event data for independent power systems is reasonable.[27] The commonality of the data correlation suggests an apparent inherent limit or constraint on the present rate of repair of major outages following extreme events.

There is an overall 50% chance of restoration by about 100 h, 90% within 200 h (4 days), and 99% by 400 h (16 days). The expected outage duration after the peak is, from Eqs. 6 and 11,

$$h - h_0 = \frac{1}{0.011} \ln\left\{\frac{1.06N_0}{n(h) - 0.003N_0}\right\} \tag{12}$$

The simple exponential fit that does not capture the minimum is given also with an $R^2 = 0.94$ by

$$P(\mathrm{NR}) = 1.03\mathrm{e}^{-0.01(h-h_0)} \tag{13}$$

This fit, with $\beta \sim 0.01$, is essentially identical to that used solely for fitting to the severe wildfire data. The outage data suggest the range for the minimum probability of non-restoration is $0.003 < P_m < 0.007$. In power loss risk assessments, this is the lowest proven value from actual experience that can be adopted for the probability of non-restoration.[28]

6.2 Faster Restoration: Hurricanes, Snowstorms, and Cyclones Compared

Let us now examine and compare the data for seven less severe extreme events—Hurricanes Matthew, Nate, and Ophelia, Cyclone Gita, and winter storms Emma, Grayson, and Riley—with shorter overall total restoration times of up to some 300 h. Nate quickly downgraded from hurricane to tropical storm strength shortly after landfall, and Ophelia also downgraded before striking Ireland. The initial outage peaks are not broad, so there is no need to correct the time origin.

Figure 3 demonstrates that each event has its own well-defined trend. Despite the data scatter, there are clearly two groupings with distinctly different slower or faster restoration slopes, and either group can contain a snowstorm or a hurricane event. The trends are also independent of location, as can be seen by pairs Nate and Grayson, and Ophelia and Matthew following nearly the same trajectories. In particular, Eire/Republic of Ireland has data for both groupings, again showing that restoration trends are independent of event type, location, and outage magnitude. As confirmation, the successive winter storms Quinn and Riley possessed identical restoration characteristics, suggesting that the unaltered rate of repair between events may be the maximum attainable. It might the overall degree of destruction and the degree of difficulty especially for access that determine restoration timing, not the type of event.

The Nate best fit exponential curve is given by, with $R^2 = 0.95$,

$$P(\mathrm{NR}) = 1.0\mathrm{e}^{-0.11h} \tag{14}$$

However, for Ophelia, with $R^2 = 0.85$,

$$P(\mathrm{NR}) = 1.0\mathrm{e}^{-0.025h} \tag{15}$$

These slope β-values of 0.11 and 0.025 in Eqs. 14 and 15 for milder events can be directly compared to that of 0.011 and 0.01 given by the Eqs. 11 and 13 fits to the more severe events. Therefore, according to the data, recovery from power disruption due to major hurricanes and fires can be expected to typically take twice to 10 times longer than for smaller events even with massive deployment of restoration crews. As further elaborated in Sect. 7, the reason for the difference in characteristic timescale must be the "degree of difficulty" of restoration since entirely different storm "types" in different regions all follow exponential non-restoration trends, even if the power systems were widely different in scale and outage number, despite the restoration techniques and methods employed being essentially identical.

When the less severe hurricane data is examined in more detail, the Irma higher non-recovery probability precedes a faster decline than for comparable events. Figure 4 shows the area-by-area breakdown, since the overall regional trend is the summation of the parts (as in Eq. 3). The least initially damaged cities and less flooded regions with easier access were fully restored by 200–300 h, except for the heavily inundated Naples/Collier region, which confirms that damage and access difficulty dominates recovery.

Overall, the results show no systematic relation between the total restoration time and the event scale or number of outages. The well-defined steps or periodic plateau visible in the data are at precisely daily intervals. The restoration probability (or outage number) only slightly changed overnight, presumably as repair crews rested, and these microtrends further show the unavoidable human involvement.[29]

[27] During this paper's review data were obtained for the on-going Hurricane Florence (CAT 1) with extensive flooding in the United States, which follow the predictions given by Eq. 11.

