How Fragility Modelling Assumptions Influence Power System Resilience Assessments

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RISK and RESILIENCE DAY 19 March 2026

SUPERGEN ENERGY NETWORKS

Background & Research Gap

~1 Million
customers without power for up to 7 days

Storm Arwen[1]
2021
UK

Extreme weather increasingly threatens transmission networks. Fragility curves quantify component failure probability vs. hazard intensity, but modelling assumptions vary widely, and those choices can significantly alter system-level resilience estimates.

Extreme Weather Hazard > Fragility Curves > Cascading Failures > Resilience Metrics

▲ *modelling assumptions vary widely*

Research Question:
How do fragility curve assumptions shape grid resilience estimates?

?

Power System Resilience

The ability to limit the **extent, severity and duration** of system degradation following an extreme event.

Extent	Severity	Duration
How much the system is affected	How badly it is degraded	How long it takes to recover

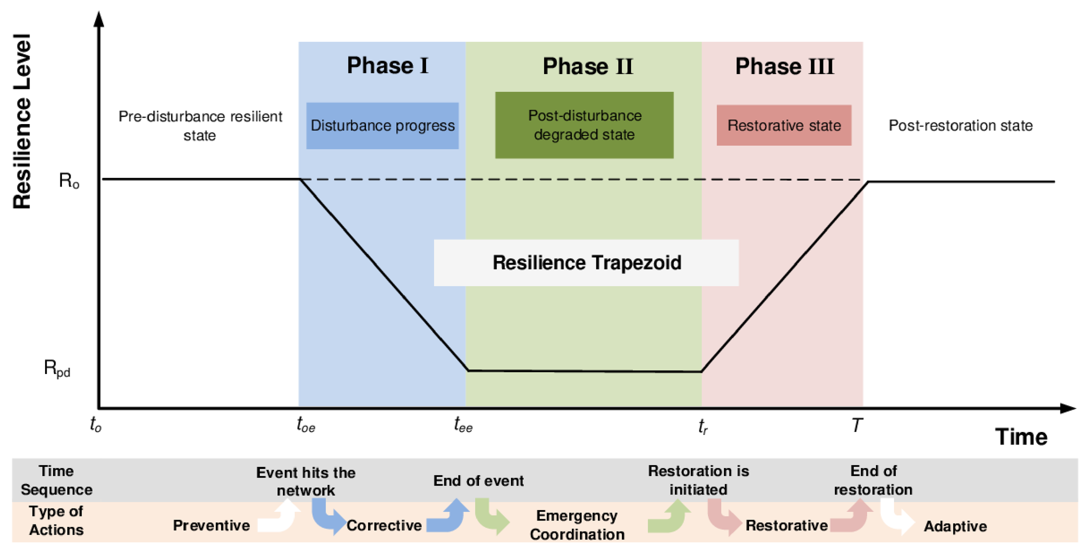


Fig. 1: Resilience trapezoid: three phases from event onset to restoration[2]

Assumption A: Asset Health

Ofgem's CNAIM/NARM health scores H derived from age, corrosion and loading.

H(t) $H_{new} \cdot e^{\beta \cdot t} \cdot F_{cond} \cdot F_{rel}$
Asset health index

PoF $K\left(1 + CH + \frac{(CH)^2}{2!} + \frac{(CH)^3}{3!}\right)$
Failure probability, shifts curve left as H increases

Higher H	Curve shifts left	Tail risk grows
more deterioration	fails at lower wind speed	CVaR most sensitive

