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Extreme Weather Risks to Renewable Power Systems: Taxonomy of Structural Impacts and Vulnerabilities

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The escalation of climate change-driven extreme weather, combined with the energy transition toward Variable Renewable Energy (VRE), creates complex failure modes in power systems. This paper proposes a formalized vulnerability taxonomy to address these evolving failure modes, distinguishing three types: Type I (Structural Fault), Type II (Dynamic Instability driven by low inertia), and Type III (Thermal Derating and cumulative aging). A review of modeling frameworks, ranging from statistical fragility curves to high-fidelity electro-thermal simulations, is conducted for each type. The analysis highlights some limitations of static availability models and advocates for a multi-physics approach to accurately characterize vulnerabilities facing the emerging climatic stress and grid modernization.

Keywords: power system, vulnerabilities, extreme weather, renewable integration, compound risk, HILP events, windstorms, heatwaves, wildfires, cold spells, lightning, flooding, storage,

Introduction High Impact Low Probability (HILP) extreme weather events constitute the primary exogenous driver of system-wide failures, accounting for approximately 50% of service interruptions in European power systems [50]. Conventionally, vulnerability frameworks focus on *structural integrity* of physical assets, employing state-based fault models, such as fragility curves, to map meteorological intensity to the physical component destruction probability[3, 28, 35].

However climate change intensifies the magnitude of extreme events, while the massive integration of Variable Renewable Energy (VRE) fundamentally alters the grid's failure logic. Beyond structural fault, the transition introduces novel functional vulnerabilities, specifically inertia depletion and thermodynamic sensitivity, where assets remain structurally intact but become operationally unstable [15]. Despite existing resilience frameworks dedicated to extreme weather events[48], the literature currently lacks a formalized taxonomy that strictly distinguishes these VRE-specific failure modes from traditional structural limits, raising concerns about the completeness of risk representations in current planning models.

Contributions This paper proposes a three-types vulnerability taxonomy (named hereafter Type I, II, III) focusing on extreme weather, and evaluates associated mathematical frameworks with each type, analyzing the trade-offs between physical fidelity, data availability, and computational scalability.

1. Structural Infrastructure Fault

Type I vulnerabilities represent the susceptibility of grid assets to component faults under extreme weather. Component faults occur when environmental stressors exceed structural design limits. Table 1 synthesizes component fault mechanisms and the induced system-wide failures identified across a component-based state-of-the-art review.

Historical data attribute 59.5% and 29.8% of weather-related disturbances to conventional transmission lines and substations, respectively [50], explaining the emphasis on these assets in most-cited resilience reviews [3, 28, 35]. However table 1 shows that VRE and BESS assets introduce vulnerabilities coexisting with conventional failure modes, raising two analytical challenges.

First, unlike transmission outages managed via $N-1$ flow redistribution, the structural destruc-

Table 1. Type I Vulnerability Taxonomy: Component Fault Mechanisms and System-Wide Effects