[28] In reliability terminology, $99.993 < P(R) < 99.997\%$.

[29] Noting that $(N–n)$ is nearly constant overnight, these human-induced steps cause regular cycles of the instantaneous restoration intensity, $I = dn/dh$, periodically peaking in the morning and declining overnight.

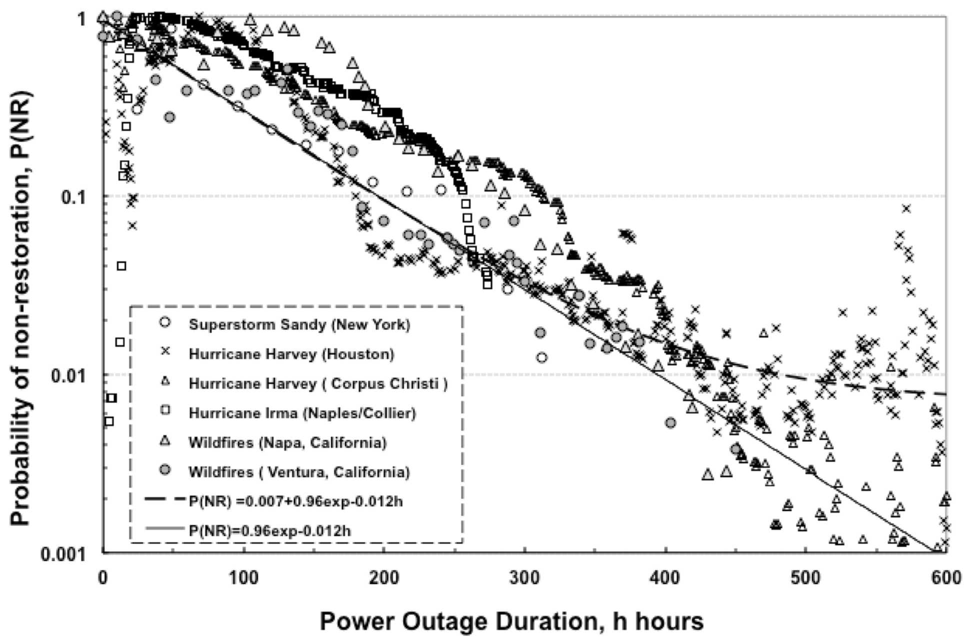

Fig. 2 Outage probability data for Hurricanes Harvey and Irma compared to Superstorm Sandy and Californian wildfires, and to the theoretically-based trend lines from Fig. 1 and Eq. 10

6.3 Dynamic Restoration Rates Compared to the Universal Learning Curve

An important finding is the slope parameter value of $\beta \sim 0.01$ for major events in Eqs. 11 and 13, as it suggests a lower restoration rate limit for modern power systems.

The systematic difference in non-restoration probability [between groups (6.1) and (6.2)] occurs despite the instantaneous dynamic non-restoration rates being comparable. Calculated using Eq. 2, the rates, λ, for Hurricanes Harvey and Irma vary dynamically as shown in Fig. 5, and are not constant with time. The rate data follow the form of a Universal Learning Curve trend (Duffey and Saull 2008), declining exponentially towards a persistent minimum after 250 h. The lowest non-restoration outage rate for extreme events is in the range $10^{-5} < \lambda_m < 5{\cdot}10^{-3}$ per elapsed restoration hour. The minimum value is close to the lowest failure rate attained in modern technological systems where risk is dominated by the human contribution.

In Fig. 6, the presence of learning is further demonstrated by comparing the Irma non-restoration rate for the first 250 h to the non-dimensional Universal Learning Curve (ULC) that has been shown to be applicable for technological and warfare systems that exhibit learning and error correction (Duffey and Saull 2008; Duffey and Ha 2013; Duffey 2017a, b). The ULC has the non-dimensional form,

$$E^* = (\lambda(h) - \lambda_m)/(\lambda_0 - \lambda_m) = \mathrm{e}^{-3N^*} \tag{16}$$

The value of the learning rate "constant" ~ 3 was independently determined from data for thousands of events in multiple modern technological systems (Duffey and Saull 2008). For the Irma data, $N^* = h/250$. The agreement with the present work demonstrates that extreme events exhibit fundamentally similar restoration management trends due to possessing the identical physical and statistical learning behavior inherent in all human decision making, skill acquisition, error correction, recall, and recognition (Ohlsson 1996; Duffey 2017c).

