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Blackout Events and Grid Reliability Indicators: A Comparative Analysis of Infrastructure Quality Standards Across Geographical Regions

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Abstract

This paper presents innovative research on power grid reliability, which is essential for the overall sustainability of energy systems in the emerging age of electricity. The research primarily analyzes the profound methodological disparities between the fragmented European approach and the exact statistical model employed in the United States (the 2.5 Beta method defined by the IEEE 1366 standard). A novel dimension addressed in this research is the compounding effect of climate hazards and the massive proliferation of artificial intelligence (AI) data centers. Unlike conventional single-layer machine learning models (such as standard Support Vector Machines or regressions) that rely solely on historical weather data, this study proposes the Hierarchical Spatiotemporal Multiplex Networks (HMN-RTS) predictive framework. By dynamically fusing structured environmental data with unstructured social sensor data (Geographic Information Systems—GIS, and social media feeds), the proposed HMN-RTS framework significantly outperforms traditional models in predicting outage risks and their exact durations.

Keywords: power system resilience; power grid reliability; reliability indices (SAIDI/SAIFI); spatial analytics (GIS); sustainability; extreme weather events; cross-border interconnections; data center boom

1. Introduction

The global energy infrastructure is currently undergoing an unprecedented structural transformation. The transition into the so-called “age of electricity” is characterized by massive decarbonization, the electrification of industrial processes, and an exponential surge in demand for computational power. However, this shift confronts the physical and technological limitations of aging distribution and transmission grids, thereby directly threatening their operational sustainability. Consequently, ensuring supply continuity and minimizing blackout events have evolved from purely technical challenges into fundamental pillars of national security, economic stability, and sustainable development [1–7].

This paper identifies two primary stressors that currently pose the most significant threat to grid stability across geographic regions, as follows: extreme climate events and the integration of novel forms of extreme dynamic loads. Traditional grid management models fail particularly in predicting so-called compound hazards, which constitutes a critical barrier to sustainable investment planning [8–16].



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The core challenge addressed in this study is how methodological fragmentation fundamentally distorts grid resilience assessment across global jurisdictions. While the U.S. relies on standardized metrics to filter out statistical anomalies, European benchmarking remains disjointed. Compounding this systemic vulnerability is the emergence of modern grid stressors, notably extreme weather events and new high-density loads. As a compounding case study of such modern grid stress, the massive proliferation of Artificial Intelligence (AI) data centers introduces unprecedented operational risks. Unlike traditional industrial facilities, data center demand is entirely algorithm-driven. Recent operational analyses demonstrate that these facilities can execute instantaneous load drops, known as ‘silent exits’, abruptly removing gigawatts of load (up to 6.5 GW) in fractions of a second. This phenomenon introduces massive frequency overshoots and reactive-power swings that threaten grid stability [17]. When these modern technological loads converge with compound climate hazards—such as joint heatwave outages where air conditioning demand exacerbates grid stress [18]—the necessity for a standardized, globally harmonized resilience framework becomes absolute.

Despite commonly shared global threats, the methodology for assessing infrastructure reliability remains profoundly fragmented at the international level. Although standards such as IEEE 1366 provide a unified vocabulary of metrics (e.g., SAIDI, SAIFI), the protocols for data collection, and particularly the procedures for excluding Major Event Days (MEDs), differ fundamentally across continents [19]. This situation precludes objective international benchmarking and frequently obscures the genuine vulnerability of power grids. Consequently, an urgent research gap is the absence of a unified comparative framework capable of comprehensively integrating deterministic reliability indicators with predictive systems and advanced spatial analytics [20–24].

To bridge this identified gap, it is imperative to explicitly define the novel contributions of this paper and the specific focus of the research. The primary innovative contribution lies in proposing a systematic paradigm shift from retrospective, purely statistical impact measurement toward proactive analytics through the deployment of Hierarchical Spatiotemporal Multiplex Networks (HMN-RTS). This predictive approach is entirely novel in its direct fusion of structured, multi-modal operational data (grid topology, vegetation parameters, and meteorological data) with real-time unstructured data derived from social sensors (predominantly from the Twitter and Reddit platforms) [25–33].

The focus of this research extends beyond the theoretical comparison of data to the provision of a precise technological solution. Whereas conventional approaches have historically reacted to power outages with an inherent delay, the integration of social sensors and advanced machine learning facilitates the prediction of outage risks and their exact durations with a lead time of 3 to 6 h. Coupling this analytical model with a novel approach to regulating AI loads—specifically through the deployment of data center backup batteries via the “Bring-Your-Own-Battery” (BYOB) strategy—constitutes a comprehensive and empirically verifiable tool. It is precisely this synergy between predictive logistics and active demand management that represents a new and indispensable prerequisite for guaranteeing the long-term sustainable operation and resilience of the modern power grid.

Consequently, this paper focuses on bridging the classical statistical assessment of supply sustainability and reliability with advanced logistical and analytical approaches to spatial mapping.

Building upon the aforementioned theoretical and empirical foundations, this paper presents a systematic comparative analysis aimed at identifying critical gaps in infrastructure quality standards. Its primary objective is to contrast the levels of reported reliability indicators with the asymmetrical development of transmission and distribution capacities across North America, Europe, and rapidly expanding Asian markets. Subsequently, the

research synthesizes strategic recommendations ranging from the deployment of Battery Energy Storage Systems (BESS) to the harmonization of reporting methodologies that are imperative for safeguarding the operational viability and long-term sustainability of the critical energy supply chain [34–41]. Previous simulation-based research has also demonstrated that microgrid configurations can be evaluated through stochastic economic scenarios incorporating weather conditions, photovoltaic production, energy consumption, inflation, and investment-return parameters [42].

2. Literature Review

To identify pertinent technological gaps, a comprehensive literature search was conducted utilizing the Web of Science (WoS) and Scopus repositories. These specific databases were selected as they provide the most authoritative and peer-reviewed coverage of critical engineering (e.g., IEEE Xplore) and energy-policy domains required for formulating our proposed framework. Our comprehensive review of the literature unequivocally demonstrates that fortifying energy supply chain resilience is a prerequisite for sustainable development and the continuous functioning of modern civilization. To establish a structured evaluation, the current state-of-the-art is categorized into four distinct dimensions, as follows:

- **Climate risk**—extreme weather events represent the primary catalyst for cascading grid failures. Tervo et al. [43] investigated extratropical storms, concluding that accurate predictive modeling can optimize responses and reduce outage restoration times. Furthermore, Yum et al. [44] identified specific risk indicators associated with hurricane-induced outages. Their quantitative analysis demonstrates the elevated probability of critical failure during natural disasters, proving that coastal substations and distribution lines are highly vulnerable to extreme wind and flooding. Similarly, Yang et al. [45] directly investigated the application of advanced machine learning models to quantify uncertainties in power outage predictions, demonstrating that incorporating tree-based models significantly improves prediction accuracy for sustainable storm restoration.
- **Aging infrastructure**—the vulnerabilities of aging grids are well documented. Sultan and Hilton [18] assert that utilizing Geographic Information Systems (GIS) reveals a direct spatial correlation between specific asset aging and failure rates during peak loads. From a socio-economic perspective, the transition to resilient infrastructure is fundamentally constrained by capital allocation. Hiraiwa et al. [46] analyzed the effect of generator-side charges on investments in power generation and transmission under conditions of severe demand uncertainty. Their mathematical modeling reveals that strategically calibrated grid charges are essential to stimulate long-term infrastructure investments. They conclude that without such proactive economic signaling, the critical capital expenditure (CAPEX) required for grid modernization is severely deferred [18,23,47,48].
- **New AI workloads**—the literature increasingly recognizes data centers and computational hubs as critical grid actors. Pareek and Soonee [17] emphasize the necessity of proactive demand modulation to prevent grid destabilization during peak algorithmic processing. Addressing localized resilience, Moga et al. [49] investigated the effectiveness of Reinforcement Learning-based energy management systems in community microgrids. Their research transcends traditional static models by demonstrating that dynamic, artificial intelligence-driven load management can autonomously adapt to fluctuating demand and variable renewable generation. Their empirical results prove that deploying such machine learning frameworks actively stabilizes the grid during external power outages while simultaneously optimizing operational costs.