Asset	Weather Hazard	Structural Fault Mechanism	System-wide Failure
Overhead Lines & Towers	Extreme Wind	**Structural Collapse:** Towers buckling; lines snapping [40]; flying debris impact [34]	**Cascading Overloads:** Post-contingency flow redistribution; thermal limit violations on parallel paths; accelerated cascade propagation (contagion) **Topological Islanding:** Graph partitioning; isolated load pockets; local demand imbalance; partial blackouts
	Ice & Snow	**Ice Overloading:** Excessive ice weight; tower collapse [8]; line breakage [23]	
	Lightning	**Shield Wire Severing:** Protective wire cutting; **Insulator Flashover:** insulator destruction; direct strike line burning [55]	
	Wildfires	**Phase-to-Ground Faults:** Smoke-induced sparks; conductor sagging to ground contact [55]	
	Flooding	**Foundation Erosion:** Foundation washout; landslides (saturated ground) [19]	
Substations	Extreme Wind	**Structural Collapse:** Metal frame/power bar destruction; flying object impact [55]	**Critical Node Loss:** Simultaneous multiple branch disconnection; vital transmission corridor loss **Physical Monitoring Loss:** Telemetry hardware/comm link structural destruction
	Ice & Snow	**Mechanical Breach:** Insulation cracking (ice buildup/heavy snow) [55]	
	Lightning	**Transformer Fault:** Transformer burnout; safety system destruction [44]	
	Wildfires	**Thermal Destruction:** Control wiring melting; insulation destruction; cooling oil ignition/explosions [43]	
	Flooding	**Equipment Submersion:** Site immersion; electrical hardware destruction; switch system mud clogging [39]	
Renewable Generation	Extreme Wind	**Solar: Structural Destruction:** Panel tearing [38]; support structure twisting [1] **Wind: Turbine Fault:** Blade breakage [36]; tower folding [45]	**Adequacy Deficit:** Immediate active power (P) loss; reserve margin erosion; supply shocks **Voltage Support Loss:** Local reactive power (Q) capability reduction; voltage destabilization (weak grids)
	Ice & Snow	**Solar: Mechanical Cracking:** Solar cell/glass cover cracking [37] **Wind: Icing Collapse:** Weight-induced collapse; blade snapping (ice pressure) [55]	
	Lightning	**Solar: Inverter Burnout:** Permanent electronic inverter burnout [44] **Wind: Blade Delamination:** Turbine blade splitting/shattering [36]	
	Flooding	**Solar: Inverter Submersion:** Power inverter destruction; support foundation failure [38]	
Battery Storage (BESS)	Wildfires	**Thermal Runaway:** Chemical fires; battery cell destruction [43]	**Ancillary Service Loss:** Frequency Containment Reserve/fast-ramping capability loss; low-inertia grid instability
	Flooding	**Electrochemical Destruction:** Water leakage; internal short-circuits; permanent chemical deterioration [9]	

tion of generation nodes creates immediate active power shortages against which topological redundancy alone is insufficient [42], requiring the system to absorb both network and generation disruptions simultaneously.

Second, Table 1 organizes hazards independently, reflecting current practice; yet renewable assets are sensitive to multi-variable interactions (e.g., concurrent wind and ice loading) that single-hazard assessments fail to capture [61].

Modeling Approaches for Structural Vulnerabilities Quantifying the structural vulnerabilities requires a transfer function mapping meteorological intensity $\mathcal{H}$ to a component fault state. The literature reveals a dichotomy dictated by data availability: statistical inference (conventional assets) versus deterministic modeling (emerging technologies).

For conventional transmission assets, the **fragility curve** remains the dominant modeling standard [35]. This semi-parametric approach maps hazard intensity to a component fault probability $P(\text{Fault}|\mathcal{H})$ traditionally using log-normal Cumulative Distribution Functions (CDFs) calibrated on historical fault records [44]. While computationally efficient, this framework assumes stationarity for meteorological hazards. However, climate change induces non-stationary drift in hazards distribution. Consequently, models calibrated on historical datasets fail to represent future exposure, particularly for HILP events where the tail behavior is shifting [40]. A challenge remains to accurately translate multiple hazards (like combined wind-ice loading) to one intensity fragility curve.

Conversely, the assessment of VRE technologies relies on **physics-based deterministic approaches** due to the absence of long-term operational data. By utilizing finite element analysis to simulate structural limits (e.g., stress $>$ yield strength), these models capture specific vulnerabilities of technological assets without relying on outage statistics [32], making them a more suitable approach for emerging technologies lacking historical records. While this independence from historical records allows for vulnerability characterization and subsequent risk quantification under unprecedented climate scenarios, it introduces a tractability trade-off. Integrating complex physical solvers into system-wide optimization models is computationally prohibitive. Some techniques are emerging, like the use of surrogate modeling to approximate physical behaviors via simplified polynomial functions [40], to alleviate the computational burden, but their use is not spread yet.

Finally, **Machine Learning** (ML) approaches are increasingly deployed in the literature to capture multi-variate correlations that defy analytical formulation [56]. However, ML models exhibit fundamental limitations regarding structural vulnerabilities: they interpolate effectively within the training domain, thus fail to extrapolate to HILP events [57]. ML still can serve effectively for Bayesian updating of fragility priors [47], making them a complement to fragility curves, but cannot currently replace physics-based derivations for predicting structural faults under unprecedented extreme weather conditions.

2. Dynamic Stability and Balancing Vulnerability

The energy transition fundamentally transforms power system inertia. As VRE are increasingly interfaced through Inverter-Based Resources (IBR), which lack inherent mechanical inertia, decoupling kinetic reserves from frequency deviations [25]. This absence of mechanical damping increases sensitivity to rapid meteorological transients: weather-driven disturbances trigger critical RoCoF excursions, voltage dips, or control saturation, causing system-wide collapse even with physically intact hardware [12]. Table 2 maps weather hazards to the dynamic mechanisms and system-wide failures associated, and reveals a significant discrepancy between stability requirements and existing vulnerability assessment frameworks.