7 Reducing and Managing Outage Risk for Severe Events

From the outage data analysis, general but distinct categories of restoration timescales and probability trajectory have emerged, each characterized by a range of values for the important e-folding characteristic parameter, β (Eqs. 11–15). These differences reflect the increasing impact of damage extent, complexity, and access severity in degrading error correction times and rates after an event (Duffey 2014). As explained below, this variation reflects the increasing "degree of difficulty" that faces repair crews deployed and operating in the field, which is always greater than for normal, everyday restorations.

- Type 0: Ordinary, which we may classify as the baseline of "everyday" outage restorations (Duffey and Ha 2013; IEEE 2013), with simpler equipment replacement, line repairs, and/or reconnection due to an effectively instantaneous outage. Without any significant additional damage due to extreme events and/or weather effects, or any degraded access difficulties, power restoration can be achieved usually within a few

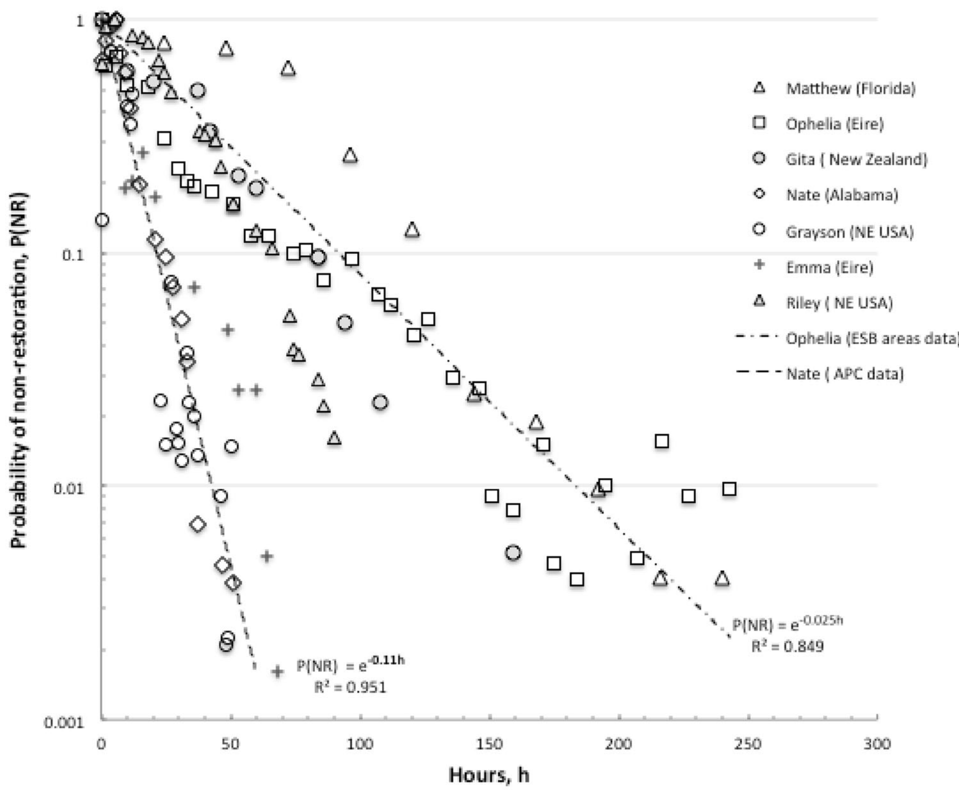

Fig. 3 Comparison of restoration trends for less severe events—Hurricanes Matthew, Nate, and Ophelia; Cyclone Gita; and winter storms Emma, Grayson, and Riley