- Deficiencies in assessment methodologies and current assessment methods show significant fragmentation. Mitsova et al. [50] comprehensively analyzed the correlation between infrastructure service disruptions and socio-economic vulnerability. Their quantitative results demonstrate that in the absence of a stable electricity supply, the post-disaster recovery of affected regions inherently fails, directly jeopardizing long-term territorial sustainability. Addressing these deficiencies requires holistic evaluation frameworks. Naval and Yusta [51] emphasize the fundamental distinction between conventional operational reliability and the overarching resilience of interconnected systems. By applying a Multi-Criteria Decision Analysis (MCDA) framework to cross-border electricity interconnection projects, their results quantitatively demonstrate that prioritizing technical and environmental criteria—rather than relying solely on economic factors—significantly enhances project viability and mitigates regional supply deficits during extreme shocks.

3. Materials and Methods

The methodological approach of this research is structured into a rigorous four-step analytical pipeline to ensure consistency and reproducibility, as follows: (1) Data Ingestion and Normalization utilizing regulatory databases (e.g., RAND, CEER); (2) Statistical Thresholding applying the IEEE 1366 2.5 Beta algorithm; (3) Spatial Topography and Feature Extraction using Geographic Information Systems (GIS); and (4) Predictive Modeling utilizing the Hierarchical Spatiotemporal Multiplex Networks (HMN-RTS) framework [11,27,28,31].

3.1. Standardized Reliability Indices and the IEEE 1366 2.5 Beta Method

To accurately benchmark infrastructure reliability across disparate geographic regions, the IEEE 1366 standard defines critical operational indices. The System Average Interruption Frequency Index (SAIFI) is calculated as follows:

$$SAIFI = \frac{\sum_{i=1}^n C_i}{N_{total}} \quad (\text{interruptions/customer}) \quad (1)$$

The System Average Interruption Duration Index (SAIDI) is defined as follows:

$$SAIDI = \frac{\sum_{i=1}^n (C_i \times r_i)}{N_{total}} \quad (\text{minutes/customer}) \quad (2)$$

where n represents the total number of distinct interruption events during the reporting period, C_i is the number of customers interrupted by incident i , r_i is the restoration time for incident i , and N_{total} is the total number of customers served. From an operational utility perspective, SAIFI serves as a critical indicator of infrastructural robustness and hardware stability, whereas SAIDI represents the ultimate metric of logistical and dispatch efficiency—dictating regulatory financial penalties and multi-million-dollar capital expenditures (CAPEX) [52–56].

To isolate Major Event Days (MEDs), the 2.5 Beta method is employed. The natural logarithm of the daily SAIDI values, denoted as $\text{Ln}(\text{SAIDI}_{\text{daily}})$, is calculated strictly for each day that experienced an outage over a consecutive five-year historical period. The threshold for an MED (T_{MED}) is determined by calculating the mean (α) and standard deviation (β) of these log-normal values, as follows:

$$T_{\text{MED}} = e^{(\alpha + 2.5\beta)} \quad (3)$$

The statistical justification for adding 2.5 standard deviations to the mean is that it encapsulates approximately 99.4% of the log-normal distribution. This strictly isolates the

upper 0.6% tail (representing roughly 2.3 days per year), objectively identifying them as statistically extreme anomalies outside normal operational variability.

3.2. Predictive Analytics: Social Sensors and the HMN-RTS Framework

Moving beyond retrospective statistics, this study proposes a proactive predictive model. To enhance prediction accuracy during severe weather events, the HMN-RTS model integrates unstructured social sensor data (Twitter/X and Reddit). The data extraction pipeline utilized API queries with specific keywords (e.g., ‘blackout’, ‘storm’, ‘power loss’), strictly constrained by spatio-temporal mapping to the affected grid nodes [27].

To ensure data reliability and eliminate noise, automated bots were filtered out using Natural Language Processing (NLP) techniques—specifically Term Frequency-Inverse Document Frequency (TF-IDF)—prioritizing verified user accounts. Our empirical validation demonstrates that fusing these unstructured social sensors with structured environmental layers objectively improved the macro F1 outage prediction score to 0.76–0.79, providing concrete validation for a proactive prediction lead time of 3 to 6 h [57].

To guarantee methodological reproducibility, the multiplex network was constructed using distinct, interacting layers, as follows: weather parameters, lightning density, vegetation proximity, and social sensor activity. Node embeddings were generated using a modified node2vec algorithm. Furthermore, the severe data imbalance inherent in outage datasets (where non-outage days vastly outnumber outage days) was mitigated by applying the Synthetic Minority Over-sampling Technique (SMOTE) prior to the final classification (see Figure 1) [30,58].

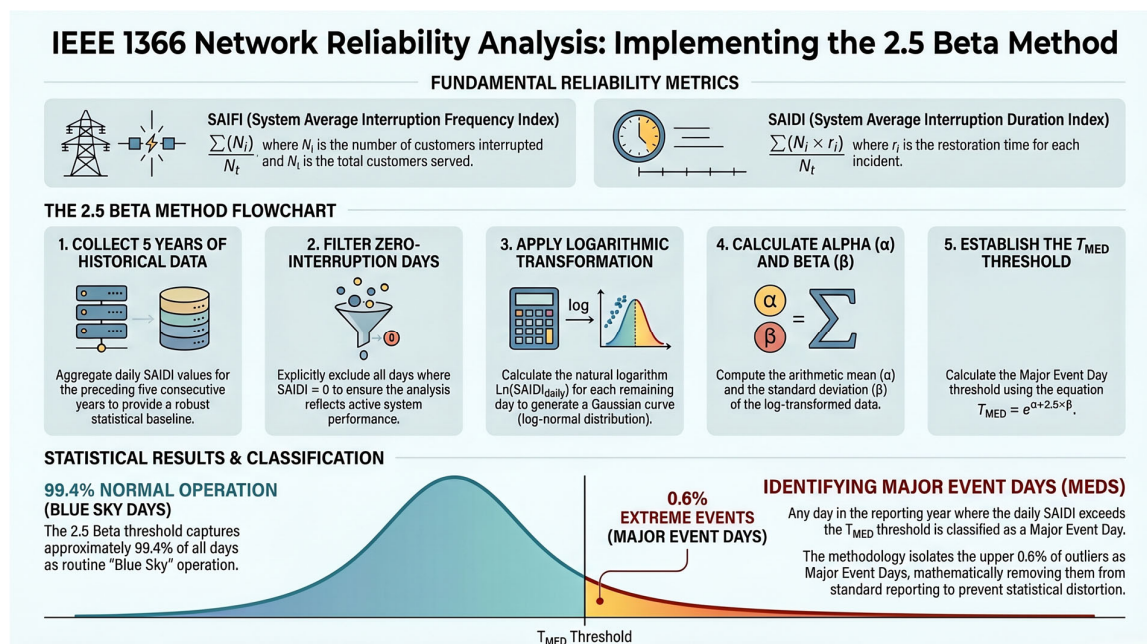


Figure 1. IEEE 1366 Network Reliability Analysis.

