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Predicting Power System Reliability and Outage Duration including Emergency Response

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Abstract. Aim. *Enable prediction and planning for large-scale unprecedented power outages of importance for emergency planning and national response actions. Predict outage probability, duration and restoration using a theoretical framework that is applicable globally.* **Methods.** *Data have been collected for power losses and outage duration for a wide range of events in Belgium, Canada, Eire, France, Japan, Sweden, New Zealand and USA. A new theory and correlation is given for the probability of large regional power losses of up to nearly 50,000 MW(e) without additional infrastructure or grid damage. For severe and rare events with damage (major floods, fire, ice storms, hurricanes etc.) the outages are longer and the restoration probability depends on the degree of difficulty that limits access and restoration. The dynamic reliability requirements for emergency back-up power and pumping systems are derived, and demonstrated using the flooding of New Orleans by Hurricane Katrina and of the Fukushima nuclear reactors by a tsunami.* **Conclusions**. *Explicit expressions have been given and validated for the probability and duration for the full range from "normal" large power losses to extended outages due to rare and more severe events with access and repair difficulty.*

Keywords: *Electricity outages, blackouts, restoration probability, resilience, emergency response, theory, disasters.*

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1. Introduction: Electric power loss and restoration

Large electric power outages completely upset modern industrial and urban complexes. Given power losses do occur, we need to know the probability of the loss, size and duration to plan adequate supply margins, deploy back-up generators, undertake emergency response and protect other critical infrastructure [1].

This is not a new topic at all, and has been extensively studied for setting power delivery performance and reliability standards [2] and coping strategies in national emergency plans [3]. But there is a gap in the literature, knowledge and data between the daily routine of providing reliable power delivery and for responding to the unexpected extreme losses due to cataclysmic disasters and extreme natural hazards. In this paper, we have tried to bridge that gap by determining the probabilities for any given MW(e) outage and the subsequent chance of restoration, including using emergency back-up systems for both everyday and extraordinary events.

Overall studies of the day-to-day reliability or dependability of the electric grid are the normal business concern of owners and operators of the power lines and plants and determines how much they are paid. Whole societies are concerned about power restoration delays, especially due to extensive damage and the societal disruption from the impact of rare or record events and natural disasters (e.g. hurricanes, typhoons, floods, tsunamis, and ice storms). It is such major disasters that are of concern for infrastructure fragility, national emergency preparedness and management decisions.

Following all power losses (aka outages or blackouts), the affected power companies, emergency management organizations and government agencies have 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 proceed "as fast as humanly possible", limited by damage, access and social disruption issues caused by flooding, storms, fires, wind, ice and snow [4], and as stated "the restoration of the grid is generally the same across all hazards" [5].

The probability of any individual loss or outage being restored is actually random, and being observed as outcomes follows the well-known and established laws of statistical physics and mechanics [6,7,8,9]. Our earlier work provided an explicit analysis of the probability and timing of power restoration for very large outages or power losses at the national level [10].

The initial loss and subsequent restoration are *independent* events, being the initial outage fault or failure followed by the repair and recovery process. The dynamic probability, $P(h)_{NR}$, of an outage of any size lasting any duration, h, hours before restoration is then simply given by, where the conventional reliability is simply the complement, $R(h) = 1- P(h)$,

$P(h)_{NR}$ = Probability of initial loss, $P(\text{MW loss})_i$ x Probability of non-restoration, $P(NR)_h$

If emergency power or back-up systems exist or are deployed or activated, we can include the *dependent* probability for continuing loss of all external and other power sources so,

$P(h)_{ELAP}$ = Probability of initial loss, $P(\text{MW loss})_i$ x Probability of non-restoration of any or all power, $P(ELAP)_h$

Hence there are three distinct probabilities to determine for: (1) the initial event outage size based on known or possible power losses for the system; (2) the subsequent recovery or non-restoration of power by some timescale; and (3) the chance of emergency back-up or "black start" systems failing to function and restore power by that time.

To derive these essential elements, the present approach combines human learning and mechanical system reliability theory, correlated to and validated by extensive power loss and restoration data for actual events.

For the initial loss exceedence probability, $P(MW\ loss)_i$, there are outage size data for the entire USA for the period 1984-2000, for losses, Q, between 1 to 40,000MW(e) [11]. A sample of similar plots by sub-region has also been presented and fitted using empirical binomial, Weibull and lognormal distributions [12]. These distributions are of course heavily weighted by the many "normal" or everyday outages, not rare catastrophic events. We also need to predict the low probability "tail" of the distribution where such standard statistical methods are *not* applicable, as clearly evident in their Fig.S-28. Murphy et al [12] also looked to see if outages were linked, and unsurprisingly 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) on power systems and the consequent universal power restoration characteristics[4]. Large natural hazard events do not respect or recognize human-drawn boundaries or arbitrary grid distribution regions, and cause event-related damage and destruction over wide swathes.

Other national power loss duration data are derived from [13] 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. The outage durations are well correlated by exponential functions derived from learning theory [10].

