Critical Infrastructure: the probability and duration of national and regional power outages

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Abstract

Power generation and distribution systems are part of a nation's critical infrastructure. Power losses or outages are random with a learning trend of declining size with increasing experience or risk exposure, with the largest outages being rare events of low probability. Data have been collected for power losses and outage duration affecting critical infrastructure for a wide range of events in Belgium, Canada, Eire, France, Sweden, New Zealand and USA. A new correlation has been obtained for the probability of large regional power losses for outage scales up to nearly 50,000 MW(e) for events without additional infrastructure damage that have been generally fully restored in less than 24 hours. For more severe events, including damage due to natural hazards (floods, fire, ice storms, hurricanes etc.), the observed variation in the duration of the outage up to more than 500 hours depends on the degree of difficulty. The irreparable fraction data range (the "tail" of the distribution) indicates that the chance of remaining unrestored is small but finite, even after several hundred hours. Therefore, explicit expressions have been given and validated for both the probability and duration for the full range from "normal" large power loss out to extended outages for rare and more "severe" events with greater access and repair difficulty.

Keywords: power, outages, critical infrastructure, severe events, prediction

I. Introduction

Power generation and distribution systems are part of a nation's critical infrastructure. Everyone everywhere on losing their electricity supply want to now how long the power will be "out". The chance of a large blackout, power loss or supply interruption is key to planning adequate supply margins, undertaking emergency response and protecting other critical infrastructure [1]. We are interested in the prediction of the probability of a large rare outage or power loss event and its duration. There is a gap in the knowledge between overall reliability studies of electric grid reliability and concerns and the impact of rare and record events and natural disasters (e.g. recent Hurricanes Katrina, Sandy, Harvey and Florence in USA) whose extensive flooding and damage caused multiple power outages and delayed restoration. It is such major disasters that are of concern for infrastructure fragility, and we need to estimate their probability or chance of occurrence and the timescales for restoration [2].

II. Method

I. Power loss and restoration data

The national power loss data is derived from Kearsley [3] for large blackouts in France, Sweden and Belgium, being for a range of 28,000, 11,400 and 2,400 MW(e) initial losses, respectively.

For the entire USA for the period 1984-2000, the IRGC report [4] gives a plot of the exceedence probability of an outage, P, versus the size, Q, in MW(e). Basically, a sample of power loss or outages were observed and counted; and similar plots by sub-region have also been presented and fitted using empirical binomial, Weibull and lognormal distributions [5]. These distributions are of course heavily weighted by the many "normal" or everyday outages, not rare catastrophic events. Since we wish to predict the low probability "tail" of the distribution such standard statistical methods are not applicable, as clearly evident in their Figure S-28. In addition, Murphy et al [5] also looked to see if outages were linked, and concluded: "…that the largest correlated failure instances were caused by extreme weather". This observation is precisely what we should expect given the large geographic scale and impact of natural hazards (storms, hurricanes, floods, ice storms and wildfires) and the consequent universal power restoration characteristics [2]. Large NH events do not respect or recognize human-drawn boundaries or arbitrary grid distribution regions, and cause event-related damage and destruction over wide swathes.

The original IRGC data were from the NERC database, and were shown as a graph with dots and lines on a log-log plot; but because of the unavailability of the data[1], we were forced to hand transcribe using enlarged images. The error so incurred is a maximum of about 5% in probability for exceeding a given power loss or outage, P_i, which is sufficient accuracy for the present purposes of rare event prediction (see below). For the observed sample total outages each has a probability, P_i, we define the likely mean or probable average outage as,

$$\bar{Q} = \overline{\sum_{\iota} P_{\iota}\, Q_{\iota}}$$

The IRGC [4] data then have an average expected outage of $\bar{Q} = 95\ MW(e)$.

Our earlier work examined the duration of very large outages or power losses at the national level [6]. The extensive power restoration data included many severe events e.g. storms, ice storms, fires, hurricanes, cyclones and floods, causing outages lasting from 24 to 800 hours over a wide range of urban, regional and international scales [2].

In all cases, the affected power companies, emergency management organizations and government agencies deployed vast numbers (sometimes many thousands) of staff, repair crews, equipment and procedures to address power recovery, evacuate people and repair damage. Essentially restoration only can and does proceed "as fast as humanly possible", limited by damage, access and social disruption issues caused by flooding, storms, fires, wind, ice and snow, and as stated by DHS [7] "the restoration of the grid is generally the same across all hazards".