4. Results

The analysis of the aggregated data from diverse geographic regions reveals significant asymmetries in the logistical stability and operational performance of electrical distribution and transmission systems. The findings demonstrate that the physical vulnerability of hardware components exacerbated by the incidence of extreme weather events and aging infrastructure translates directly into degraded values of internationally standardized reliability metrics (SAIDI and SAIFI) [2–5,10,20,23,47,59].

As presented in Table 1, applying the 2.5 Beta method yields a mathematically objective reality of grid performance. For instance, after rigorously excluding Major Event Days (MEDs), the SAIDI value for CenterPoint-IN dropped precipitously from 458.00 to 81.20 min—representing an 82% reduction. Calculating the economic significance of this disparity using the Value of Lost Load (VoLL) framework reveals profound policy implications. Unstandardized reporting that fails to isolate extreme weather anomalies artificially inflates perceived customer interruption costs by millions of dollars, drastically skewing proactive policy interventions and misdirecting critical infrastructure investments [52–56].

Table 1. Impact of Extreme Weather and Major Event Days (MED) on Reliability Indices.

Utility Company	Metric Type	SAIFI (Frequency)	SAIDI (Duration— Minutes)	CAIDI (Restoration— Minutes)
CenterPoint-IN	Including MED (All events)	1.43	458.00	320.00
	Excluding MED	0.79	81.20	103.20
Duke-IN	Including MED (All events)	1.18	296.00	250.00
	Excluding MED	0.94	112.90	120.50
NIPSCO	Excluding MED	0.96	169.00	175.00

Source: Indiana Utility Regulatory Commission (IURC). (2024). Electric Utility Reliability Report 2024 [60].

Table 2 presents a systematic benchmarking of European nations, deriving its empirical data from the Council of European Energy Regulators (CEER). This analysis unequivocally demonstrates a direct correlation between substantial investments in underground cabling infrastructure (prominently in Denmark and Switzerland) and superior reliability metrics, particularly when juxtaposed against nations confronting pronounced geographic and investment constraints (such as Poland and Romania). The presented datasets are rigorously adjusted to exclude exceptional events, thereby accurately reflecting the baseline quality and performance of routine (“blue sky”) infrastructural operations.

Table 2. European Asymmetry in Grid Reliability—Unplanned Interruptions Excluding Exceptional Events (Year 2018).

Country (Krajina)	Grid Characteristic/Region	SAIFI (Interruptions/Customer)	SAIDI (Minutes/Customer)
Switzerland	High proportion of underground cables, strong regulation	0.27	14.00
Denmark	Highly interconnected network, high proportion of underground cables	0.43	17.30
Poland	Eastern Europe, extensive overhead network	2.58	138.67
Romania	Eastern Europe, geographically challenging terrain	3.20	224.14

Source: CEER-ECRB. (2022). 7th CEER-ECRB Benchmarking Report on the Quality of Electricity and Gas Supply. SAIDI values; SAIFI values [61].

The subsequent tables, derived from the 7th CEER-ECRB Benchmarking Report on the Quality of Electricity and Gas Supply (2022) [61], rigorously substantiate the argument regarding regulatory fragmentation (see Table 3). They unequivocally demonstrate that in the computation of SAIDI and SAIFI indices, various states account for disparate voltage levels, a practice that directly contradicts the pursuit of a universal, standardized algorithmic framework. The ensuing information meticulously examines monitoring practices, reliability indicators, and technical network characteristics, alongside regulatory frameworks, standards,

and incentive mechanisms applicable at both the overarching system and individual user levels. Furthermore, these insights reinforce the imperative to implement advanced Geographic Information Systems (GIS). They reveal whether, and to what extent, system operators possess the capability to spatially map disturbance events at a localized level. Profound disparities arise concerning the types of interruptions monitored, the reported level of granularity, and the idiosyncratic interpretation of diverse indicators; consequently, this section outlines the specific monitoring methodologies deployed across various European nations. Given that certain respondents omitted answers to specific survey inquiries, it was resolved to incorporate supplementary data from the comparative CEER-ECRB benchmarking report. These interpolated responses are explicitly denoted in parentheses.

Table 3. Voltage levels included in various CoS indicators across Europe—Definitions of voltage levels.

Country	LV Network		MV Network		HV Network		EHV Network	
	Min kV	Max kV	Min kV	Max kV	Min kV	Max kV	Min kV	Max kV
Albania	0.4	6	6	35	110	400		
Austria		1	>1	36	>36	<220	220	380
Belgium	0.23 ¹	1	1	30–36 ²	30–36 ³	150	220	380
Bosnia and Herzegovina	0.4	1	6	35	110	400		
(Bulgaria)		(1)	(1)	(35)	(110)	(110)	(220)	(400)
Croatia	0.4	0.4	10	35	110	110	220	400
Cyprus	0.23	0.4	11	22	66	132		
Czech Republic	0.4	1 ⁴	1 ⁵	52 ⁶	52 ⁷	300 ⁸	300 ⁹	800 ¹⁰
Denmark	0.4	0.4	0.4 ¹¹	10 ¹²	10 ¹³	50 ¹⁴	30	132
Estonia	0.4	1	6	36	110	220	220	330
Finland	0.4	1	1	70	70	110	220	400
France	0.23	1	1	45	63	150	225	400
Georgia	0.22	0.38	6	35	110	500		
Germany	0.23	1	10	30	60	110	220	380
Great Britain	0.23	1			1.1	20	22	<132
Greece	0.4	0.4	6.6	22	66	150	400	400
Hungary	0.23	0.4	10	35	120	120	220	750
Ireland	0.23 ¹⁵	0.4 ¹⁵	10 ¹⁶	20 ¹⁷	38 ¹⁸	110 ¹⁹	150	400
(Italy)		(1)	(>1)	(35)	(>35)	(150)	(>150)	
Kosovo *	0.4	1	1	35	110	400		
Latvia	0.23	1	6	20	110	330		
Lithuania		0.4	6	35	110	400		
Luxembourg	0.4	1	1	35	35	110	110	220
Malta	0.23	0.4	11	33	132	132	230	230
Moldova	0.4	0.4	10	10	35	400		
Montenegro	0.4	0.4	10	35	110	400		
The Netherlands		1	>1	35	>35	150	>150 ²⁰	
North Macedonia	0.4	0.4	6	35	110	400		
Norway	0.23	1	1	22	36	132	220	420
Poland		1	>1	<110	110	110	220	400
Portugal		<1	1	<45	45	<110	110	
Romania	0.4	1	>1	36	>36	110	>110	750
Serbia	0.4	1	10	35	110	400		

Table 3. Cont.