First, a fundamental temporal mismatch appears in the *Dynamic Mechanism* column, where phenomena such as torsional resonance [30] and cloud-induced negative damping [10] operate in the sub-second domain (10^{-3} to 10^{0} s). Static adequacy frameworks, typically relying on 15-to-60-minute resolutions [24], inherently cannot fully capture these impulsive triggers. This temporal averaging masks frequency nadir (f_{nadir}) excursions occurring within the initial seconds of a disturbance. Frequency nadirs often occur before primary containment reserves reach full deployment [31].

Second, the *System-wide Failure* column highlights a violation of the statistical independence assumption for component faults. While structural faults (Type I) are typically staggered by the physical heterogeneity and varying resistance of assets, functional disruptions (Type II) are amplified by the homogeneity of control logic. Inverter-based resources often share identical protection settings, leading to synchronized disconnections such as wind farm cut-outs [13] or concurrent line tripping [44] when meteorological forcing reaches these logical thresholds. This spatial correlation transforms $N-1$ contingencies into $N-k$ events. The resulting power imbalance generates a steep RoCoF that outpaces balancing reserve ramping, bypassing topological redundancy. This vulnerability was empirically illustrated during the April 2025 event in Spain.

Finally, control-driven instability operates independently of structural faults. Weak grid conditions, with a low Short-Circuit Ratio (SCR), reduce voltage stiffness and the system's ability to maintain a stable reference signal. During meteorological transients, Phase-Locked Loops (PLL) fail to track the grid frequency accurately under these degraded conditions, leading to synchronization loss [4, 25]. Vulnerability assessment must then encompass both structural survivability and dynamic operational robustness to account for these non-structural outages.

Modeling Approaches for Dynamic Stability and Control Quantifying Type II vulnerabilities

Table 2. Type II Vulnerability Taxonomy: Dynamic Instability Mechanisms and System Effects

Asset	Weather Hazard	Dynamic Instability Mechanism	System-wide Failure
Renewable Generation	Extreme Wind	**Wind: Transient Stability:** Power oscillations (internal vibrations) [30]; sudden power jumps (delayed air adaptation) [2] **Wind: Emergency Shutdown:** Massive synchronized wind cluster safety shutdown [13] **Solar: Cloud Disturbance:** Rapid cloud flickering (storm fronts); inverter negative damping [10]	**Frequency Dive:** Simultaneous GW loss; steep RoCoF; immediate load shedding risk **Reserve Exhaustion:** Power loss speed outpacing primary reserve ramping **Voltage Instability:** Local reactive support loss; delayed recovery (FIDVR); potential collapse
	Wildfires	**Solar: Smoke Radiative Forcing:** Smoke radiative forcing shock; regional generation drop [17, 18]	
	Lightning	**Solar/Wind: Inverter Sync Loss:** Voltage disturbances; Phase-Locked Loop (PLL) lock loss; immediate inverter desynchronization [4]	
Overhead Lines	Extreme Wind	**Galloping-Induced Transients:** Wind-induced swinging; temporary short-circuits (clashing phases); safety relay triggering [44]	**Protective Islanding:** Simultaneous intact line tripping; isolated sub-grid creation; low-inertia collapse [22]
Substations & Control	Wind/Solar Ramps	**Ramp-Rate Exhaustion:** Net load variations exceeding control reserve ramping capability [60]	**AGC Loss of Control:** Automatic Generation Control saturation ($\Delta P > \Delta P_{max}$); permanent frequency deviation; load shedding trigger [51].
	Lightning	**Short Circuit Ratio Degradation:** Adjacent circuit isolation; increased bus Thevenin impedance; reduced voltage stiffness/short-circuit power [25]	

imposes a trade-off between the sub-second fidelity required for converter dynamics and the scalability needed for system-wide planning.

First, **High-Fidelity Time-Domain Simulation** relies on the direct numerical solution of non-linear differential equations to track the continuous temporal evolution of state variables. Unlike static approaches assuming immediate equilibrium, this method captures inertia and non-linearities like AGC saturation [51] or torsional resonance [30]. However, while essential for verifying absolute stability limits like RoCoF[25], the computational burden restricts analysis to deterministic snapshots. This renders the method intractable for scenario-based risk assessment of HILP weather requiring thousands of scenarios.