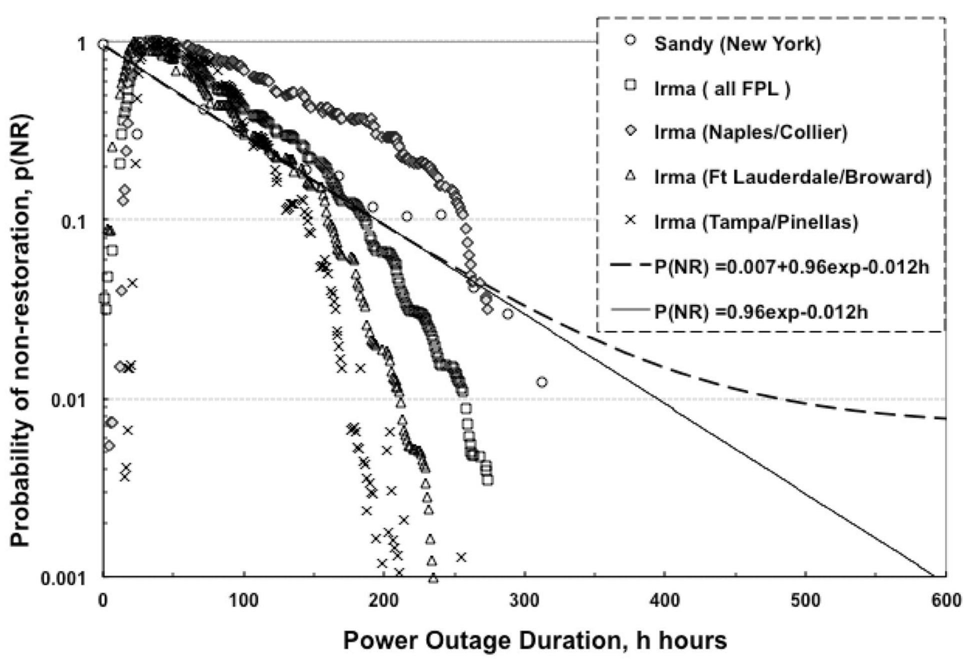

Fig. 4 Regional variations of outages for Hurricane Irma and comparison with Superstorm Sandy data and the theoretically-based fitted trend lines from Fig. 2 and Eq. 10

hours to a day (for example, damage limited to transformer fires, overload breaker trips, single tree falls).

- Type 1: Normal, $\beta \sim 0.2$, when outage numbers quickly peak due to finite but relatively limited additional infrastructure damage. Repairs are still fairly straightforward and all outages are restored over timescales of 20 to about 200 h (Fig. 3). Damage is mainly localized, repair equipment is still available with ready access, and normal or standard emergency