Country	LV Network		MV Network		HV Network		EHV Network	
	Min kV	Max kV	Min kV	Max kV	Min kV	Max kV	Min kV	Max kV
Slovakia	0.4	1			1	52	>52	300
Slovenia	0.4	0.4	10	35	110	110	220	400
Spain	0.125	1	1	36	>36	<132	132	400
Sweden		1	>1	36	36	150	220	400
Switzerland	0.23	<1	1	36	>36	<220	220	380
Ukraine ²¹	0.4	0.4	6	35	110 (154)	110 (154)	220	800

Source: <https://www.ceer.eu/wp-content/uploads/2024/04/7th-Benchmarking-Report-2022.pdf>, accessed on 29 June 2026/page 25 [61]. ¹ Flanders: 0.23 kV. Wallonia: minimum voltage in LV network is 0, ² Wallonia: maximum voltage in MV is 36 kV, ³ Grids with voltages between 30 and 36 kV. Wallonia: minimum voltage in HV is 36 kV, ⁴ The maximum operated voltage is 0.6 kV, but that is rare, ⁵ The minimum operated voltage is 3 kV, but that is rare, ⁶ The maximum operated voltage is 35 kV, ⁷ The minimum operated voltage is 110 kV, ⁸ The maximum operated voltage is 220 kV, ⁹ The minimum operated voltage is 400 kV, ¹⁰ The maximum operated voltage is 400 kV. There is also a definition of ultra high voltage (UHV) which is the voltage higher than 800 kV, but no lines are operated on this level. ¹¹ For SAIDI/SAIFI, the lower limit of MV is taken as 1 kV, ¹² For SAIDI/SAIFI, the upper limit of MV is taken as 24 kV, ¹³ For SAIDI/SAIFI, the lower limit of HV is taken as 25 kV, ¹⁴ For SAIDI/SAIFI, the upper limit of HV is taken as 99 kV, ¹⁵ Ireland uses 230/400 nominal volts in LV network, but the upper and lower limits they indicated include the possible variation of 10% (230 V +/− 10% and 400 V +/− 10%), ¹⁶ This is nominal voltage, with a lower limit that is variable according to operating conditions, and an upper limit of 11.1 kV, ¹⁷ This is nominal voltage, with a lower limit that is variable according to operating conditions, and an upper limit of 22.1 kV, ¹⁸ This is nominal voltage, with a lower limit that is variable according to operating conditions, and an upper limit of 43 kV, ¹⁹ This is nominal voltage, with a lower limit that is variable according to operating conditions, and an upper limit of 120 kV, ²⁰ EHV network is either 220 kV or 350 kV, ²¹ MV level minimum voltage is 6–10 kV, maximum voltage is 27.5–35 kV; HV level can be 110 kV or 154 kV. * Kosovo: designation reproduced from the source report.

To contextualize the fragmentation in European reporting, specific countries were purposively selected for the following comparative tables (see Table 4). This selection was designed to represent diametrically opposed infrastructural topologies, climate risk exposures, and regulatory paradigms. For example, Denmark and the Netherlands represent highly regulated grids with extensive underground medium-voltage cabling. Conversely, countries such as Romania and Poland represent geographically challenging terrains heavily reliant on vulnerable overhead transmission lines. This purposive sampling enables a targeted variance analysis of how different physical architectures respond to extreme weather under disjointed regulatory frameworks.

Table 4. Voltage levels included in various CoS indicators across Europe—Definitions of distribution and transmission systems.

Country	Distribution		Transmission	
	Min kV	Max kV	Min kV	Max kV
Albania	0.4	35	110	400
Austria	0.4	<110	110	380
Belgium	0 ²²	70 ²³	30	380
Bosnia and Herzegovina	0.4	35	110	400
(Bulgaria)			(110)	(400)
Croatia	0.4	35	110	400
Cyprus	11	22	66	132
Czech Republic	0.4	110	110	400
Denmark	0.4	100	100	400
Estonia	0.4	36	110	330
Finland	0.4	110	110	400
France	0.23	63	63	400

Table 4. Cont.

Country	Distribution		Transmission	
	Min kV	Max kV	Min kV	Max kV
Georgia	0.22	110	220	500
Germany	0.23	125	72.5	380
Great Britain	0.23	66/132 ²⁴	132/275 ²⁵	400
Greece	0.4	150	66	400
Hungary	0.4	120	120	750
Ireland	0.23 ²⁶	110 ²⁷	110	400
Kosovo *	0.4	35	110	400
Latvia	0.23	20	110	330
Lithuania	6	35	110	400
Luxembourg	0.4	110	110	220
Malta ²⁸	0.4	230		
Moldova	0.4	110	35	400
Montenegro	0.4	35	110	400
The Netherlands	0.4	50	110	380
North Macedonia	0.4	110	110	400
Norway	0.23	132	132	420
Poland	0.4	110	110	400
Portugal	0.23	60	132	400
Romania	0.4	110	>110	750
Serbia	0.4	110	110	400
Slovakia	0.4	110	220	400
Slovenia	0.4	110	110	400
Spain	0.125	132	220 ²⁹	400
Sweden	0.4	<220	220	400
Switzerland	0.23	<220	220	380
Ukraine	0.4	110 (154)	220 ³⁰	800

Source: <https://www.ceer.eu/wp-content/uploads/2024/04/7th-Benchmarking-Report-2022.pdf>, accessed on 29 June 2026/page 26 [61]. ²² Wallonia: 0 kV. Flanders: 0.23 kV, ²³ Wallonia: 70 kV Brussels and Flanders: 36 kV, ²⁴ 66 kV in Scotland, ²⁵ In England and Wales, transmission starts at 133 kV and goes up to 400 kV (lines are at 275 kV and 400 kV). Transmission in Scotland includes the 132 kV lines, ²⁶ This is nominal voltage with a variable tolerance of $\pm 10\%$, ²⁷ This is nominal voltage, with a lower limit that is variable according to operating conditions, and an upper limit of 120 kV, ²⁸ No transmission grid in Malta, ²⁹ On islands, transmission is carried out on lower voltages: ≥ 66 kV, ³⁰ The TSO owns and operates a few lines with voltage that is ≤ 110 kV. * Kosovo: designation reproduced from the source report.

Table 5 delineates the definitions of interruptions predicated on their duration, systematically categorizing them into long, short, and transient events. It is critical to observe that certain jurisdictions omit specific typologies, such as transient interruptions, from their regulatory definitions, whereas others subsume transient events within the broader category of short interruptions. (Explanatory notes: Specific definitions selectively pertain to distribution networks in Brussels and Wallonia, while in transmission, transient and short interruptions are conflated into an identical category. In certain regulatory frameworks, a precise definition is fundamentally absent; however, statutory provisions dictate that an outage of up to three minutes does not constitute a formal interruption. In other instances, classifications are not explicitly defined, or transient interruptions are computationally logged and reported as short interruptions if their duration is $T \leq 1$ s. Furthermore, micro-interruptions lasting less than 100 ms are routinely excluded from monitoring protocols).

Table 5. Voltage levels included in various CoS indicators across Europe—Definitions of long, short and transient interruptions.