Conversely, to address scalability, alternative frameworks simplify physical representations, typically through Frequency-Constrained Optimization [31] or Complex Systems Analysis [7]. While Optimization enables capacity-security trade-offs [27], its linearization assumes sufficient mechanical inertia to damp transients. This premise is invalidated in VRE-dominated systems, where the displacement of synchronous generation results in severe RoCoF gradients [58]. Consequently, these models do not adequately represent the large-signal transients induced by extreme weather [33]. Similarly, Complex Systems frameworks, while effective for cascading failure propagation [14], predominantly rely on static DC power flow approximations. Both approaches therefore abstract the initiating events, creating a critical gap: to the authors' knowledge, no established framework currently couples system-wide scope with the fidelity required for converter-driven instabilities.

3. Thermal Derating and Efficiency Degradation

Type III vulnerabilities manifest as continuous, thermodynamics-driven erosion of system performance, decoupling asset physical integrity from operational availability, and imposing exogenous ceilings on technically functional components. To systematize these interactions, Table 3 provides a hazard-component mapping that identifies specific thermal inhibition mechanisms across the asset base. The analysis distinguishes between reversible *operational derating* (e.g., dynamic line rating adjustments) and irreversible *latent degradation* (e.g., semiconductor fatigue).

Three coupled dynamics deplete steady-state reliability margins.

First, the correlation between thermodynamic derating and load surges creates a structural

Table 3. Taxonomy of Type III Vulnerabilities: Thermal Derating and Degradation

Asset	Weather Hazard	Thermal Stress Mechanism	System-wide Failure
Overhead Lines	Extreme Heat	**Ampacity Derating** *(Reversible):* Dynamic Line Rating (DLR) reduction; conductor annealing prevention [11, 21]	**Congestion:** Preventive curtailment; redispatch costs; load shedding risks.
	Wildfires	**Ionized Air Derating** *(Reversible):* Air gap dielectric strength reduction (smoke); voltage reduction requirement [43]	
Substations	Extreme Heat	**Thermal Aging** *(Cumulative):* Arrhenius-driven paper insulation degradation; Remaining Useful Life (RUL) reduction [6]. **Loading Limit** *(Reversible):* Forced transformer throughput derating; hot-spot temperature management	**Capacity Fade:** Long-term reliability erosion; immediate throughput bottlenecks.
	Ice & Snow	**SF6 Liquefaction** *(Reversible):* Gas-insulated switchgear pressure drop; compromised arc-quenching capabilities [21]	
Renewable Generation	Extreme Heat	**Solar: Efficiency Drop** *(Reversible):* PV semiconductor bandgap narrowing; CSP dry-cooling penalties [37]. **Solar: UV/Heat Fatigue** *(Cumulative):* Accelerated EVA delamination; moisture ingress (Mortality Debt) [38]	**Yield Erosion:** ”Supply-Demand Squeeze”; low efficiency/peak cooling load coincidence. **Latent Fragility:** Failure risk increase during subsequent shocks.
	Wildfires	**Solar: Optical Derating** *(Reversible):* Smoke aerosol spectral scattering; GHI reduction; particulate soiling [43]	
	Ice & Snow	**Solar/Wind: Surface Occlusion** *(Reversible):* Snow coverage (optical path block); ice-altered aerodynamic profiles [46]	
	Low Wind	**Wind: Reduced output** *(Reversible):* Meteorological stillness; reduced output capacity (Dunkelflaute) [20]	
Thermal Generation	Extreme Heat	**Thermodynamic Derating** *(Reversible):* Turbine mass flow/cycle efficiency reduction; high ambient T° impact [11]	**Baseload Deficit:** Firm capacity forced derating; peak load periods.
	Drought	**Cooling Scarcity** *(Regulatory):* Environmental water intake temp limits; plant throttling [29]	
Battery Storage (BESS)	Extreme Heat	**Safety Derating** *(Reversible):* BMS charge/discharge rate limits; HVAC capacity saturation [21]. **Cell Degradation** *(Cumulative):* Irreversible capacity fade (SOH loss); high-temperature cycling [9]	**Availability Loss:** Ancillary services/energy arbitrage unavailability; stress events.