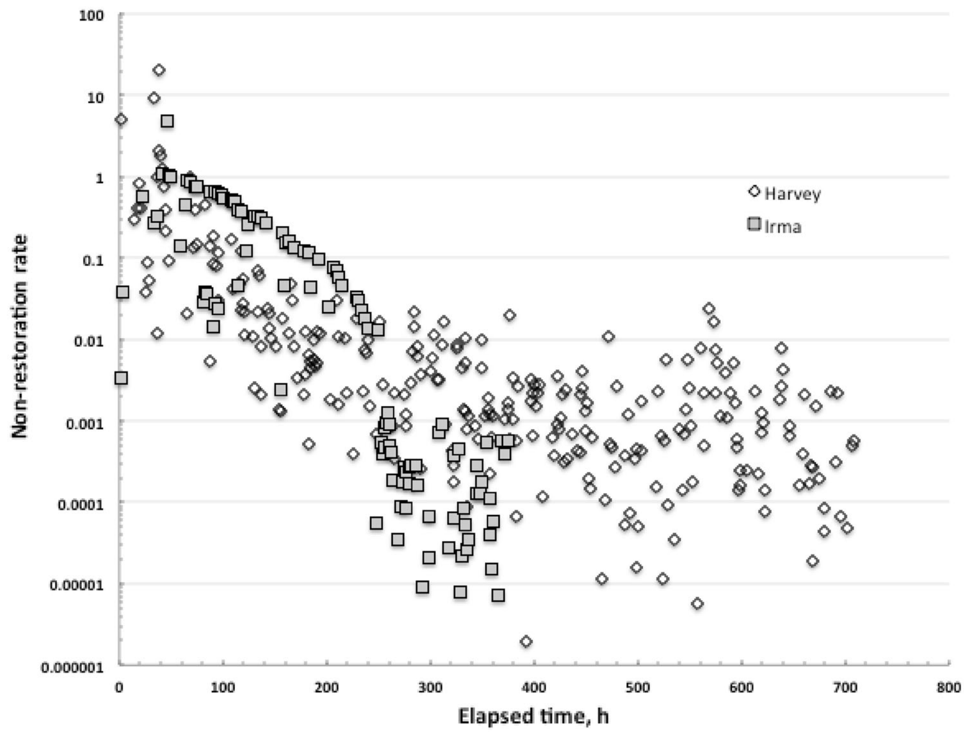

Fig. 5 Hurricanes Harvey and Irma instantaneous non-restoration rates

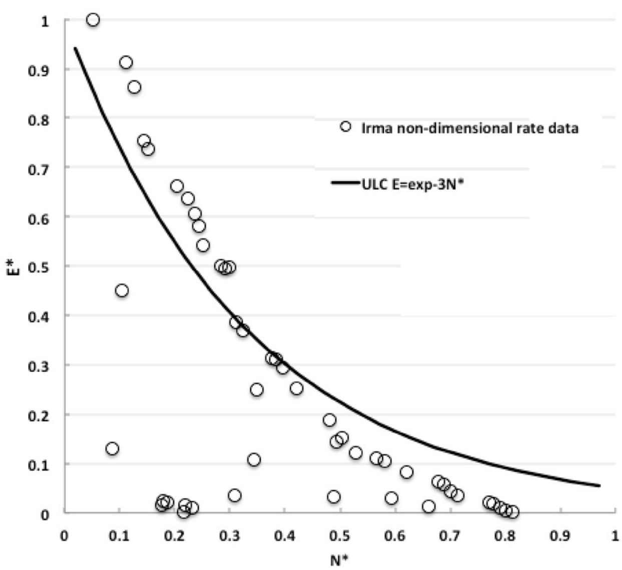

Fig. 6 Comparison of Irma non-restoration rate data to the non-dimensional Universal Learning Curve (ULC) (Duffey and Saull 2008)

response/repair procedures apply directly (for example, damage that causes multiple failed transformers, switchgear issues, and/or power distribution faults).

- Type 2: Delayed, β ~ 0.1–0.02, progressively reaching peak outages in 20 or so hours, as extensive but repairable damage causes lingering repair timescales of 200–300 h before almost all outages are restored (Fig. 4). For Type 2 damage, planning and executing repairs may require specialized equipment. Restoration may be hindered due to severe or persistent adverse weather conditions, which require significant modification or adaptation of standard emergency response/repair procedures (for example, damage plus flooding, snow/ice, strong winds, or extreme cold).
- Type 3: Extended, β ~ 0.01, with perhaps 50 or more hours before outage numbers peak due to continued damage and significant loss of critical infrastructure. Restoration repair timescales last for 300–500 h or more (Fig. 2). Residual outages persist, due to additional damage and major difficulties beyond Type 2 in gaining access for repairs. There is potentially significant social disruption that requires the use of nonstandard emergency response/repair procedures (for example, severe damage plus uncontained fires, emergency evacuations, and impassable roads).
- Type 4: Extraordinary, β ~ 0.001 or less, for a cataclysmic event with the electric distribution system being essentially completely destroyed and not immediately repairable. Complete restoration timescales can be many months, because the system has to be partially or totally rebuilt. As a consequence, normal emergency response/repair procedures are inapplicable (for example, damage plus entire power system collapse or destruction as recently occurred in Puerto Rico and Haiti).

The different β-values reflect increased repair difficulty and include increasing workload, fatigue, and stress. Crisis response, disaster risk, and emergency managers all need to recognize which type of event they are facing, particularly since severe Types 2 and 3 events are challenging to society. For a conservative or upper bound estimate, the estimated $P(\mathrm{NR})$ from Eq. 11 with $\beta \sim 0.011$ can be multiplied by a factor of two to encompass the data scatter.