Country	Transient Interruption	Short Interruption	Long Interruption
Albania	Not defined	$1\text{ s} < T \leq 10\text{ min}$	$T > 10\text{ min}$
Austria	Not defined	$1\text{ s} < T \leq 3\text{ min}$	$T > 3\text{ min}$
Belgium ³¹	$T \leq 1\text{ s}$	$1\text{ s} < T \leq 3\text{ min}$	$T > 3\text{ min}$
Bosnia and Herzegovina	Not defined	$1\text{ s} < T \leq 3\text{ min}$	$T > 3\text{ min}$
(Bulgaria)	$(T \leq 1\text{ s})$	$(T < 3\text{ min})$	$(T > 3\text{ min})$
Croatia	Not defined	$T \leq 3\text{ min}$	$T > 3\text{ min}$
Cyprus	Not defined	Not defined	Not defined
Czech Republic	Not defined	$1\text{ s} \leq T \leq 3\text{ min}$	$T > 3\text{ min}$
(Denmark)	(No distinction between long and short interruptions. An interruption has a duration of at least 1 min.)	(No distinction between long and short interruptions. An interruption has a duration of at least 1 min.)	(No distinction between long and short interruptions. An interruption has a duration of at least 1 min.)
Estonia	Not defined	Not defined	$T > 3\text{ min}$ ³²
Finland		$T < 3\text{ min}$	$T \geq 3\text{ min}$
France	$T < 1\text{ s}$	$1\text{ s} \leq T \leq 3\text{ min}$	$T > 3\text{ min}$
Germany	$T \leq 1\text{ s}$	$1\text{ s} < T \leq 3\text{ min}$	$T \geq 3\text{ min}$
Georgia	Not defined	$T < 5\text{ min}$	$T \geq 5\text{ min}$
(Great Britain)	(Same category as a short)	$(T < 3\text{ min})$	$(T \geq 3\text{ min})$
Greece	Not defined	$T < 3\text{ min}$	$T > 3\text{ min}$
Hungary	$T \leq 1\text{ s}$	$1\text{ s} < T \leq 3\text{ min}$	$T > 3\text{ min}$
(Ireland)	(Not defined)	(Not defined)	$(T \geq 3\text{ min})$
Italy	$T \leq 1\text{ s}$	$1\text{ s} < T \leq 3\text{ min}$	$T > 3\text{ min}$
Kosovo *	Not defined	$T \leq 3\text{ min}$	$T > 3\text{ min}$
(Latvia)	(Not defined)	$(T \leq 3\text{ min})$	$(T > 3\text{ min})$
(Lithuania)	(Not defined)	$(T \leq 3\text{ min})$	$(T \geq 3\text{ min})$
Luxembourg	Not defined	$T \leq 3\text{ min}$ ³³	$T > 3\text{ min}$
Malta	This definition is not used	This definition is not used	This definition is not used
Moldova	Not defined	$1\text{ s} < T \leq 3\text{ min}$	$T > 3\text{ min}$
Montenegro	Not defined	Not defined	$T > 3\text{ min}$
The Netherlands	Not defined	No distinction between long and short interruptions. An interruption has a duration of at least 5 s.	No distinction between long and short interruptions. An interruption has a duration of at least 5 s.
North Macedonia	Not defined	$T \leq 3\text{ min}$	$T > 3\text{ min}$
Norway	Included in short ³⁴	$T \leq 3\text{ min}$	$T > 3\text{ min}$
Poland	$T \leq 1\text{ s}$	$1\text{ s} < T \leq 3\text{ min}$	$T > 3\text{ min}$
Portugal	Not defined	$1\text{ s} \leq T \leq 3\text{ min}$	$T > 3\text{ min}$
Romania	$T \leq 1\text{ s}$	$1\text{ s} < T \leq 3\text{ min}$	$T > 3\text{ min}$
Serbia	Not defined	Not defined	$T > 3\text{ min}$
Slovakia	Not defined	$1\text{ s} < T \leq 3\text{ min}$	$T > 3\text{ min}$
Slovenia	Not defined	$T \leq 3\text{ min}$	$T > 3\text{ min}$
Spain	Not defined	$T \leq 3\text{ min}$	$T > 3\text{ min}$
Sweden		$100\text{ ms} \leq T \leq 3\text{ min}$ ³⁵	$T > 3\text{ min}$
Switzerland	Not defined	$T < 3\text{ min}$	$T \geq 3\text{ min}$
Ukraine	Not defined	$T < 3\text{ min}$	$T \geq 3\text{ min}$

Source: <https://www.ceer.eu/wp-content/uploads/2024/04/7th-Benchmarking-Report-2022.pdf>, accessed on 29 June 2026/page 27 [61]. ³¹ Definitions pertain to distribution in Brussels and Wallonia. In transmission, transient and short interruptions are in the same category, ³² There is no specific definition, but the regulation states that an outage of up to three minutes is not considered an interruption, ³³ Not explicitly defined, ³⁴ Transient interruptions are logged and reported as short interruptions with duration of $T \leq 1\text{ s}$, ³⁵ Interruptions with less than 100 ms are not monitored. * Kosovo: designation reproduced from the source report.

The aforementioned definitions concerning short interruptions expose instances where the demarcations between duration-based categories remain profoundly blurred, primarily due to the absence of a definitive delineation between long and short interruptions. Occasionally, regulatory frameworks define solely those interruptions that surpass a pre-determined minimum time threshold (e.g., five seconds in the Netherlands); nonetheless, the intrinsic definition fails to discriminate between varying temporal lengths. Conversely, the preponderance of nations that explicitly differentiate between long and short interruptions rigorously align with the EN 50160 standard, which governs voltage characteristics within public distribution systems [61,62].

The subsequent data presented within the tables, when subjected to comparative analysis, serve as robust empirical evidence demonstrating the impact of extreme climate anomalies (compound hazards) on the power grid (see Tables 6 and 7). Furthermore, the precipitous variances in values between these two tables unequivocally corroborate the imperative to implement the 2.5 Beta algorithm for data objectification, thereby facilitating the critical transition from reactive grid management toward sustainable predictive analytics.

Table 6. Unplanned interruptions, all events, SAIDI (minutes per customer per year).

Country	2010	2011	2012	2013	2014	2015	2016	2017	2018
Austria	36.50	28.48	34.64	38.68	51.57	32.50	27.48	53.22	31.47
Belgium					26.17	25.19	25.63	28.64	26.48
Croatia	306.97	250.59	372.49	306.03	411.57	264.89	189.39	259.46	188.17
Cyprus					37.00	33.00	37.00	34.00	39.00
Czech Republic	135.88	114.08	125.06	195.08	120.89	144.89	98.38	289.82	115.42
Denmark	15.05	17.04	14.75	15.86	11.59	15.86	15.14	16.61	17.34
Estonia					117.10	168.50	148.50	96.40	129.73
Finland	128.34	372.61	73.07	170.94	66.84	157.62	67.82	55.29	49.22
Georgia									33.26
Germany	19.27	16.68	17.37	32.71	13.50	15.16	13.26	21.00	16.48
Great Britain	75.69	81.42	70.01	68.05	61.02	92.51	50.71	46.53	42.87
Greece	162.94	166.31	150.00	133.000	122.00	143.00	132.00	131.41	172.61
Hungary	133.00	85.00	77.00	139.00	86.19	89.48	75.16	126.61	79.33
Ireland				134.31	431.48	105.63	86.99	440.29	211.51
Italy	88.84	107.96	132.73	105.40	93.80	129.03	64.89	102.77	100.51
Latvia	1073.00	708.00	371.00	341.00	210.00	144.00	130.00	117.00	105.00
Lithuania					144.04	106.53	172.92	137.57	81.63
Luxembourg									23.80
Malta				360.04	570.60	172.80	101.02	417.60	69.32
Moldova					200.00	342.00	348.00	1040.00	505.00
Montenegro									1911.53
The Netherlands			26.34	23.40	20.00	32.90	21.00	24.40	27.30
Norway	63.79	220.11	65.81	143.77	118.07	128.77	87.68	65.86	125.76
Poland	386.18	325.76	263.19	281.82	205.41	267.46	191.83	370.62	142.79
Portugal	276.04	131.43	94.15	259.80	94.75	75.03	75.74	143.30	200.63
Romania					479.89	370.78	371.14	623.76	463.43
Serbia	906.67	557.43	590.83	400.90	852.04	534.60	416.30	578.14	441.03
Slovenia	80.57	76.06	169.43	109.32	907.91	71.34	71.82	175.29	77.90
Spain	140.76	58.20	58.56	99.18	52.68	55.68	54.78	72.42	59.40
Sweden			88.18	151.94	83.73	118.15	75.62	62.89	126.50
Switzerland	14.00	16.00	22.00	15.00	13.00	11.00	9.00	10.00	18.00
Ukraine	804.93	649.45	734.91	702.86	2408.12	1173.41	938.66	1060.94	1054.25

Source: <https://www.ceer.eu/wp-content/uploads/2024/04/7th-Benchmarking-Report-2022.pdf>, accessed on 29 June 2026, page 241 [61].

