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A Modeling Approach to Reexamining Electricity-Law Behavior in Actual Power System an Outage Data

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Abstract
Large-scale power systems power outages are known to behave statistically in a complex manner, and there is increasing evidence that they follow power-law distributions in both size and frequency. Empirical outage data was revisited in this research so that it can critically explore the validity and the extent of power-law models that can be used to explain the dynamics in outages. We measure this consistency of the power-law behavior with use of updated datasets and strict statistical fitting methods. The power-law models are also contrasted with other heavy-tailed distributions like log-normal and Weibull, and these differences were also pointed out on implications of such results on system reliability modeling and risk-assessment. The results are used to improve the knowledge of outage phenomena and provide knowledge on designing more resilient power infrastructure.

Keywords: ***Power system outages, Power-law distribution, Heavy-tailed models, Reliability analysis, Risk modeling, Complex systems, Empirical data analysis, Infrastructure resilience, Statistical fitting, Outage frequency modeling.***

1.Introduction

The modern power grid is a sprawling, complex, and tightly coupled infrastructure, serving as the backbone of industrialized societies. With the increasing penetration of renewable energy sources and the growing reliance on interconnected systems, the challenge of ensuring uninterrupted power supply has escalated. Traditional fossil-fuel-based generation is rapidly being replaced by more variable and decentralized sources such as wind and solar, which introduce spatio-temporal fluctuations. These fluctuations, especially under adverse conditions, can trigger disturbances of varying magnitudes, from small-scale outages to catastrophic blackouts. A recurring observation in analyzing these events is the prevalence of power-law behavior in the distribution of outage sizes and durations a hallmark of heavy-tailed phenomena.

Over the past two decades, researchers have consistently reported that the sizes of outages, whether measured in energy loss, affected consumers, or duration, do not follow Gaussian or exponential distributions. Instead, they exhibit fat tails, meaning that extreme events, while rare, are not as improbable as one might expect under classical assumptions(1). This statistical characteristic implies that massive outages although infrequent occur more often than standard probabilistic models would predict. Understanding the nature and origin of such statistical signatures has important implications for grid reliability, risk assessment, and the design of mitigation strategies.

The presence of power-law distributions in failure phenomena is not unique to power systems. Similar patterns are observed in a wide array of natural and engineered systems, including earthquakes, forest fires, financial market crashes, and even military conflicts. For example, the number of deaths in battles or natural disasters has been shown to follow power-law distributions with exponents typically ranging from 1.5 to 1.8. These distributions indicate the systems' intrinsic vulnerability to cascading failures and signal the possible presence of critical dynamics operating near a tipping point.

In the context of power systems, two primary theoretical frameworks have been proposed to explain the emergence of power-law distributions: Self-Organized Criticality (SOC) and Highly Optimized Tolerance (HOT). SOC, originally introduced by Bak, Tang, and Wiesenfeld, suggests that systems naturally evolve to a critical state where minor disturbances can trigger events of all sizes. In this view, power systems are perpetually tuned to a point of marginal stability where small perturbations, such as local faults or weather-related damage, may escalate into widespread outages. SOC has been instrumental in modeling cascading failures in power grids and offers a compelling explanation for the scale-invariant nature of blackout distributions.

On the other hand, the HOT paradigm, proposed by Carlson and Doyle, presents a different perspective. It argues that power systems are not random or unstructured but rather deliberately designed and optimized to withstand expected threats. However, this very optimization, while enhancing performance under typical conditions, creates vulnerabilities to rare but severe events. Under the HOT framework, the power-law distributions arise not from self-organization but from constrained optimization processes under uncertainty. For example, the limited availability of maintenance crews and resources may lead to longer restoration times for certain outages, especially those in less accessible areas(2).