An excellent report on how to address outage risk due to weather utilized Florida as a case study (U.S. Office of the President 2013). Suggested power supply improvements include strengthening grid poles and transmission structures, elevated substations, and use of underground cabling. FPL had invested heavily in such system “hardening,” and has stated that the return has been measured in significantly decreased supply system damage (FPL 2017, §3):

> Over the last 11 years, FPL has invested nearly $3 billion to make the energy grid smarter, stronger and more storm-resilient, and those investments are paying off for customers. No hardened transmission structures—the backbone of our system—were lost. All of FPL’s substations were up and running within a day following Irma. Hardening helped make the system more resilient and provided for a much faster restoration. In fact, FPL lost only a fraction of its poles, which today numbers 1.2 million, as compared with Wilma—with early estimates of approximately 2500 downed (0.2%) during Irma as compared with roughly 12,000 during Wilma.

The present Irma data and analysis actually show no reduction in customer outage restoration time or non-restoration probability, however, compared to the totally independent hurricanes Superstorm Sandy, Matthew, and Ophelia occurring elsewhere. Therefore, no improvement in restoration times can be directly attributed to the hardening process alone, in accord with other viewpoints on enhancing grid reliability (Stephens 2017). This does not suggest responses were inadequate: brave and devoted professionals worked as quickly and efficiently as possible. There is simply an inherent limit on the achievable rate of repair.

Government agencies, private businesses, and emergency organizations will learn from these previous disasters (Duffey and Saull 2008; Thompson 2012), including the improvement of storm and fire damage mitigation measures. The Federal Emergency Management Agency (FEMA) provides overall emergency support[30] but actually building, operating, securing, and protecting critical infrastructure like the power grid and power plants is the role and licensed responsibility of the private sector or some separate quasigovernmental or authorized entity (DHS 2008; FEMA 2016; ESB 2017). The current allocation of management responsibilities between electric utility investments, local government emergency preparedness, and federal government national disaster response works well most of the time, but should be further refined.

Cost–benefit analysis as a basis for risk improvements cannot work across such diverse entities and interests. To improve outage risk management due to extreme events and disasters, and optimize local, business, and national investments, the suggested focus and “smart grid” priorities, including emergency planning for cities and utilities, should be:

- increasing diversity and robustness of supply and delivery;
- designing for ease and rapidity of restoration;
- managing emergency system response capability;
- improving communications and emergency planning;
- removing or reinforcing vulnerable structures and facilities;
- revising existing extreme event occurrence criteria;
- enhancing flood barriers and controls on all vulnerable regions;
- reducing major fire and flooding risk exposure; and
- revisiting national preparedness arrangements and agreements.

8 Conclusion

This research demonstrated the common dynamic trends in outage restoration after damage due to extreme events or disasters. New data were collected and analyzed from Hurricanes Irma, Harvey, Matthew, Nate, Ophelia, and Superstorm Sandy (covering Categories 1 through 5), Snowstorms Grayson, Quinn, and Riley, Cyclone Gita, Storm Emma, and extensive wildfires in California. Extending earlier work and utilizing statistical techniques have successfully reduced this whole panoply of disasters to a common comparative basis. The data for non-restoration probability are all well correlated by simple exponential functions consistent with the result from previous work, dependent on and grouped by the degree of damage and social disruption (Types 1–4).

The present results provide a new method for making outage time predictions in repairable power systems following disasters. These estimations can be used for emergency planning and risk assessment purposes, independent of event type.

[30] FEMA’s primary mission remains “to support our citizens and first responders to ensure that as a Nation we work together to build, sustain, and improve our capability to prepare for, protect against, respond to, recover from, and mitigate all hazards” (FEMA 2016).

Recovery times from power disruption due to major hurricanes and fires are typically twice to 10 times longer than for less severe events. Over three orders of magnitude, the restoration trends are identical for major wildfires and most severe hurricanes despite their totally disparate origins. This similarity confirms the influence of human learning and decision making in effecting repairs. We also quantify the systematic deterioration in restoration rates and times for extreme events that can be attributed to continuing poor access and repair difficulty.

The minimum attainable non-restoration rate and outage probability are in accord with independent data for modern technological systems. Suggestions are made for the priorities for local, business, and national disaster management investment.

A key point is that the power restoration processes for the many and various disaster types share the same fundamental physical basis. The power restoration rate follows the scientific laws of probability and human learning that dominate risk in all modern technological societies.

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