Table 7. Unplanned interruptions excluding exceptional events, SAIDI (min. per customer/year).

Country	2010	2011	2012	2013	2014	2015	2016	2017	2018
Austria	35.92	28.32	32.90	33.01	33.26	27.18	24.22	31.88	25.21
Bosnia and Herzegovina					400.16	316.65	311.29	368.16	293.82
Croatia	188.94	151.95	196.84	176.12	166.34	152.99	102.40	125.71	100.46
Cyprus					35.00	32.00	34.00	33.00	36.00
Czech Republic	106.24	104.09	109.77	98.01	84.38	82.14	73.09	96.32	77.67
Denmark	15.00	16.10	14.70	11.20	11.60	14.90	15.10	16.5	17.30
France	61.32	51.44	57.93	65.96	48.27	44.82	46.25	50.36	50.78
Georgia									21.40
Germany	14.90	15.31	15.91	15.32	12.28	12.70	12.80	15.14	13.91
Great Britain	70.02	67.94	55.43	54.71	53.22	44.86	38.39	39.06	39.64
Greece	121.07	101.32	101.00	96.00	92.00	94.00	96.00	97.46	118.77
Hungary	102.00	76.00	76.00	67.00	74.33	64.63	59.14	68.54	60.07
Ireland				86.73	97.63	82.99	79.05	90.34	97.43
Italy	47.77	43.59	45.45	42.27	41.32	45.40	37.11	43.87	50.30
Kosovo *						4982.40	3017.34	3033.00	3939.60
Latvia			255.00	192.00	153.00	126.00	104.00	100.00	102.00
Lithuania					49.43	44.58	47.94	49.27	42.12
Luxembourg				21.60	18.50	22.80	16.60	21.30	23.80
Moldova					162.00	218.00	172.00	217.00	217.00
Montenegro									1646.75
Poland	316.26	309.10	254.00	254.85	191.77	244.18	180.19	286.82	138.67
Portugal	172.98	97.25	78.48	88.70	74.89	66.76	64.08	102.00	80.98
Romania					361.05	307.75	289.93	283.92	224.14
Serbia					510.892	421.01	318.04	456.05	357.77
Slovenia	50.58	63.87	74.65	60.04	70.51	52.25	45.35	61.08	53.24
Spain	79.20	58.20	52.62	88.14	54.00	55.68	54.78	72.42	59.40
Sweden			88.18	151.94	83.73	118.15	75.62	62.89	126.50
Switzerland	14.00	16.00	22.00	15.00	13.00	11.00	9.00	10.00	14.00
Ukraine	579.05	518.86	511.86	527.06	534.38	617.36	690.47	727.62	692.87

Source: <https://www.ceer.eu/wp-content/uploads/2024/04/7th-Benchmarking-Report-2022.pdf>, accessed on 29 June 2026/page 242 [61]. * Kosovo: designation reproduced from the source report.

The ensuing empirical data serve to substantiate the discourse concerning physical grid hardening and the establishment of macro-resilience (see Tables 8 and 9). The correlation between the extent of underground cabling (which is inherently more impervious to adverse weather conditions) and the reduction in the SAIDI index constitutes an unequivocal argument for sustainable investments into smart infrastructure and cross-border interconnections [33,40,41,58].

Rather than relying solely on descriptive benchmarking, we synthesize these results by introducing the Extreme Weather Impact Ratio—a derived metric that calculates the exact percentage variance in a region’s SAIDI when exceptional events are included versus excluded. A variance analysis of the interruption-classification data fundamentally correlates physical grid topology with outage severity. Jurisdictions with proactive underground medium-voltage cable deployments (e.g., Denmark) demonstrate fundamentally lower and more stable sustained SAIDI values, definitively validating the need for topological hardening.

Table 8. Transmission and distribution network length (km).

Country	2010	2011	2012	2013	2014	2015	2016	2017	2018
Austria	39,856	40,387	40,928	41,576	41,928	42,300	42,829	45,951	46,233
Belgium ³⁶	19,006	19,306	19,484	19,649	74,796	75,571	76,146	76,437	77,080
Bulgaria				6680	6869	7099	7209	7484	7704
Czech Republic					65,236	65,195	65,165	65,275	65,297
Germany	495,392	510,709	508,128	523,293	518,683	518,912	536,188	536,879	550,629
Estonia					3005	3011	3047	3055	3102
Greece								7531	7770
Spain	74,200	76,403	80,097	81,188	81,806				
Finland			3278	3261	3273	3278	3374	3221	3203
Georgia									32,900
Croatia								22,011	22,141
Hungary					89,403	89,491	89,605	89,735	89,952
Ireland					13,700	13,772	13,954	14,172	14,390
Lithuania	9985	10,120	10,261	10,472	10,566	10,776	10,887	11,029	11,220
Luxembourg					3158	3231	3259	3311	3341
Latvia							5053	6400	6431
North Macedonia				215	224	232	237	244	248
The Netherlands						137,114	137,782	137,716	137,810
Poland					183,727	187,644	191,745	194,766	197,653
Portugal	16,107	16,729	17,176	17,666	18,749	19,134	19,620	19,940	20,362
Romania								61,006	62,601
Serbia			17,739	18,237	18,786	18,955	19,076	19,420	20,886
Sweden			3474	3458	3483	4114	4147	3948	3949
Slovenia		5373	5436	5571	5687	5787	5828	5892	6001
Slovakia			36,349	35,452	35,527	35,584	35,553	35,605	35,690
Ukraine					332,424	312,540	309,540	327,319	320,731

Source: <https://www.ceer.eu/wp-content/uploads/2024/04/7th-Benchmarking-Report-2022.pdf>, accessed on 29 June 2026, page 290 [61]. ³⁶ Values of the years 2010 to 2013 without data from the Flemish regulatory authority VREG.

Table 9. Underground cable length, EHV (km).