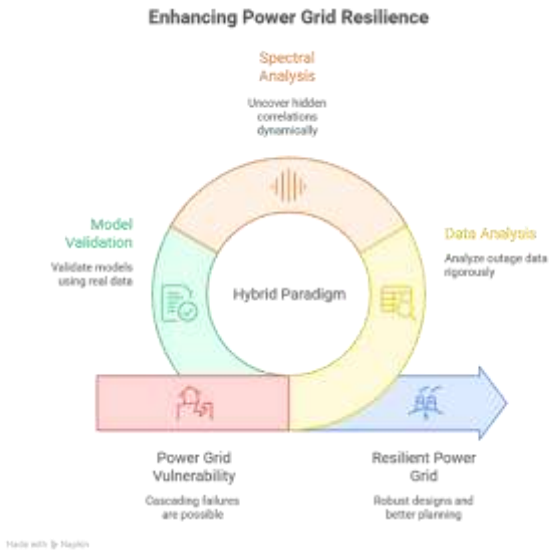

FIGURE 1 Enhancing Power Grid Resilience

Empirical studies have attempted to validate these models using real-world outage data. Early analyses focused on large blackouts in North America, New Zealand, and China, showing energy-based outage distributions with exponents between 1.3 and 2.0. More recent work has expanded the dataset scope, incorporating transmission and generation outages from various operators such as CAISO (California), MAVIR (Hungary), BPA (Bonneville), and ENTSO-E (Europe). These studies affirm that both small and large outages follow heavy-tailed distributions and suggest a certain uniformity in the statistical properties across different regions and timeframes.

The present work revisits these observations using a broader and more granular dataset, incorporating forced outages due to individual component failures rather than only large blackout events. This approach offers a more comprehensive picture of the power system's operational fragility. The authors apply rigorous statistical methodologies to fit power-law models to outage duration and unavailable energy, segmenting the data into short- and long-duration events using a 24-hour threshold an operationally meaningful cutoff derived from industry practices and expert interviews. Their goal is to discern whether the observed power-law behaviors persist across different regimes and what mechanisms might underpin them(3).

Moreover, the authors conduct power spectral analysis on the temporal sequences of outage events to uncover hidden correlations and dynamic features. By analyzing the frequency domain characteristics, they seek to determine whether the signals exhibit 1/f noise a signature often associated with SOC systems. Surprisingly, while outage events show signs of correlation suggestive of SOC behavior, the outage durations themselves are dominated by uncorrelated (white noise) features. This contrast leads to a nuanced conclusion: the initiation of outages may be governed by SOC-like dynamics, but the restoration process is better explained by HOT principles where optimization and resource allocation play a dominant role.

Ultimately, this study underscores the importance of differentiating between the mechanisms that govern event occurrence and those that dictate event resolution. It challenges the notion that a single unifying theory can explain all aspects of power system failures and points instead to a hybrid paradigm, where both self-organized and optimized behaviors coexist. The implications are significant for grid operators and policy-makers. Recognizing the statistical structure of outages and the dual nature of their causes can inform more robust designs, predictive maintenance strategies, and better emergency response planning.

This renewed exploration of power-law behavior in power outage data, leveraging updated empirical evidence and refined analytical tools, contributes to a deeper understanding of how complex energy systems fail and how they might be made more resilient.

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2.Methods

1. Data Collection and Categorization

To ensure a robust and representative analysis, outage data were collected from several public and institutional sources across multiple countries and regions. These datasets originate from Transmission System Operators (TSOs), electricity market platforms, and regulatory agencies(4). The study focused strictly on forced (unplanned) outages, excluding all scheduled or planned maintenance events to isolate naturally occurring system failures.
The collected data included information from:

- ENTSO-E (European Network of Transmission System Operators for Electricity) – Covering both generation and transmission unavailability across European control areas.
- CAISO (California Independent System Operator) – Offering detailed reports on generation outages within the California region.
- MAVIR (Hungarian Transmission System Operator) – Providing data specific to generator unit failures in Hungary.
- GME (Gestore dei Mercati Energetici, Italy) – Presenting records of production unit outages via its Inside Information Platform.
- BPA (Bonneville Power Administration, USA) – Supplying data on outages in both transmission lines and transformer infrastructure.
- AESO (Alberta Electric System Operator, Canada) – Reporting mixed transmission infrastructure outages.