For the restoration phase, we had previously collected extensive power recovery data for many severe events e.g. storms, ice storms, fires, hurricanes, cyclones and floods, causing outages lasting a maximum of 800 hours over a wide range of urban, regional and international loss scales. The extent of the outage is represented by the number reported by the power distributors of those connections/

customers remaining "without power", so the probability of non-restoration is the fraction of the initial outages that have not been restored. For all outage events, this electric power non-restoration probability, *P(NR),* is 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 [4].

We need to design and determine the effectiveness of the emergency systems for limiting damage, restoring the infrastructure, and managing consequences For actual (not hypothetical) major events**,** there are key performance data available during loss of power from: (a) restoration of power in nuclear power plants following loss-of-grid connection but without additional damage ;(b) back-up pumping systems failing to adequately protect the city of New Orleans from flooding by Hurricane Katrina [14]; and (c) the emergency generators and external power repair not cooling and preventing the melting down of the Fukushima nuclear reactors in Japan after an earthquake and tsunami. The data analysis shows the characteristic failure rates that underpin the determination of the probability of extended power loss for these diverse major emergency systems [15].

We will provide the general expressions for the three probabilities based on the facts emerging from the massive losses observed in entire human, designed, operated and controlled power systems.

2. Methods: Assumptions and theoretical development

The first key assumption is that the power losses, outages and

restorations are indeed random, whatever the cause, but all depend on human actions including emergency management decisions . Secondly, because humans learn and think, a systematic trend exists with increasing experience or risk exposure so that, as shown by the data, we should expect larger outage events to have lower probability. Thirdly, the chance of restoration or recovery of any individual initial outage or loss of power depends on the ability and experience gained by emergency managers and crews so also demonstrates a learning trend. Finally, because the probability of any individual outage happening and being restored is actually random, the observed outcome distribution follows the well-known and established laws of statistical physics[6,7,8,9].

After any prior or during any present risk exposure or accumulated experience, ε, the learning hypothesis theory [8] defines the rate of decrease of the observed failure rate, $\lambda(\varepsilon)$, as proportional to the rate, $\frac{d\lambda}{d\varepsilon} \propto \lambda, \frac{d\lambda}{d\varepsilon} = -k\lambda$. For the present case the instantaneous failure rate, $\lambda(\varepsilon)$, is equivalent to the observed rate of change of the number of power loss outages. Solving, this rate is given by,

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

Here, λ_0 and λ_m are the initial and smallest attainable rates, respectively, and k is the proportionality constant. As usual, the prior probability over some prior risk exposure interval, ε, is,

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

To evaluate these rates and probabilities, we adopt the simplest approach consistent with the physical situation and model the power loss outcomes as emergent events, without examining the root cause or systemic origins of each and every event, and then test the approximations and results against the data.

2.1. Probability of initial power loss or blackout size

In the past, we have observed portions of an entire power system (a plant, power line, distribution control…) causing initial outages that form some known or assumed distribution of overall loss sizes. The measure of the relative risk exposure or loss 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, $\overline{Q}$, so $\varepsilon \equiv Q/\overline{Q}$. We may assume for each and every different outage, $\lambda_0 = 1/\varepsilon$, implying individual outage events are independent (which they are in practice); and that the outages are usually nearly completely restored, so we may take, $\lambda_m \ll \lambda \approx \lambda_0 e^{-k\varepsilon}$.

Therefore, from Equations (1) and (2) the probability of any initial power loss or outage, becomes simply the intriguing double exponential,

$$P(\text{MW loss})_i = P(Q)_i = 1 - e^{-\frac{\overline{Q}}{kQ}\left\{1 - e^{-\frac{kQ}{\overline{Q}}}\right\}}. \quad (3)$$

The obvious and sensible limits are:

(a) small outage or loss

$kQ/\overline{Q} \to 0,\ P(Q)_i = 1;$

(b) infinitely large loss

$kQ/\overline{Q} \to \infty,\ P(Q)_i = 0;$

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

$Q/\overline{Q} \to 1,\ P(Q)_i = 1 - e^{-\{1 - e^{-1}\}} = 0.74$

2.2. Dynamic probability of outage duration and restoration

We observe that after the initial loss, power is progressively and eventually restored to every individual customer or connection, where the relevant risk exposure measure is now the elapsed outage time, so $\varepsilon \equiv h$, in hours. So the probability of any duration of any individual outage of any initial size at any elapsed time is then simply given by

$$P(h)_{NR} = P(Q)_i \times P(NR)_h. \quad (4)$$

The data for electric power non-restoration probability, $P(NR)_h$, 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 [4] . The instantaneous probability of non-restoration, $P(NR)_h$, of any individual outage in the entire system in any interval is obtained by dividing Equation (1) by the total possible number requiring restoration, being the initial individual outage number count. The general exponential form of the *instantaneous* probability of non-recovery or continuing failure then is [6],

$$P(NR)_h = P_m + (1 - P_m)e^{-\beta h}, \quad (5)$$

Here, $k \equiv \beta$, and depends on the degree of difficulty for storms, fires, floods and hurricanes, and P_m is due to the few irrecoverable outages Substituting Equations (3) and (5) into (4), and noting $P_m << 1$,

$$P(h)_{NR} = (1 - e^{-\frac{\bar{Q}}{kQ}\left\{1 - e^{-\frac{kQ}{\bar{Q}}}\right\}})\left(P_m + e^{-\beta h}\right). \quad (6)$$