[1] We have asked a lead author for access to the original data files and numbers forming the basis for the plot. Surprisingly for such important records, the actual NERC data for the USA are proprietary (privately owned) so the line drawings are apparently all that are publically or openly accessible.

II Theory

The first key assumption is that the power outages are indeed random, whatever the cause. Secondly, there should exist a learning trend declining with increasing experience or risk exposure. Thirdly, as shown by the data, we should also expect the largest outages to be rare events of lower probability. The learning hypothesis theory, where the rate of decrease of the failure rate, λ, at any risk exposure or experience, ε, is proportional to the rate, has a failure rate given by [8]:

$$\lambda(\varepsilon) = \lambda_m + (\lambda_0 - \lambda_m) e^{-k\varepsilon} \quad (1)$$

Here, λ_0 and λ_m are the initial and smallest attainable rates, respectively, and k is the proportionality constant. Hence, as usual, the probability is

$$P_i(loss) = 1 - e^{-\int \lambda(\varepsilon) d\varepsilon} = 1 - e^{-\left(\frac{(\lambda - \lambda_m)}{k}\right)} \quad (2)$$

Therefore, we take the failure rate, λ, as equivalent to the power loss or outage rate. The measure of the relative risk exposure or experience measure is self-evidently actually directly proportional to the power outage magnitude, ε=f(Q), which we can scale relative to the average outage magnitude, $\bar{Q}$. We may assume the outages are always essentially completely restored, so we may take, $\lambda_m \ll \lambda \approx \lambda_0 \, e^{-k\varepsilon}$.

As a first approximation, we adopt the following simplest values consistent with the physical situation. The risk exposure depends on the relative outage magnitude, $\varepsilon \equiv Q/\bar{Q}$, with $\lambda_0 = 1/\varepsilon$, implying all outage events are independent. Therefore, the probability of any power loss or outage, becomes simply the intriguing double exponential,

$$P_i(loss) = 1 - e^{-\frac{\bar{Q}}{kQ}\left\{1 - e^{-\frac{kQ}{\bar{Q}}}\right\}} \quad (3)$$

Obvious limits are:

(a) small outage or loss $kQ/\bar{Q} \to 0$, $P_i(loss) = 1$;

(b) infinitely large loss $kQ/\bar{Q} \to \infty$, $P_i(loss) = 0$;

(c) average loss, assuming that k=1,

$$Q/\bar{Q} \to 1, \; P_i(loss) = 1 - e^{-\{1 - e^{-1}\}} = 0.74$$

III. Outage duration

The probability of any outage of any size lasting duration, D, is then simply given by multiplying the probability of loss by the probability of non-restoration, P(NR).

The probability of any individual outage being restored is actually random, and being observed as outcomes follows the well-known and established laws of statistical physics as described in [8] and [9]. Therefore, the data for electric power non-restoration probability, P(NR), for all outage events are all well correlated by simple exponential functions, dependent on and grouped by the degree of difficulty as characterized by the extent of infrastructure damage, social disruption and concomitant access issues [2]. A typical generalized best fit was derived from a wide range of severe events , including hurricanes, ice storms, floods, and wildfires [2] , with h measured in hours after the peak outage,

$$P(NR) = P_m + P_0^* e^{-\beta h} \approx 0.007 + e^{-0.014h} \tag{4}$$

Therefore, in general ,

$$P(D>h) = P_i(loss)\ x\ P(NR) \tag{5}$$

Substituting Equations 3) and (4) into (5),

$$P(D > h)) = (1 - e^{-\frac{\bar{Q}}{kQ}\left\{1 - e^{-\frac{kQ}{\bar{Q}}}\right\}})\left(P_m + P_0^* e^{-\beta h}\right) \tag{6}$$

To a good approximation, since $P_0^* \approx 1 \gg P_m$,

$$P(D > h)) \approx (1 - e^{-\frac{\bar{Q}}{kQ}\left\{1 - e^{-\frac{kQ}{\bar{Q}}}\right\}})\, e^{-\beta h} \tag{7}$$

The limits are:

(a) small outage or loss ; $P(D > h)) \approx e^{-\beta h}$
(b) infinitely large loss ; $P(D > h)) \approx 0$
(c) average loss with k=1 ; $P(D > h)) \approx 0.74\, e^{-\beta h}$