Where data access was limited due to API constraints or interface restrictions, automated data scraping tools were developed to collect the full breadth of historical records without breaching data access policies.
Each dataset contained multiple fields per outage event, typically including:

- Timestamps for the beginning and end of the outage
- Affected asset identifier (e.g., transformer, line, generation unit)
- Installed and unavailable capacity (MW)
- Classification tags (e.g., planned/unplanned, automatic/manual)

Only records clearly marked as unplanned (e.g., labeled “Forced,” “Unplanned,” or “Auto”) were retained for analysis.

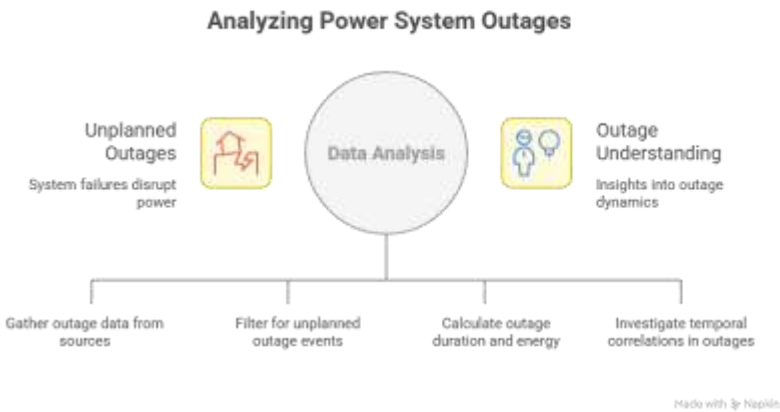

FIGURE 2 Analyzing Power System Outages

2. Outage Metrics and Preprocessing

For each outage record, two primary metrics were derived:

- Outage Duration (Tu): Calculated as the time difference between the start and end of the event, typically measured in hours.
- Unavailable Energy (Eu): Estimated by multiplying the outage duration by the unavailable power, assuming a constant power level throughout the outage period(5).

3. Spectral Analysis of Outage Time Series

To investigate temporal correlations and potential evidence of self-organized behavior in outage events, we performed power spectral analysis on three time series derived from the data:
To benchmark the interpretation of spectral shapes, synthetic signals combining Brownian motion and white noise were generated and analyzed in parallel. These helped us distinguish true correlations from noise artifacts and provided a reference for assessing the empirical results (6).

Summary

This methodological framework integrates empirical data acquisition, power-law modeling, and spectral analysis to explore the statistical structure and temporal dynamics of power system outages. The dual treatment of energy loss and duration, combined with the segmentation at a 24-hour threshold, allows us to disentangle different outage behaviors. Spectral analysis further adds a dynamic perspective, shedding light on the underlying mechanisms whether random, optimized, or self-organized that govern these critical infrastructure events.

3.Results

This section presents a comprehensive analysis of forced outage events across different power system components, drawing from a diverse and geographically distributed dataset. We separately investigate generation outages and transmission-related outages, measuring both in terms of unavailable energy (Eu) and unavailable duration (Tu). Our central aim is to evaluate whether these variables follow power-law distributions and to interpret the nature of the scaling exponents across regions and outage types. Moreover, we explore how maintenance response behaviors differ between short- and long-duration events and how this affects the statistical structure of the data.

1. Outage Statistics in Generation Units

Outages in electricity generation facilities ranging from nuclear to gas-fired and renewable-based units are examined first. For this analysis, we utilize data from multiple European control areas under ENTSO-E, as well as North American and national grids (California's CAISO, Hungary's MAVIR, and Italy's GME). These datasets include both partial outages (derating) and total shutdowns. In both cases, the unavailable energy was estimated by multiplying the outage duration by the unavailable power during the event(7).
The probability distributions of unavailable energy (Eu) for generation units display a clear heavy-tailed character. In all cases examined, the distributions follow a power-law behavior over multiple orders of magnitude. The estimated exponents (τ_E) range between approximately 1.34 and 2.01, varying by region:

- Hungary (MAVIR) displays one of the lowest exponents at $\tau\_E \approx 1.34$, indicating a heavier tail, meaning large-scale generation outages occur more frequently relative to other grids.
- CAISO (USA) shows a relatively higher exponent near 2.01, suggesting less frequent extreme generation losses.
- In European data, regions such as Germany (DE_AMPRION), France (FR), and Great Britain (GB) exhibit exponents between 1.54 and 1.86.