A good working approximation is, $P_m << e^{-\beta h}$,

$$P(h)_{NR} \approx (1 - e^{-\frac{\bar{Q}}{kQ}\left\{1 - e^{-\frac{kQ}{\bar{Q}}}\right\}})e^{-\beta h} \quad (7)$$

The limits are again:

(a) small outage or loss, $P(h)_{NR} \approx e^{-\beta h}$

(b) infinitely large loss, $P(h)_{NR} \to 0$

(c) average loss with k~1, $P(h)_{NR} \approx 0{,}74\, e^{-\beta h}$

2.3. Dynamic probability of extended outage while deploying emergency and "black start" back-up systems

This is an important and more complicated situation, as while overall system restoration is ongoing, emergency back-ups are sometimes deployed locally or grid-wide, being diesel generators, gas turbines or "black start" alternate power plants. Hence, the probability of extended power loss of initial size, Q, depends on the probability, $P(ELAP)_h$, of power not having been already restored by both normal and emergency means, so,

$$P(h)_{ELAP} = P(Q)_i \times P(ELAP)_h. \quad (8)$$

To evaluate, $P(ELAP)_h$, we must combine the non-restoration probability, $P(h)_{NR}$, with the on-going failure to successfully deploy or actuate any or all back-up emergency systems [15,16]. The overall *dependent* probability, $P(ES)$, for any such emergency or back-up system to *not* be successfully deployed or activated is conventionally characterized as exponentially dependent on an overall system average failure rate, λ_{ES} [17].The dynamic probability density of extended failure or loss of all power, $dP(ELAP)_h/dh$, is then the multiplicand of the dynamic probability of the continuing failure of system recovery, $P(NR)_h$, times the probability density, $\frac{dP(ES)}{dh} = \lambda_{ES}\, e^{-\lambda_{ES} h}$, being the changing rate of the probability for unsuccessful emergency restoration [15, 16]. Over the prior elapsed or available restoration time, h, we then have,

$$P(ELAP)_h = \int_0^h \frac{dP(ELAP)_h}{dh} dh = \int_0^h P(h)_{NR} \frac{dP(ES)}{dt} dh$$

Integrating by parts, and since, $P_m << e^{-\beta h}$,

$$P(ELAP)_h = \int_0^h \left(e^{-\beta t}\right) \lambda_{ES}\, e^{-\lambda_{ES} h} dh = \left(\frac{\lambda_{ES}}{\beta + \lambda_{ES}}\right)\left[1 - e^{-(\beta + \lambda_{ES})h}\right]. \quad (9)$$

The limits are obvious:

(a) great restoration difficulty, $\beta << \lambda$, $P(ELAP)_h \approx 1 - e^{-\lambda_{ES} h}$

(b) perfectly reliable backup, $\lambda = 0$, $P(ELAP)_h = 0$

(c) at very long times, $h \to \infty$,

$$P(ELAP)_h \to \left(\frac{\lambda_{ES}}{\beta + \lambda_{ES}}\right).$$

Substituting (9) into (8), the extended loss probability is,

$$P(h)_{ELAP} = \left(\frac{\lambda_{ES}}{\beta + \lambda_{ES}}\right)(1 - e^{-\frac{\bar{Q}}{kQ}\left\{1 - e^{-\frac{kQ}{\bar{Q}}}\right\}})\left[1 - e^{-(\beta + \lambda_{ES})h}\right]. \quad (10)$$

Important parameters are the failure rate ratio, $\Psi = \lambda_{ES}/(\beta + \lambda_{ES})$, and the key characteristic time, or e-folding timescale, $1/(\beta + \lambda_{ES})$. Therefore, for any given initial power loss, Q, the measure of improved resilience, $R_{ES}(Q)$, by successfully utilizing emergency back-up systems is the steadily declining probability ratio, from Equations (7) and (10),

$$R_{ES}(Q) = \frac{P(h)_{ELAP}}{P(h)_{NR}} = \Psi\left[1 - e^{-\lambda_{ES} h}\right]. \quad (11)$$

The role of the ratio of the key failure rate parameters is now self-evident, with recovery timing depending on which failure rate dominates. This result can be generalized for deploying any number of independent redundant and/or diverse back up systems with differing failure rates [15].

3. Results: Comparisons and verification with data

To set the parameters and validate the theory of Section 2, we can now sequentially and systematically compare the predictions of Equations (3) (7) and (10) with large-scale loss and restoration data. The events considered all fully include emergency responses, human actions, procedural guidance, specialized repair crews, and management decisions.

3.1. National and regional outage data compared to theory

The original USA outage data from the NERC database for 1984-2000 were shown in [11] as a graph with dots and lines on a log-log plot; but because of the unavailability of the actual data[1], we were forced to hand transcribe using enlarged images. The error incurred is a maximum of about 5% in probability for exceeding a given power loss or outage, $P(Q)_i$, which is sufficient accuracy for the purposes of rare event prediction (see below). For the observed sample of outages, we define the likely mean or probable average outage as,

$$\bar{Q} = \overline{\sum_i P_i\ (Q) \times Q_i}.$$

[1] Our requests were declined for access to and use of the original data files and numbers for the plots in [11,12]. Surprisingly, the actual NERC data for the USA are proprietary (privately owned) so the line drawings are apparently all that are publically or openly accessible.