IV General equation for rare events

The more general form of this new EVD Equation (3) is, for any variable, x, where the over bar is the relevant or selected average value:

$$P_i(x) = 1 - e^{-\frac{\bar{x}}{kx}\left\{1 - e^{-\frac{x}{k\bar{x}}}\right\}} \tag{8}$$

There are just two "adjustable" parameters, the average ,$\bar{x}$, and the learning constant, k, where both have physical significance. This equation can be compared to typical arbitrary three-parameter Generalized Extreme Value Distributions (GEVD) quoted elsewhere [10] of the general form:

$$P_i(x) = 1 - e^{-1+\xi\left(x - \frac{\psi}{\beta}\right)^{-1/\xi}} \tag{9}$$

For the conventionally-named distributions:

- Gumbell Type 1 ξ=0
- Frechet Type 2 ξ>0
- Weibull Type 3 ξ<0

Ockham's Razor suggests using the simplest. The reader is of course free to adopt whatever best suits the purpose and represents appropriately the physics and logic of the situation.

IV Results

I. National outage data 1984-2000 compared to theory

The demonstration of using this simple theory, Equation (3), as a basis for correlation and comparison to data is shown in Figure 1, obtained by simply adjusting the single parameter, k=2. The theoretically-based probability then has an uncertainty of order ±20% compared to the transcribed data, sufficient for present estimating purposes where the predictive larger losses of Q_M > 40,000 MW(e) have a probability of approximately 0.003 or less. The probability, of having an average system outage, P_i(loss) = 0.74 in this case is ~97MW(e), compared to the P_i (loss) =0.86 observed. This result is sufficiently encouraging to examine comparisons with other loss data as follows.

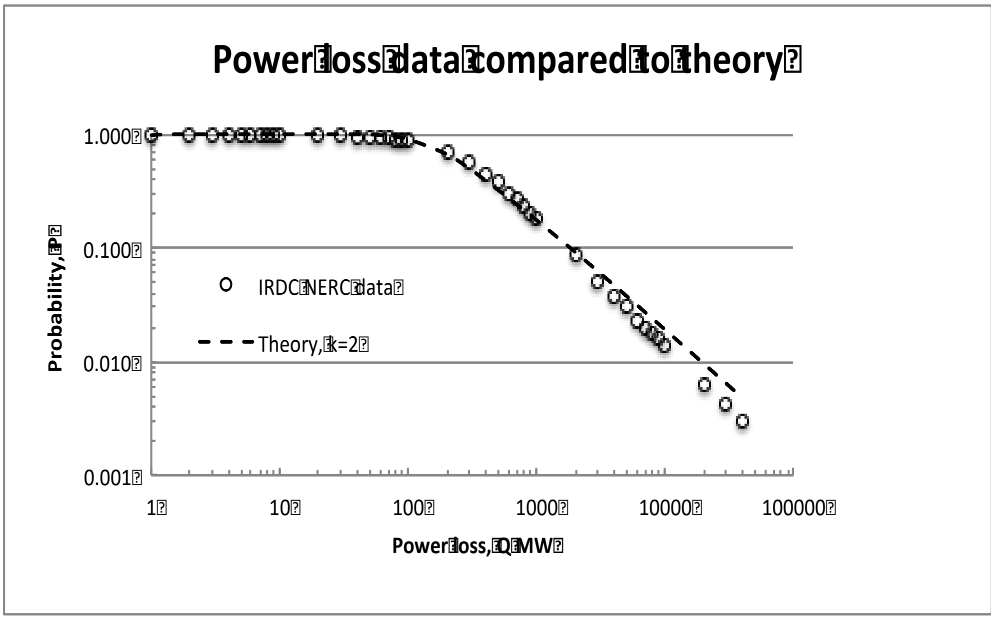

Figure 1 Initial test o USA power loss probabaility and theory

II. Regional power loss data compared to theory

A recent paper has data plots in 2016 for all eight NERC regions [5]. The individual probabilities are naturally one order lower for the largest recorded regional power losses, suggesting that the average outage, $\bar{Q}$ and the best-fit k-value change significantly.