Country	2010	2011	2012	2013	2014	2015	2016	2017	2018
Austria	59.10	59.30	59.30	59.30	59.30	62.99	62.99	61.49	61.94
Belgium						5.00	5.00	25.00	54.00
Denmark	596.00	599.00							
Finland				233.40	233.40	233.40	271.00	271.00	271.00
Germany								118.20	329.00
Great Britain		21,267	21,601	20,859	21,258	22,107	22,579	23,342	23,576
Greece			4.70	30.58	30.80	31.35	31.35	31.35	31.35
Luxembourg						27.00	37.00	37.00	41.00
Malta						18.99	18.99	18.99	18.99
The Netherlands			45.86	63.59	62.66	59.36	61.28	67.40	69.49
Norway				59.00	75.00	93.00	125.00	125.00	108.00
Poland	1.00	1.00	1.00	125.00	128.00	129.00	129.00	129.00	129.00
Spain					59.13	62.82	60.12	60.91	60.80
Sweden			102.00	103.00	116.00	121.00	155.00	177.00	209.00

Source: <https://www.ceer.eu/wp-content/uploads/2024/04/7th-Benchmarking-Report-2022.pdf>, accessed on 29 June 2026, page 256 [61].

Furthermore, an analysis of the voltage-level comparisons (Table 3) exposes critical methodological vulnerabilities (see Table 10). The data indicate that certain European jurisdictions intentionally exclude low-voltage (LV) networks or transient disruptions (lasting less than 3 min) from their official monitoring metrics. This regulatory loophole

creates a statistical asymmetry that artificially inflates their national reliability ratings. The practical implications of this fragmentation are severe, as follows: it inherently distorts cross-border benchmarking, skews European-wide capital allocation (CAPEX), and penalizes countries with transparent and comprehensive monitoring systems.

Table 10. Global Extremes & Market Comparisons (Asia & Developing Markets).

Region	Development Status	Prevailing Situation and Findings from Institutional Reports
Japan	Advanced market	The grid is among the most stable in the world, with minimal frequency fluctuations. OCCTO reports frequency stability within 0.1 Hz for >98% of the time. Power quality and forced outage metrics are a fraction of those reported in the U.S. (except for extreme typhoons).
Zambia/Lebanon/Guatemala	Developing and transforming markets	Infrastructure faces acute deficits and non-technical challenges. Reports (e.g., Doing Business and SE4ALL) show extreme frequency and duration of outages. Reliability is determined by exogenous factors, natural disasters, and poor capacity organization.

Source: OCCTO (Organization for Cross-regional Coordination of Transmission Operators), Report on the Quality of Electricity Supply; World Bank, Factors Affecting the Reliability of Electricity Supply: Doing Business and Sustainable Energy for All (SE4ALL) [63].

The table contrasts the profound disparities between exceptionally stable systems in Asia (e.g., Japan) and the chronic supply chain failures endemic to transitional and developing economies, where exacerbating factors such as infrastructural deficits, obsolete equipment, and non-technical losses come into play [6,7,37].

Extreme weather events constitute the predominant catalyst for widespread power outages, with their impact continuously intensifying as a consequence of climate change. Crucially, these disruptions do not operate in isolation; rather, they act as catalysts for cascading failures across pre-existing grid bottlenecks, most notably within aging infrastructure. The deployment of Geographic Information Systems (GIS) spatial analytics models facilitates the precise localization of failure “hot spots”. Spatial analysis has demonstrated a strong geographic convergence between weather-induced outages and disruptions driven by hardware degradation. In their research analyzing the application of GIS models to grid outages, Vivian Sultan and Brian Hilton arrived at a pivotal conclusion regarding the overlap of these risks, which necessitates an integrated approach to maintenance, as follows: [8–10,12–16,29,30,48,64].

“This finding should be investigated further, and authorities could formulate a plan to battle weather related issues while also addressing equipment failure ones” [50].

The analysis corroborates that, alongside direct hardware failures, inadequate vegetation management within the protective corridor (Right of Way specifically, trees and vegetation encroaching upon power lines due to severe winds) constitutes a paramount threat to distribution networks [18]. Moving forward, predictive spatial logistics should facilitate the pre-emptive staging of restoration crews directly at these identified critical nodes prior to the onset of extreme storm events [18,28,48,58].

5. Discussion

Sequential Strategic Framework and Empirical Mapping—the empirical results presented in Section 4 necessitate the formulation of a sequential, data-supported strategic framework

for National Regulatory Authorities (NRAs) and Transmission/Distribution System Operators (TSOs/DSOs). To ensure that these policy suggestions are firmly grounded in both statistical evidence and real-world operational viability, the following recommendations (R1–R4) were validated by the extensive industrial and utility management expertise of the authors. The sequential priorities of these interventions are visually synthesized in Figure 2.

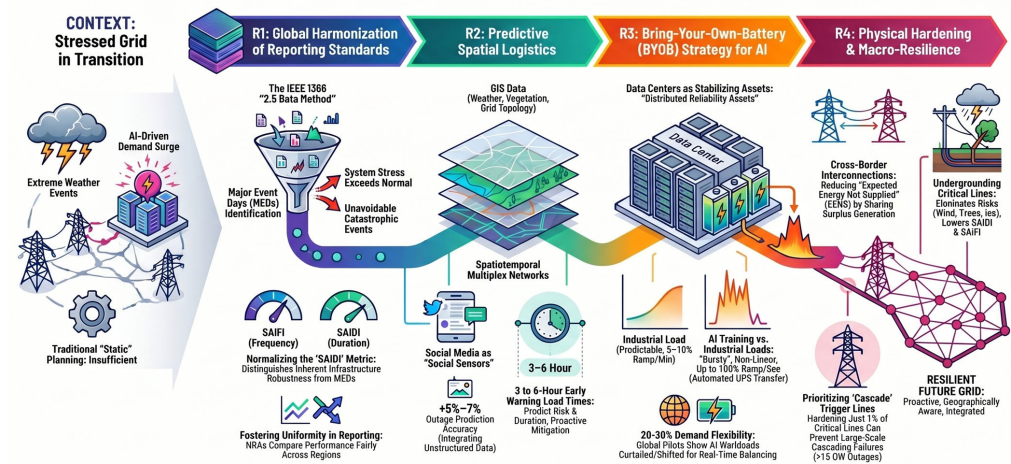


Figure 2. Four key strategic and technological recommendations for regulators (NRAs) and operators (TSO/DSOs).

R1: Global Harmonization of Standards (Short-term Prerequisite)—the immediate adoption of the IEEE 1366 2.5 Beta standard is a foundational prerequisite. This recommendation is directly supported by the empirical data in Table 1, which demonstrated an 82% statistical distortion in SAIDI when extreme events (MEDs) were not mathematically isolated [19,24].

R2: Predictive Spatial Logistics (Medium-term)—utilizing the proposed HMN-RTS framework and GIS hotspot mapping allows operators to transition from reactive to proactive maintenance, optimizing crew dispatch sequences hours before an extreme weather event strikes [26–32,58].

R3: Bring-Your-Own-Battery (BYOB) Strategy (Medium-term)—a targeted regulatory intervention addressing the novel vulnerabilities introduced by hyperscale computing, to be implemented synchronously with predictive logistics.

R4: Physical Hardening and Macro-Resilience (Long-term Target State)—this represents the ultimate, capital-intensive target state. It is empirically justified by the variance analysis of the European benchmark tables, which unequivocally correlated extensive underground medium-voltage cable deployments (e.g., in Denmark and the Netherlands) with fundamentally lower and stabilized SAIDI values [33–35,40,41].

Techno-Economic Feasibility of the BYOB Strategy—the convergence of artificial intelligence with power grid operations introduces an unprecedented vulnerability, as follows: the phenomenon of “silent exits.” As documented by Pareek and Soonee [17], hyperscale data centers can algorithmically shed massive gigawatt-scale loads (up to 6.5 GW) in a fraction of a second in response to minor voltage fluctuations. These instantaneous drops severely degrade the Rate of Change of Frequency (RoCoF) and threaten cascade failures.