The data [11] then have an expected average outage of $\bar{Q} = 95\, MBm(\text{e})$. As a basis for correlation, the comparison of the theory to data is shown in Fig.1, obtained by simply adjusting the single parameter, k=2, in Equation (3) so the overall outage distribution shape is reclaimed with,

$$P(Q)_i = 1 - e^{-\frac{\bar{Q}}{2Q}\left\{1-e^{-\frac{2Q}{\bar{Q}}}\right\}}. \qquad (12)$$

The theoretically-based probability then has a maximum uncertainty of order ±20% compared to the transcribed data, sufficient for present estimating purposes where the predictive larger losses for $Q_i > 40{,}000$ MW(e) have a probability of approximately 0.003 or less. The probability, of having an average system outage, $P(\bar{Q})$ = 0.74 compared to the $P(\bar{Q})$ =0.86 observed.

A recent paper presented similar data plots for all eight NERC regions [12] which were fitted using totally empirical distributions. The individual probabilities are naturally one order lower for the largest recorded regional power losses since the average local outage, $\bar{Q}$ and the best-fit k-value change significantly [18].

Furthermore, given this new theory, we can now predict the probability of a total (100%) blackout, being "a catastrophic power outage of a magnitude beyond modern experience" [1]. As an example, for the NPPC-region case, this probability is *P (57,700 MW (e))* = 0.0015, and represent a pure *quantitative* prediction of an unimaginable and not previously experienced outage.

Power loss data compared to theory

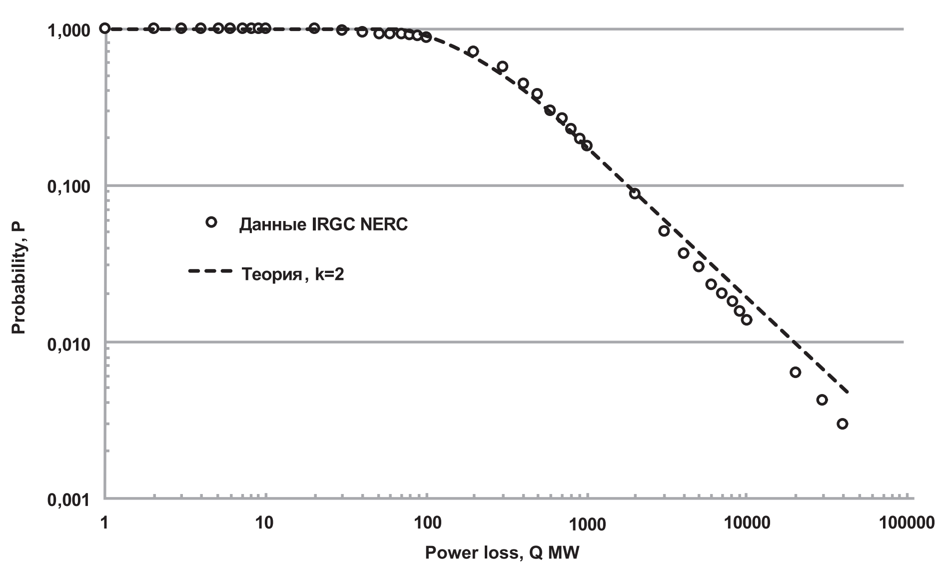

Fig. 1. Comparison of fitted theory to overall probability of any given power loss size (data extracted from [11])

For no major damage, the country-wide losses data were generally caused by overall transmission and distribution failures or overloads, cascading through the system but with no additional physical damage due to flooding, fires or hurricanes etc [13]. The data all follow the Equation (5) exponential learning curve, each 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 shown in Fig.2. the best fit of Equation (5) to the overall pooled data for four events in three countries, with a coefficient of determination, R^2 = 0.69, is

$$P(NR) = e^{-0,43h}. \quad (13)$$

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 the Q_i MW(e) size or scale of the initial outage.

The agreement of the trends is sufficiently encouraging to examine comparisons with loss data with additional damage and difficulty as follows.

3.2. Severe events compared to theory

The probability of *local distribution* 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, $R(t) = 1\text{-}P(NR)$.

Summaries for 17 distinct events are listed in Tab.1. and more details can be found in [4]. They caused very different losses, since on average the size or scale of the overall outage at any time is roughly proportional to the number "without power" or individual outages reported, $n(h)$, so $n(h) \propto Q(h)$. The USA average 24/365 per customer use is about 10,000 kWh, so these events correspond to an initial power loss range of order $8 < Q < 10{,}000$ MW(e). Therefore, although generally only a fraction of the entire regional distribution system, they can be the entire local electricity grid (as for the Florida Keys) or urban community (as in Queens);

As opposed to traditional plots of the numbers of outages versus time for different events (see e.g. [5]), the present formulation normalizes all the events, and demonstrates it is not solely 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.