Table 1 Regional largest power losses (data from EIA and Murphy et al [5])

Region	Capacity, MW(e) (EIA)	Largest loss, MW(e) (NERC)	Fractional loss
FRCC	47700	5000	0.1
MRO	33000	7000	0.21
NPCC	57700	15000	0.26
RFC	NA	49000	
SERC	129000	40000	0.31
SPP	51800	9000	0.17
TRE	71100	11000	0.15
WECC	139400	14000	0.1

These large region–to-region variations in losses are evident in the Table 1, where the maximum outages that have been experienced in 2016 are compared to the corresponding regional capacities reported by the EIA for 2016 [5; and www.eia.gov/electricity/data/eia411/]. It can be seen that the fraction of power lost in a region can range from 10% up to 30% of the total capacity, with the magnitudes differ by nearly a factor of ten (an order of magnitude).

Previous experience with learning theory suggests that it should be possible to compare the regional data in a non-dimensional manner, normalizing to the maximum outage sizes, Q/Q_m. Once again hand transcribing from the plots in [5], a comparison calculation is shown in Figure 2 for just two randomly chosen NERC regions, using average losses, $\bar{Q}$, of 5500 MW(e) and 1900 MW(e) for RFC and NPCC, respectively. In both cases, k=0.001, this low value implying no discernable learning from prior outages, or in this case no evidence of fundamental differences between the two distribution systems.

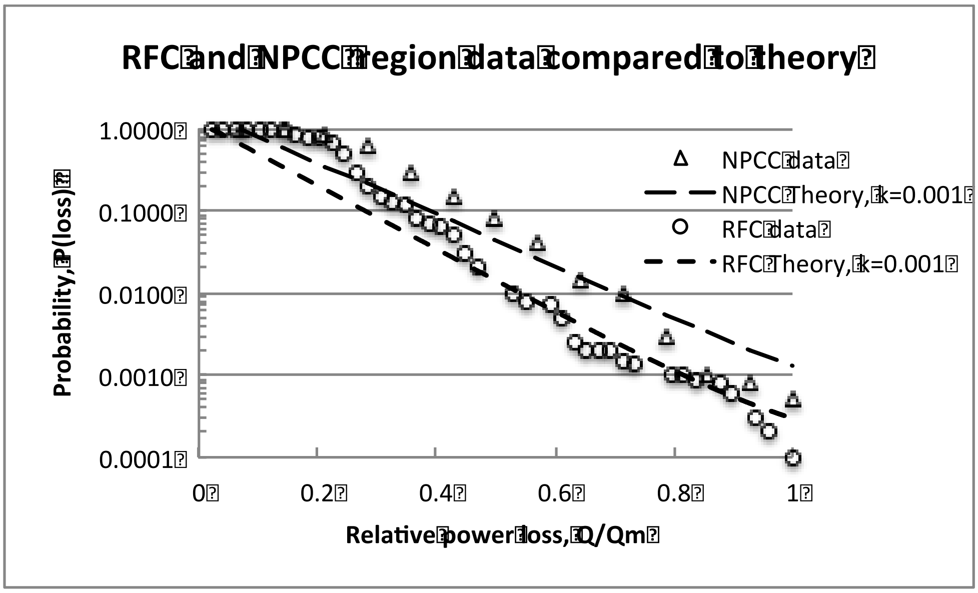

Figure 2 Regional power loss data compared to theory

Furthermore, given this new theory, we can now predict the probability of a total (100%) regional blackout, being "a catastrophic power outage of a magnitude beyond modern experience" [1]. As an example, for the NPPC case, this probability is P (total loss 57700 MW (e)) = 0.00015, and represent a pure *quantitative* prediction of an unimaginable and not previously experienced outage.

V Predicting the duration of the outage

I National Data

We can define the probability of non-restoration, $P(NR)$, at any time as the ratio of the power loss remaining, $Q(h)$, to the initial power loss, Q_0. When there is no additional disruption, access difficulty, or grid damage the restoration is rapid..
Every national restoration data in [3] follows an exponential learning curve, with its own e-folding rate of between 0.3-0.8 per hour, and coefficients of determination all of, R^2 =0.9. As an average estimate, in Figure 3 the best fit to the overall pooled data for four events in three countries , with a coefficient of determination, R^2 = 0.69, is