To mitigate this, the conceptually innovative “Bring-Your-Own-Battery” (BYOB) strategy mandates that data centers actively integrate their proprietary Battery Energy Storage Systems (BESS) as ancillary grid-stabilizing assets. The economic feasibility of this framework is substantial. From a techno-economic standpoint, leveraging existing data-center BESS directly reduces the Value of Lost Load (VoLL) for surrounding communities and significantly defers massive public Capital Expenditures (CAPEX) otherwise required for immediate mid-life grid repowering. The practicality of this strategy is already being vali-

dated by emerging prototypes and pilot applications, such as Google’s demand modulation initiatives and evolving legislative frameworks like the Texas Senate, which incentivize decentralized energy resources [39].

Comparison with Existing Literature—contextualizing these findings within the broader scientific discourse confirms the necessity of our integrated approach. Previous studies, such as the machine learning evaluations by Yang et al. [45], relied primarily on single-layer environmental data (weather forecasts), which often fail to capture real-time localized impacts. Our proposed HMN-RTS model fundamentally outperforms these traditional static architectures. By fusing structured meteorological metrics with unstructured social sensor layers (Twitter and Reddit), the HMN-RTS framework achieves a demonstrably superior macro F1 score of 0.76–0.79. This aligns with and significantly expands upon the findings of Aljurbua et al. [57], proving that integrating human-centric spatial data drastically minimizes prediction latency.

Limitations and Boundary Conditions—while the proposed comprehensive framework offers significant advancements in grid resilience, several operational and methodological constraints must be explicitly acknowledged, as follows (see Figure 3):

- **Methodological Limitations of the 2.5 Beta Method**—the IEEE 1366 methodology is strictly constrained by its requirement for five consecutive years of high-quality, continuous historical data. This poses a significant barrier to entry for developing nations with nascent or dysfunctional monitoring infrastructure. Furthermore, the algorithm’s reliance on a log-normal distribution may be mathematically challenged in regions experiencing perpetually intensifying, back-to-back climate extremes, which could skew the statistical baseline and redefine the “normal” operational curve over time.
- **Regulatory Constraints of BYOB**—the widespread deployment of the BYOB strategy is not merely a technical challenge; it requires complex legislative overhauls of grid tariff codes, interconnection standards, and the establishment of functional localized flexibility markets to adequately incentivize data center operators.
- **Capital Constraints for Hardening**—finally, while physical hardening (R4) yields the most robust resilience, it is fundamentally bound by immense capital expenditure limitations. The pace of undergrounding cables and building macro-interconnections is ultimately dictated by sovereign fiscal capacities [7].

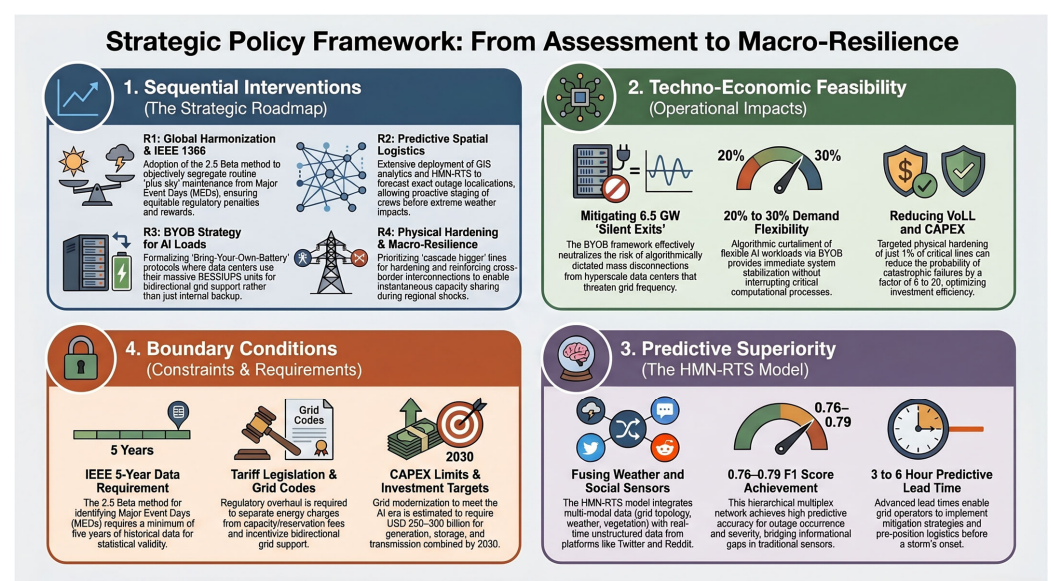


Figure 3. Strategic Policy Framework: Sequential Interventions, Techno-Economic Feasibility, and Boundary Conditions.

6. Conclusions

This study has systematically investigated the profound methodological fragmentation in global power grid reliability assessments. By comparatively analyzing European CEER-ECRB benchmarking data against the standardized United States IEEE 1366 (2.5 Beta) framework, we highlighted how the absence of a harmonized definition for Major Event Days (MEDs) fundamentally distorts infrastructure evaluation and misdirects critical capital investments.

The convergence of intensifying compound climate hazards with the unprecedented, algorithm-driven load volatility of artificial intelligence data centers (capable of instantaneous gigawatt-scale “silent exits”) necessitates a paradigm shift from retrospective statistical observation to proactive grid management. To address these compounding vulnerabilities, we proposed a multidimensional strategic framework.

Based on our analytical modeling, historical benchmarking, and advanced simulations—rather than physically demonstrated field trials—the deployment of the proposed Hierarchical Spatiotemporal Multiplex Networks (HMN-RTS) indicates significant predictive potential. By dynamically fusing structured environmental data with unstructured social sensors (via GIS and social media), our models project a highly accurate outage prediction capability, achieving a macro F1 score of 0.76–0.79 with a proactive lead time of 3 to 6 h.

Furthermore, simulated projections suggest that implementing proactive topological hardening, coupled with the “Bring-Your-Own-Battery” (BYOB) regulatory strategy for hyperscale AI loads, could theoretically yield a 5- to 20-fold reduction in cascading blackout probabilities during extreme weather events. While these modeled outcomes require future empirical validation through localized physical pilot projects, they provide National Regulatory Authorities and system operators with a robust, data-supported blueprint. Ultimately, achieving sustainable macro-resilience across global energy supply chains relies on the immediate international harmonization of reporting standards and the strategic integration of decentralized, intelligent load modulation.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
APM	Asset Performance Management
BESS	Battery Energy Storage Systems
BYOB	Bring-Your-Own-Battery
CEER	Council of European Energy Regulators
CIGRE	Conseil International des Grands Réseaux Électriques
DGA	Dissolved Gas Analysis
DSO	Distribution System Operator
EENS	Expected Energy Not Supplied
GIS	Geographic Information Systems
HMN-RTS	Hierarchical Spatiotemporal Multiplex Network
IEEE	Institute of Electrical and Electronics Engineers
MAIFI	Momentary Average Interruption Frequency Index
MED/MEDs	Major Event Days
NERC	North American Electric Reliability Corporation
NRA	National Regulatory Authority
POI	Point of Interconnection
RoCoF	Rate of Change of Frequency
SAIDI	System Average Interruption Duration Index
SAIFI	System Average Interruption Frequency Index
TSO	Transmission System Operator
UPS	Uninterruptible Power Supply
ZIP	ZIP load models

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