“supply-demand squeeze”. As noted by [59], extreme heat simultaneously compresses the reserve cushion from both vectors: it degrades asset efficiency (supply) while spiking cooling requirements (demand), forcing the system to operate near its technical boundaries for extended durations.

Second, the spatial autocorrelation of these stressors neutralizes geographical diversification strategies. Unlike localized equipment damages, extreme weather affects vast geographic areas [53]. As a result, power generation drops across several neighboring regions simultaneously. A manageable local deficit turns into a regional paralysis: importing power becomes difficult because neighboring countries face the exact same shortages at the same time [52].

Thirdly, the analysis isolates latent fragility mechanisms (tagged as *Cumulative*) which, unlike reversible derating, permanently erode the asset’s Remaining Useful Life (RUL). As illustrated by the PV delamination case in Table 3, thermal stress induces initially asymptomatic defects that compromise component hermeticity [38]. This creates a systemic mortality debt: assets surviving extreme weather persist with degraded reliability margins, significantly increasing their conditional fault probability during subsequent disturbances [49].

Finally, while a substantial body of literature is emerging regarding the impact of extreme temperatures on demand surges [59] and renewable generation availability [5], studies investigating the direct vulnerability of transmission network infrastructure remain scarce. Yet, this vulnerability gap

Table 4. Comparative Summary of the Three Vulnerability Types

	Type I: Structural Fault	**Type II: Dynamic Instability**	**Type III: Thermal Derating**
Failure Mode	*Binary:* intact / destroyed	*Functional:* intact hardware, lost stability	*Continuous:* gradual performance erosion
Onset Timescale	Seconds to minutes	Sub-second (ms to s)	Hours to seasons
Reversibility	*Irreversible:* destruction (repair/replacement required)	*Reversible:* reconnection / resynchronisation	*Mixed:* reversible derating + irreversible aging
Detection	*Observable:* physical damage	*Latent:* no visible damage	*Progressive:* monitoring required
Primary Driver	Mechanical stress	Inertia depletion / control logic	Heat accumulation
Fault Correlation	*Low:* asset-specific failure thresholds	*High:* synchronized protection triggering	*High:* region-wide meteorological forcing
Modeling	Fragility curves; physics-based FEA	Time-domain simulation; frequency-constrained optimization	Electro-thermal models; static transfer functions
N-1 **Adequacy**	Partially captured	Not captured	Not captured

translates into operational risks, as thermal stress imposes continuous thermodynamic constraints that reduce permissible transmission capacity (ampacity) [16].

Modeling Approaches for Capacity Derating and Degradation Modeling thermal vulnerability requires shifting from static thresholds to cumulative state tracking, as thermal derating stems from heat accumulation. The literature addresses this computational challenge via three stratified approaches.

At the component level, **mechanistic electro-thermal models** solve differential equations to derive performance limits from physics principles [6] or PV mechanical fatigue [32]. This granular approach uniquely captures latent degradation and complex interactions, such as wildfire smoke spectral effects [18, 45]. High computational costs often restrict usage to single-asset analysis. Conversely, system-scale assessments predominantly rely on static transfer functions where asset performance at time t is calculated solely based on current weather conditions, assuming memoryless system. Implementations include deriving PV and wind output via fixed efficiency curves applied to climate projections [26], establishing statistical correlations between historical hazards and capacity factors [5], or applying instantaneous air-density corrections to power curves [41]. Although scalable [54], the systematic resetting of asset health at each timestep obscures cumulative aging dynamics, such as insulation life-loss [16] or delamination [38]. This simplification underestimates system failure risks during prolonged heatwaves, with damages driven by exposure duration.

Conclusion Table 4 synthesizes each vulnerability type. This taxonomy identifies distinct entry points for operational actors. For Transmission System Operators (TSOs), Type II highlights the need to monitor Short-Circuit Ratio thresholds and RoCoF exposure in real-time operational planning, beyond static N-1 contingency screening. For infrastructure planners, Type I calls for integrating non-stationary hazard distributions into asset investment cycles, particularly for VRE assets currently lacking actuarial fragility records. For regulators, Type III indicates that adequacy metrics should incorporate state-dependent asset health, as memoryless capacity credit assessments may overestimate firm capacity during sustained heatwaves. Future work will enrich this classification to include targeted mitigation strategies, quantified restoration delays, and conduct a global resilience analysis adapted to these evolving operational and meteorological constraints.

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