$$P(NR) = e^{-0.43h} \tag{10}$$

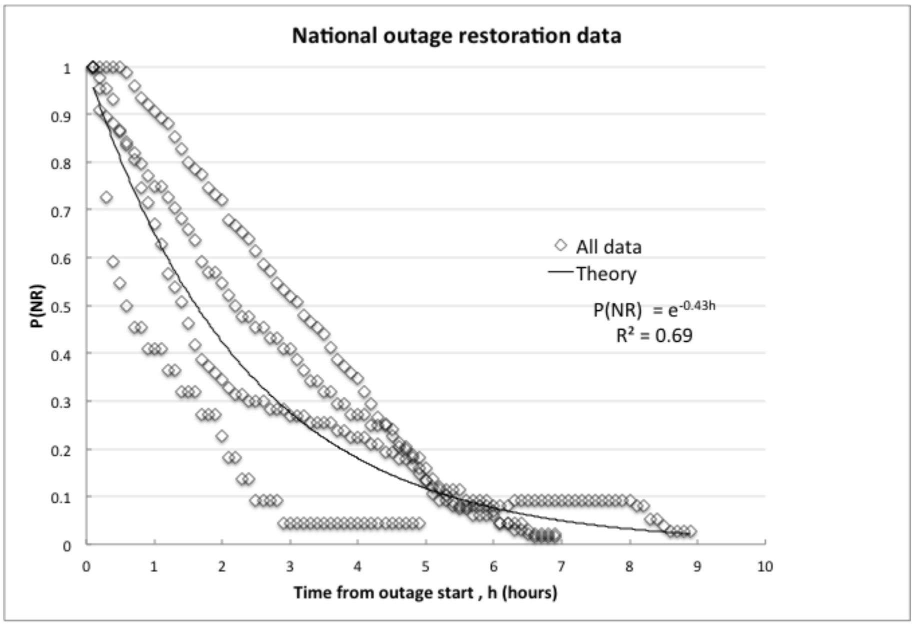

Figure 3 National duration data compared to present theory

It can be seen that even for these massive blackouts restoration was accomplished in less than 10 hours, despite the factor of ten differences in MW(e) size or scale of the initial outage. The causes were generally overall transmission and distribution failures or overloads, cascading through the system but with no additional physical damage due flooding, fires or hurricanes etc.

To compare the different power loss and outage number data sets, clearly, on average the number of outages at any time, $n(h)$, is proportional to the size or scale of the overall power loss at that time, so $n(h) \propto Q$. The probability of power system non-recovery is, $P(NR) = n(h)/N_0$, the ratio of the outages remaining, $n(h)$, to the total (initial or maximum) number,N_0, being the complement of the usual reliability, $R(t) = 1-P(NR)$.

II Regional data and severe events

As opposed to traditional plots of the numbers of outages versus time for different events (see e.g. [11]), the present formulation normalizes all the events, and demonstrates it is not the number of outages that affects characteristic recovery timescales. The data clearly show groupings between "normal" and "extreme" events restoration, with the "normal" group being faster; and events with more extreme damage and/or access difficulty clearly have much slower restoration and longer durations, by at least a factor of ten to twenty.

This key issue of the extent of damage is reflected in and by the characteristic or e-folding "degree of difficulty" parameter, β per hour; and the minimum achievable or even not restorable by, P_m. For system design and recovery planning purposes from the actual data we define the loss event categories as (see Figures 3 and 4):

- Type 0: Ordinary, 0.8>β>0.3, due to an effectively instantaneous outage with essentially no additional damage, which we classify as outage restorations that are relatively rapid, taking less than a day with simple equipment replacement, breaker resetting, line/grid repairs, and/or reconnection.

- Type 1: Normal baseline, β ~ 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 hours.
- Type 2: Delayed, β ~ 0.1–0.02, progressively reaching peak outages in 20 plus hours, as extensive but repairable damage causes lingering repair timescales of 200–300 hours before almost all outages are restored.
- 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 hours or more with residual outages lasting even longer.
- 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 (e.g. Haiti, Costa Rica, and NAIC "catastrophic outages").

The data for Superstorm Sandy are shown (open circles) purely as an example, because it represents a "long term outage" as specifically defined by FEMA [1, p32]. The exponential form and trends do not change with overall duration.