As shown by Equation (5), the key issue is the extent of damage, social disruption or access difficulty as reflected in and by the characteristic or e-folding "degree of difficulty"

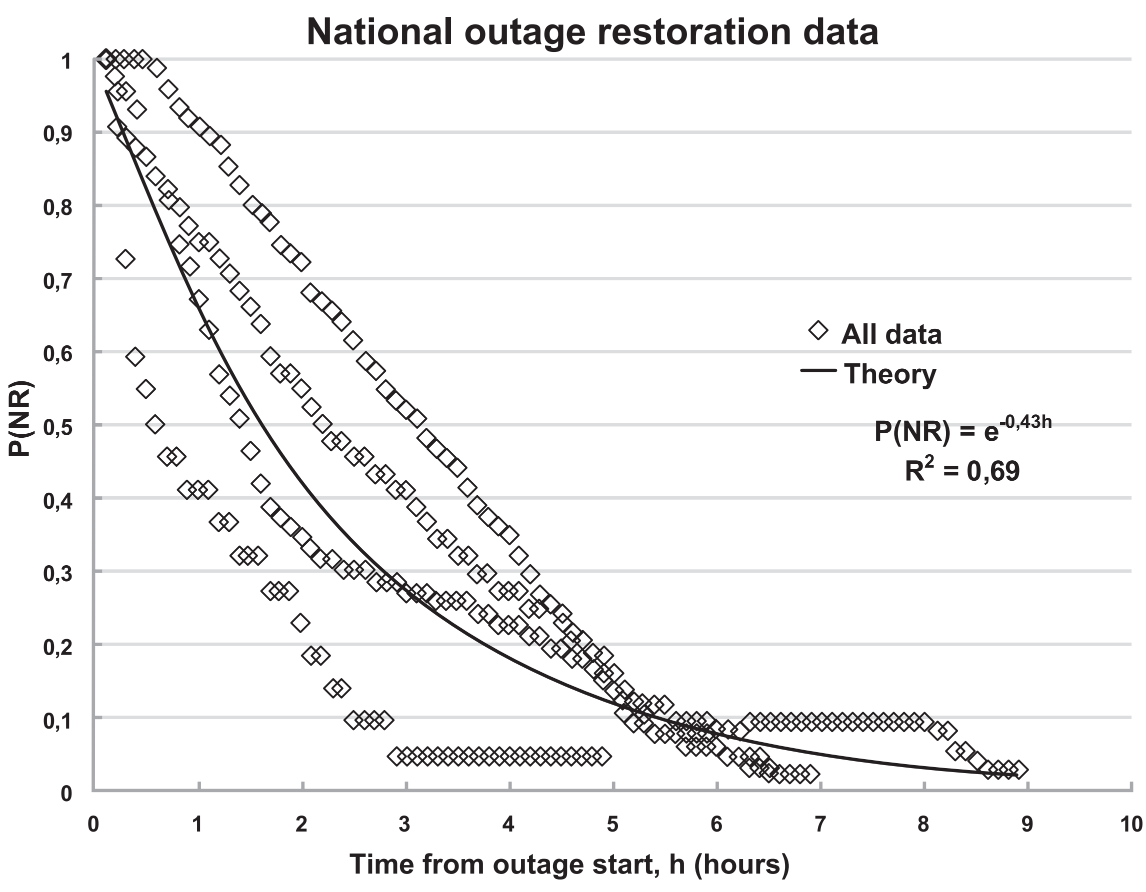

Fig. 2. Overall restoration trends for large scale national power outages

Table 1. Power Outage Data Summary
(Event key: A= Alaska earthquake, B=Baseline; SS=Sandy, E=Storm Emma, F= Florence, G=Cyclone Gita, H=Harvey, HQ= Quebec ice storm, I=Irma, Ma=Matthew, MI= Michael, N=Nate, NH-New Hampshire ice storm, O=Ophelia; Q= Storm Quinn, R=Storm Riley, S=Snowstorm Grayson, T=Storm Toby, W=wildfires)

City and/or region	Data source (event)	Span h	Maximum N_0
Queens, NY	NYPSC/ConEd(B)	88	25,000
New York, NY	ConEd (SS)	336	1,345,000
Florida	FDO (Ma)	240	10,234,174
Houston, TX	CPE (H)	800	109,244
Corpus Christi	AEP (H)	800	201,635
Florida South	FPL (I)	400	1,810,290
Florida NW	Duke-FL (I)	400	1,610,280
Tampa, FL	TECO (I)	400	330,103
Florida Keys	FKEPC/KES(I)	400	60,000
Florida Gulf	Gulf Duke (MI)	320	396,700
Alabama	APC-SCS (N)	60	156,000
N&S Carolina	Duke Energy(F)	190	542,780
Eire, EU	ESB (O)	240	385,000
Eire, EU	ESB (E)	60	127,000
NE, USA	Eversource (S)	50	25,796
NE, USA	Eversource (R)	90	220,378
NE, USA	Eversource (Q)	120	209,706
New Hampshire	NHPS (NH)	312	432,600
New Jersey	Jersey CP&L (T)	37	31,656
Quebec, Canada	HydroQuebec (HQ)	286	1,393,000
Taranaki, NZ	Powerco (G)	160	26,000
Napa, CA	PGE (W)	450	359,000
Ventura, CA	SCE (W)	450	8,400
Anchorage, AK	ChugachMP&L(A)	28	21,713
Totals		5,801	20,061,455

parameter, β per hour. For system design and recovery planning purposes from the actual data we define the loss event categories as (see Fig. 3):

• Type 0: Ordinary, $0.8>\beta>0.3$, 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, $\beta \sim 0.2$, 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 hours.