These findings reinforce previous empirical studies that reported power-law tails in blackout and outage events. However, our analysis extends beyond traditional blackout records by including smaller forced generation events, demonstrating that even routine outages follow the same statistical regime as more catastrophic failures.We also examined outage duration (Tu) across these same systems. Here, the distributions are again consistent with power-law scaling, with fitted exponents (τ_T) generally between 1.8 and 2.2, depending on the dataset. For instance:

- ENTSO-E GB shows a particularly steep slope, with $\tau\_T \approx 2.09$.
- Hungary MAVIR shows $\tau\_T \approx 2.15$, again aligning with the inference that European grid events tend to have fewer extreme-duration outages compared to their energy equivalents.
- ENTSO-E DE_AMPRION shows $\tau\_T \approx 1.83$, slightly lower than other European peers (8).

To better understand the differences in maintenance response, the duration data was segmented at a 24-hour threshold, based on industry conventions that distinguish rapid routine fixes from longer, resource-intensive repairs. This segmentation reveals a notable bifurcation in scaling behavior:

- For Tu ≤ 24 hours, the power-law exponent values tend to be lower ($\tau\_T \leq 1.5$), suggesting that while many short-term outages occur, they are less variable and possibly constrained by operational protocols.
- For Tu > 24 hours, the exponents increase ($\tau\_T \approx 1.85$–2.20), highlighting that prolonged events are rarer and subject to additional stochastic or logistical complexities.

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These results suggest that short-term maintenance follows one operational regime, likely bounded by staffing and repair guidelines, whereas long-term outages reflect a broader distribution of restoration challenges, perhaps affected by equipment access, spare part logistics, or grid topology.

2. Outage Statistics in Transmission Infrastructure

Transmission infrastructure, covering lines, transformers, switches, and circuit breakers, plays a critical role in the continuous delivery of power across vast distances. Transmission outages are less frequent but often more disruptive due to their potential for cascading failures.

We analyzed transmission-related outage durations using datasets from BPA (USA), AESO (Canada), and ENTSO-E (for inter-control area connections). Again, power-law distributions were observed across the board. For example:

- BPA Transmission Lines showed $\tau_T \approx 1.85$, consistent with expectations for infrastructural failures that may be spread across remote or challenging terrains.
- BPA Transformers, however, exhibited a significantly lower exponent of $\tau_T \approx 1.09$, indicating longer durations and more substantial restoration challenges. This aligns with the intuition that transformers being large, specialized assets take longer to repair or replace.
- AESO (Alberta) had a steeper exponent, $\tau_T \approx 2.37$, suggesting effective restoration protocols or a relatively compact grid.

Additionally, we analyzed transmission outages between specific pairs of European control areas, including DE_50HZ–PL_CZ, NO–SE, PT–ES, and SE–DK_CA. These datasets revealed small exponent values ($\tau_T \approx$ 1.00–1.25), suggesting more frequent extreme-duration outages. This could be due to the complexity of cross-border grid operations, international coordination delays, or infrastructure vulnerability along interconnection corridors(9).

Interestingly, when aggregating all pairwise control-area data, the overall exponent for ENTSO-E transmission outages becomes $\tau_T \approx 1.54$, an intermediate value reflecting a mixture of highly variable regional characteristics.