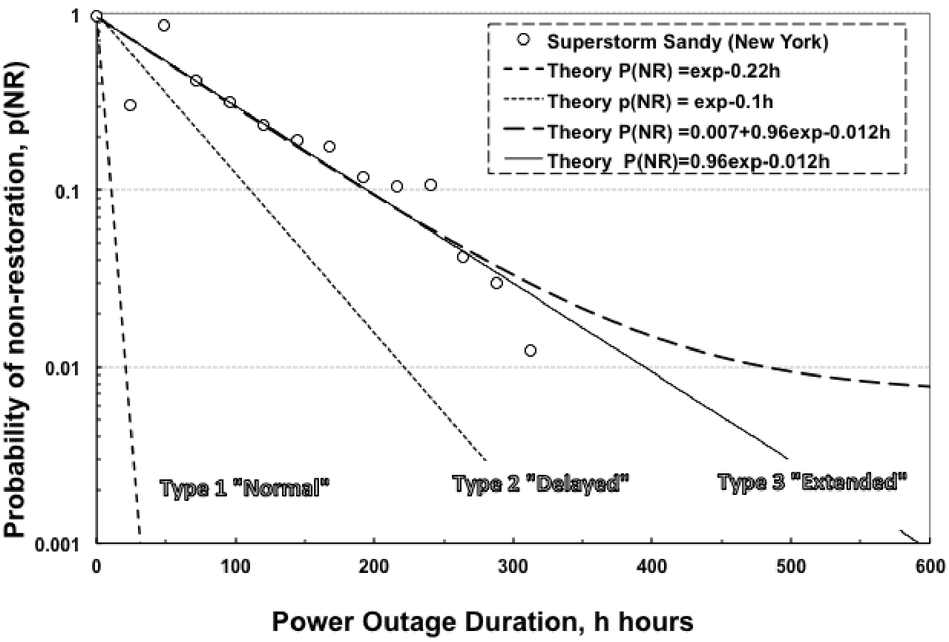

Figure 4 Simplified categories of outage restoration difficulty and timescales.

These categories allow for more refined emergency response and communication, and more realistic restoration planning. This observed variation in the degree of difficulty (0.01 <β <0.2) implies an average repair rate spread of 20 simply due to the damage extent. The irreparable fraction data range (the "tail" of the distribution) indicates that the chance of remaining unrestored is small but finite, say $0.003<P_m<0.01$,even after several hundred hours. As an example, for every million outages at first, despite achieving over 99% restoration after 600 hours several thousand could still be left without power.

III Cyber attacks

The US DHS [11,12] makes the not unreasonable assumption that the restoration curve for power outages or "virtual" damage due to cyber attacks is similar to that for known severe events, like hurricanes and ice storms. By this analogy, cyber attacks causing power outages are postulated to simply increase the restoration timescales and numbers, which we would interpret as reflecting an increased "degree of difficulty" with β reducing further. The publically available data [13] shows a cyber attack caused power outages by disconnecting networks and operator control before being restored after "several hours" .We would now classify this event as a Type 1 "normal" outage, with a P(NR) range of "cyber degree of difficulty" $0.1<\beta<0.22$, because there was no concomitant or additional access, physical damage, or societal disruption affecting recovery of the power system infrastructure and associated computing/communication networks.

Ockham's Razor suggests using the simplest. The reader is of course free to adopt whatever best suits the purpose and represents appropriately the physics and logic of the situation.

VI Conclusions

Power generation and distribution systems are part of a nation's critical infrastructure. Power losses or outages are random with a learning trend of declining size with increasing experience or risk exposure, with the largest outages being rare events of low probability. Data have been collected for power losses and outage duration affecting critical infrastructure for a wide range of events in Belgium, Canada, Eire, France, Sweden, New Zealand and USA.

Using simple theory, a new correlation has been obtained for the probability of large regional power losses for outage scales up to nearly 50,000 MW(e) for events without additional infrastructure damage that have been generally fully restored in less than 24 hours.

For more severe events , including damage due to natural hazards (floods, fire, ice storms, hurricanes etc.), the observed variation in the duration of the outage up to more than 500 hours depends on the degree of difficulty. The irreparable fraction data range (the "tail" of the distribution) indicates that the chance of remaining unrestored is small but finite, even after several hundred hours.

Therefore, explicit expressions have been given and validated for both the probability and duration for the full range from "normal" large power loss and to extended outages in rare and more "severe" events with greater access and repair difficulty. These expressions enable prediction and planning for large-scale unprecedented outages of interest for emergency planning and national response actions.

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