• Type 2: Delayed, $\beta \sim 0.1$–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, $\beta \sim 0.01$, with perhaps 50 or more hours before outage numbers peak due to continued damage and significant loss of critical infrastructure causing access difficulty. Restoration repair timescales last for 300–500 hours or more with residual and complex outages lasting even longer.

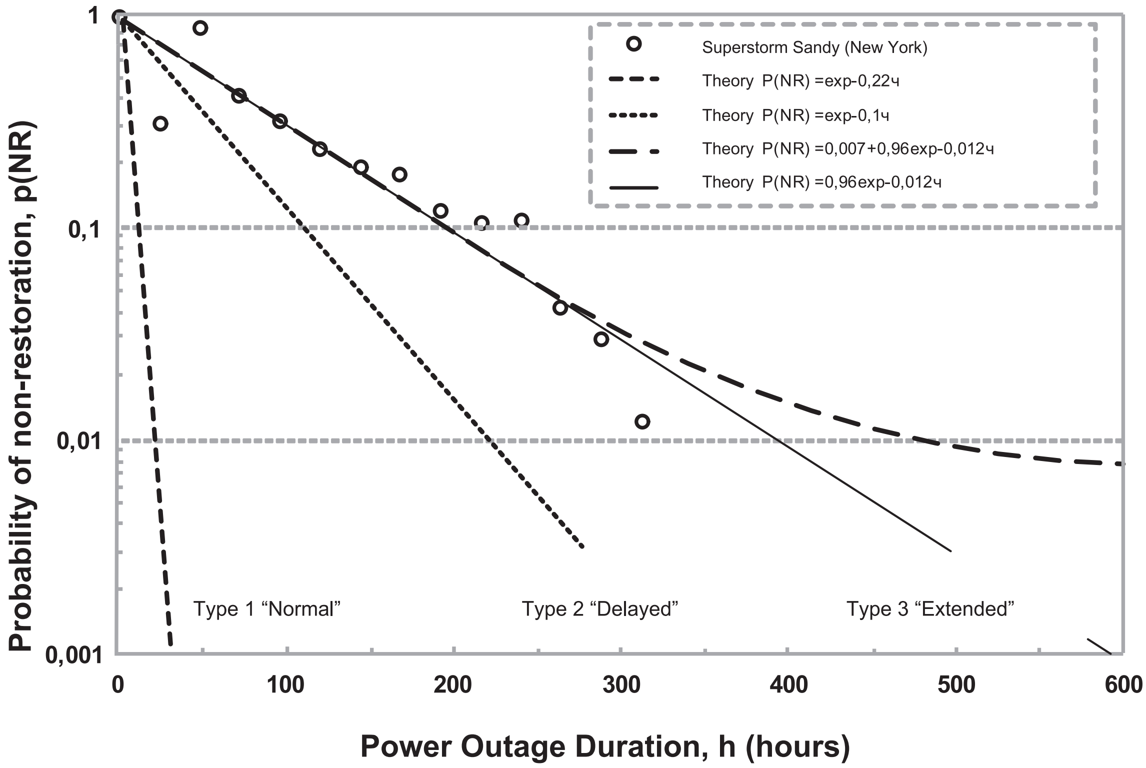

Fig.3. Simplified categories of outage restoration difficulty and timescales.

• 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" [1]).

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.

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.

The US DHS [5] 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 [5, 19] 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<β<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.

For a hypothetical national catastrophic outage number of 100 million, as shown in Figures 2 and 3, and Equation (7), for some 150,000 the outage duration can be expected to exceed several hundred hours.

3.3 Emergency response data for the Hurricane Katrina and Fukushima nuclear events compared to theory

We validate the method by comparing to cases of successively more severe power outages of national importance and impact, due to the loss of power. The events share the common feature of deploying engineered systems, back-up generators, pumping or cooling systems for which power has to be supplied somehow.

The overall, integral and needed emergency system failure rate, λ_{ES}, can be derived from the data for outage restoration in major facilities and with progressively greater difficulty:

(a) The needed failure rate for critical engineered systems without damage is derivable from outage restoration data to avoid core overheating following offsite power