As with generation data, we applied the 24-hour segmentation to transmission outages:

- For $Tu \leq 24$ hours, the data lacked sufficient power-law characteristics or sample size to yield reliable exponents.
- For $Tu > 24$ hours, strong power-law behavior re-emerged, reinforcing the idea that extended outage events are governed by different system dynamics, possibly including inter-agency cooperation, complex routing adjustments, and greater exposure to extreme weather events or physical damage.

3. Summary of Exponent Behavior

A consolidated view of the exponent results shows clear differences across outage types and durations:

- Energy-related exponents (τ_E) mostly fall between 1.3 and 2.0, consistent with blackout statistics from previous literature.
- Duration-related exponents (τ_T) range from ~1.0 for transformers and inter-area transmission to ~2.2 for generation units and compact grids like AESO.
- Short duration outages (<24h) tend to show lower τ_T values (~1.1–1.5), indicating more frequent mid-length events.
- Long duration outages (>24h) stabilize at higher τ_T values (~1.85–2.2), revealing a fat-tailed distribution indicative of self-organized or optimized systemic behaviors.

These findings collectively support the hypothesis that heavy-tailed outage behavior is ubiquitous across modern power systems, regardless of geography or grid structure. Importantly, the results offer new granularity, suggesting that short- and long-duration outages may emerge from distinct operational and systemic regimes a distinction with implications for reliability planning, maintenance optimization, and infrastructure investment.

4.Conclusion

This study offers a detailed re-examination of forced outage patterns in modern power systems, with particular focus on whether the statistical distributions of outage duration and unavailable energy follow power-law behavior. By integrating empirical data from multiple independent grid operators across North America and Europe, we present a broad and comparative analysis of both generation and transmission outages. The findings confirm that power-law distributions are not limited to large-scale blackouts but also characterize everyday, component-level outages within electrical infrastructure.

The distributional analysis reveals that unavailable energy (Eu) and outage duration (Tu) frequently exhibit heavy-tailed behavior, with power-law exponents ranging approximately between 1.3 and 2.2, depending on the outage type, system component, and geographical region. These results highlight the systemic nature of risk in power systems: extreme outages, although infrequent, are significantly more likely than would be predicted by classical exponential or Gaussian models. Such scale-free patterns underscore the need for statistical tools and risk frameworks that account for the potential of rare but high-impact events.

Importantly, the study introduces a practical and operationally meaningful 24-hour threshold to distinguish between short- and long-duration outages. This segmentation reveals a qualitative shift in statistical behavior: short-term outages tend to follow flatter power-law slopes (indicating more frequent mid-scale disruptions), while longer outages exhibit steeper slopes, pointing to rarer but more severe events. This distinction reflects underlying differences in how systems respond to and recover from failures—short-term outages are more often routine, while long-term events may involve logistic delays, cross-regional coordination, or significant equipment constraints.

Beyond static distributions, our application of power spectral analysis sheds light on the temporal structure of outages. We find that while the sequence of outage occurrences exhibits 1/f-type noise, indicative of long-range correlations or self-organized criticality (SOC), the durations themselves appear largely uncorrelated, aligning more closely with Highly Optimized Tolerance (HOT) frameworks. This suggests a dual-process mechanism: the initiation of outages may be governed by cascading dynamics and emergent fragility, while the recovery process is shaped by design choices, operational strategies, and logistical constraints.

Together, these findings present a more nuanced picture of failure dynamics in power systems. Rather than being purely random or wholly deterministic, outage behavior emerges from the complex interaction between system design, operational protocols, and inherent vulnerability to stochastic disturbances. Recognizing this hybrid structure is crucial for risk-aware planning, asset prioritization, and real-time response optimization.

Ultimately, this research reinforces the importance of grounding resilience planning in empirical evidence and statistically robust models. As power grids evolve under the pressures of climate change, decentralized energy, and cyber-physical interdependencies, understanding the real-world patterns of system failure becomes increasingly vital. Future work should extend this analysis to incorporate real-time sensor data, weather-driven outage triggers, and probabilistic restoration modeling—tools that can bridge the gap between statistical theory and actionable engineering.

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Conflicts of interest

The authors have no conflicts of interest to declare

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