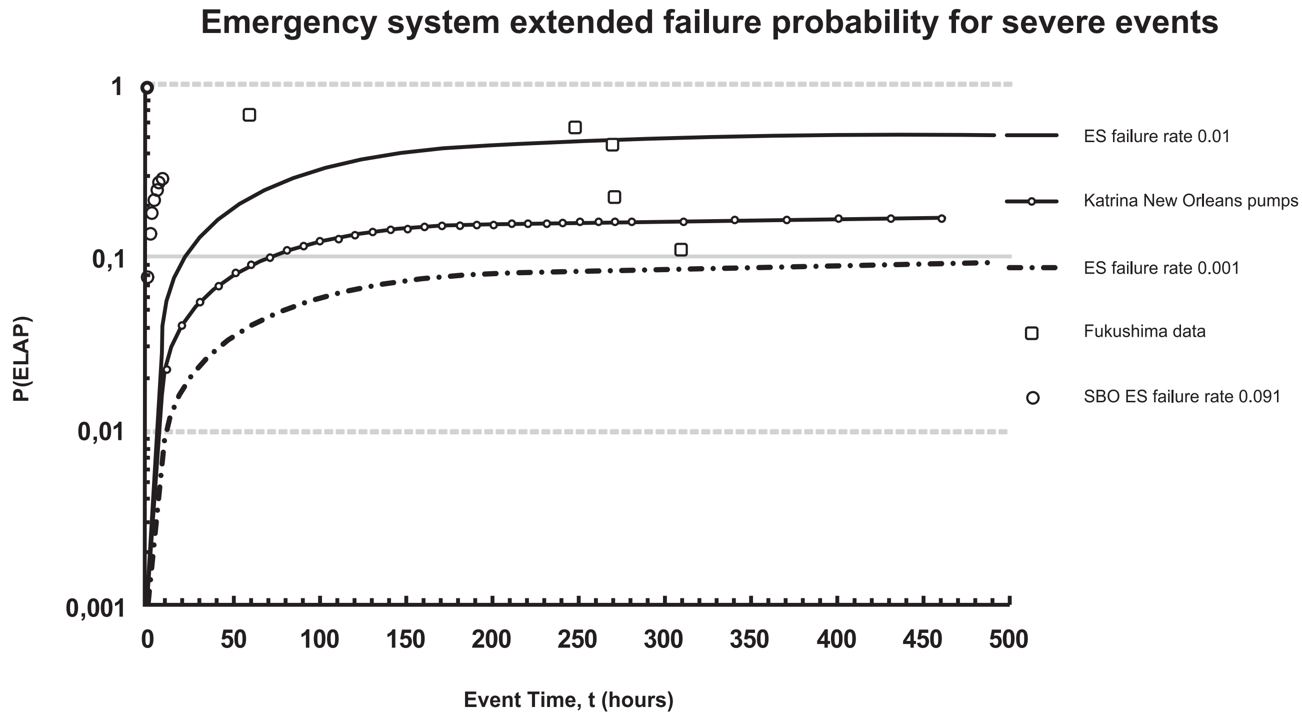

Fig.4. The probability of extended systems failure, $P(ELAP)_h$, for differing emergency system (ES) failure rates, and comparison to data from the Hurricane Katrina and Types 1 and 3 nuclear plant events

loss[1] for multiple US nuclear plants [20]. These restoration events can be considered "normal" or Type 1 with β~0.22 without additional major damage or difficulty, as in minor ice storms, localized fires, and urban outages such as the Queens blackout in New York city [4,15]. In addition, the "Failure probabilities for operator to recover AC power" using emergency batteries and diesel generators (DGRs), $P(ES)_{DGR}$,after the onset of SBO were calculated in [21] for a "representative" large PWR unit. The best fit theoretical line through the nine tabulated points [21, Table 4-13], with elapsed time, h, hours, is, with R^2=0.99,

$$P(ES)_{DGR} = 0.8\ e^{-0.087h} \quad (14)$$

This result implies an average integral emergency generator failure rate of λ_{DGR}~ 0.09 per hour. Using this rate, the long-term probability of extended outage is $P(ES) \sim \Psi=\lambda/(\beta+\lambda) = 0.09/(0.22+0.09) \sim 0.29$, or nearly 30%..

(b) For analyzing even more demanding conditions, a more severe event was the inundation of New Orleans by Hurricane Katrina in 2005, causing extensive record flooding and infrastructure damage [14]. The failure of emergency flood-prevention systems to successfully deploy and operate to avoid flooding is a known example of a high degree of difficulty in managing the consequences of a major disaster also causing loss of power. The extensive reports show: "The system's performance was compromised by the incompleteness of the system, the inconsistency in levels of protection, and the lack of redundancy" [14, Volume 1]. Several hundred flood prevention pumps were distributed in four regions but many became inoperable, themselves failing due to flooding, power loss and/or forced evacuation [14, Vol VI , Figs 12, 16, 19 and 22].

The *integrated* emergency systems failure rate, λ_{ES} , of the flood prevention systems and of the back-up emergency pumps to operate, was determined from the fractional operating pump data [14, 18]`. The fitted dynamic probability for successful overall emergency pump system operation, $P(ES)_h$,correcting for the running total, for hours, h, after the Katrina event started, was

$$P(ES)_h = 0.8\ e^{-0.003h} \quad (15)$$

Hence, for these diverse flood prevention and emergency backup systems, the implied time-averaged failure rate is λ_{ES}~0.003 per hour; while at h= 0 hours, there is an initial operating probability of $P(ES)_h$ ~0.8, or approximately 80%. This initial fraction is *identical* to that for the "normal" nuclear plant events (see Equation (14)), and only slightly lower than the US ACE stated availability expectation of 90%. But this high value only exists at the beginning not throughout the event, progressively decreasing (to 20-30 %) over several hundred hours as the developing damage, flooding extent and restoration access issues worsen.

(c) Finally, combined LOSP/LOOP of extensive duration was caused to the nine nuclear reactors at Fukushima by the Great NE Japan offshore earthquake and the result-

[1] In nuclear reactor risk analyses, these event sequences are traditionally termed Station Blackout (SBO) following loss of onsite and/or offsite power (LOSP/LOOP), and the designs include multiple diesel generator and battery back up systems.

ing record tsunami [22,23].The engineered system failures were power line damage and unexpected overtopping of sea walls and flood barriers, resulting in loss of power, disrupted controls, failures of emergency cooling systems, and damage to back-up systems and pumps. Power was not restored in sufficient time to manage or prevent the occurrence of major damage, with highly difficult and demanding conditions including explosions and radiation contamination. Restoration attempts for power and cooling included simultaneous emergency efforts to restore grid power from damaged offsite power lines, provide power onsite, and use whatever back-up, battery, pump, mobile, or other even ad hoc systems that could be deployed.

Using Equation (9) we calculated the actual severe event non-restoration or extended failure probability data for such apparently disparate Type 3 events, with $\beta \sim 0.01$ [15]. In Fig. 4, the extended failure data for Fukushima Daiichi Units 1–6 and Daiini Units 1, 3, and 4 is compared with the predicted probability of extended systems failure, $P(ELAP)_h$ for Hurricane Katrina using the actual emergency pump failure rate , λ_{ES} =0.003, as deduced above (see Equation (15)). Also shown are the calculated effects of a wider range of better (λ_{ES}=0.001) or worse (λ_{ES}=0.01) emergency or back up systems failure rates. For comparison, the shorter timescale Type 1 "normal" nuclear plant SBO results (β=0.22) are shown using the emergency systems failure rate of $\lambda \sim 0.091$ that was derived from the published nuclear plant SBO calculations [21].

Discussion

Therefore, we have shown that for all these "extended" Type 3 events or major disasters, the actual emergency systems failure rate range encompassing that actually observed is $0.001<\lambda_{ES}<0.01$ per hour. This range includes different engineered systems, multiple redundant/diverse generators, relevant human and management actions, access and repair difficulty issues, and restoration and procedural processes during emergency recovery and disaster response. The probability of a prolonged or very extended outage has been shown to be non-negligible.

Taking the observed β and λ rate values as typical for any severe event, the critical time, $t^* = 1/(\beta+\lambda) = 1/(0.01+0.003) \sim 77$ hours, and is dominated by the restoration difficulty; while at very long times, $P(ELAP)_{h\to\infty} \to \ \psi = 0,003/0,013 \sim 0,23$, or about a 25% chance of extended systems failure or non-recovery even with emergency restoration. Hence, for major events we should expect power and pumping outage durations lasting at least several days, even with multiple backup systems available or externally supplied.

In sections 3.1,3.2 and 3.3 we have been able to intercompare completely disparate and hitherto apparently unrelated separate outage events, all the way from major losses to recovery and deploying back up and emergency generating systems. The unifying physical mechanism is the link between theoretically–based statistical theory [6,7,8] and the understanding of the importance of human learning behavior [9] on system recovery and required resilience[1,25].

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 and inter-compared for power losses and outage duration affecting critical infrastructure for a wide range of severe events in Belgium, Canada, Eire, France, Sweden, New Zealand and USA, including Hurricane Katrina flooding New Orleans and the Fukushima reactor meltdowns.

The unifying mechanism is the theoretically–based statistical learning theory combined with the understanding of the importance of human behavior on system recovery and resilience. Using this 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.

The theory was extended to more severe events with extended outage durations, including damage due to natural hazards (floods, wildfires, ice storms, tsunamis, hurricanes etc.). The observed variation in recovery timescale of up to more than 600 hours depends on the degree of restoration difficulty. The irreparable fraction (the "tail" of the distribution) indicates that the chance of remaining unrestored is small but finite, even after several hundred hours. For the first time, the impact on restoration probability using emergency systems has also been quantified.

Therefore, explicit expressions have been obtained 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 major repair difficulty. This new formulation enables prediction and planning for large-scale unprecedented outages of interest for emergency planning and national response actions.

Appendix: 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:

$$P_i(x) = 1 - e^{-\frac{\bar{x}}{kx}\left\{1-e^{-\frac{x}{k\bar{x}}}\right\}}. \tag{A1}$$

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 for power outages [23] and floods [24] of the general form:

$$P_i(x) = 1 - e^{-1+\xi\left(x-\frac{\psi}{\beta}\right)^{-1/\xi}}. \quad \text{(A2)}$$

For the conventional "named" distributions:

- Gumbell Type 1 $\xi=0$
- Frechet Type 2 $\xi>0$
- Weibull Type 3 $\xi<0$

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, available data and logic of the situation.

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The authors' contribution

The author presents the theoretical justification and practical application of the original innovative risk-analysis concept of the structurally complex human-machine systems operation that allows predicting the consequences of the occurrence and impact of the unexpected and emergency situations of different nature on them with acceptable accuracy.

To validate the presented concept, the author collected and compared data on the power loss and outage durations affecting critical infrastructure for a wide range of severe events in Belgium, Canada, Eire, France, Sweden, New Zealand and USA, including Hurricane Katrina flooding New Orleans and the Fukushima reactor meltdowns.

Conflict of interests

The author declares the absence of a conflict of interests.