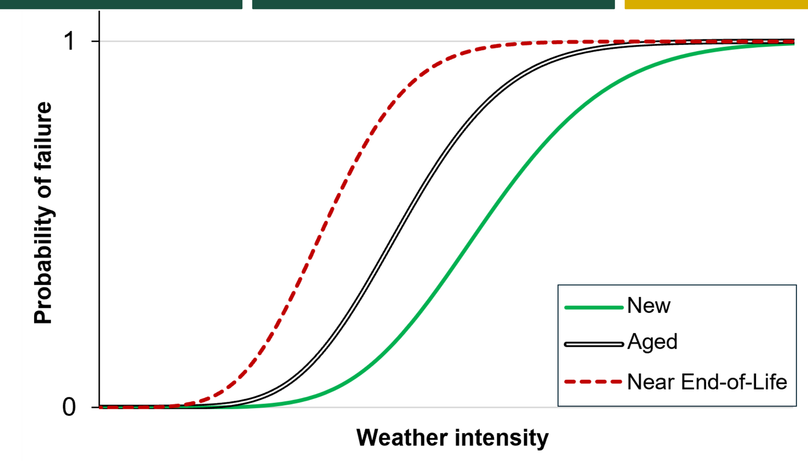


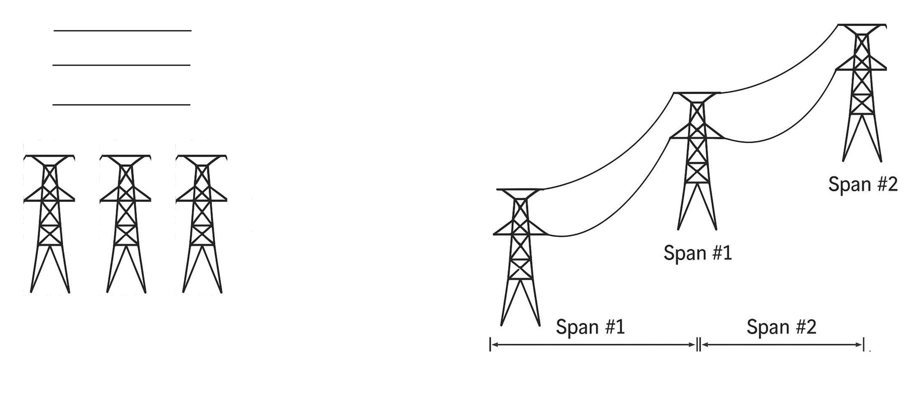
Fig. 2: Fragility curves shift left as asset health deteriorates

Assumption B: Tower–Line Interactions

Tower collapse transmits mechanical tension to adjacent towers via conductor. A 3-tower 2-line prototype captures this coupling.

Independent model
Each tower/conductor fails separately. Corridor PoF = combined individual probabilities.

Interactive model
Collapse transmits stress to neighbours. Short span: mutual support. Long span: cascade amplification.



Short exposure: Mutual support → Interactive < Independent PoF

Long exposure: Cascade amplification → Interactive > Independent PoF

Assumption C: Spatio-Temporal Dynamics

Storm epicentre moves hourly. Attack angle θ and distance continuously update each component's fragility parameters.

θ = 90° (perpendicular wind) → maximum structural stress on towers

μ $\mu_{base} - P_{norm(H)} + \frac{\cos(\theta)}{5}$
Location param, shifts left with health deterioration and favourable angle

σ $\sigma_{base} - \frac{P_{norm(H)}}{10} + \frac{\cos(\theta)}{50}$
Scale param, narrows (steeper curve) as health worsens

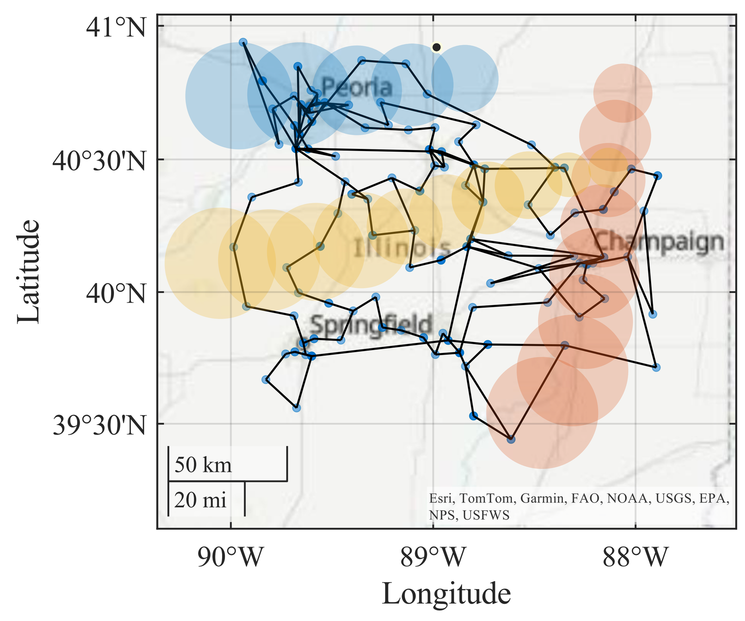


Fig. 3: Three storm trajectories over ACTIVSg200 Illinois network; circles = hourly epicentres

Sequential Monte Carlo Framework

Layer 1
Weather Scenarios
Storm location, trajectory, max intensity & duration

Layer 2
Component Vulnerability
Asset-specific fragility curves map hazard to failure probability

Per-scenario simulation loop:

1. **Identify:** Exposed components in storm impact zone per hour
2. **Map:** Apply fragility curves → determine component failures
3. **Cascade:** DC power flow → overload detection → removal → repeat until stable
4. **Advance:** Record system state; use as t+1 initial condition
5. **Repeat:** Until event duration elapsed
6. **Quantify:** Compute EDNS, VaR_{95}, $CVaR_{95}$ across full ensemble

Cascading failure model
Quasi-static DC OPF · iterative overload detection & component removal · load shedding & generator tripping · convergence: $\Delta EDNS < 10^{-6}$

Study Cases: ACTIVSg200 Illinois

200	179	1.48 GW
Buses	Lines	Peak Demand

Windstorm max speed: 30–60 m/s (hurricane-force)
Random entry location & trajectory

Four modelling scenarios:

		Health	T–L	Spatio-T
Case 1 BASELINE	All three assumptions active (A + B + C)	Health ✓	T–L ✓	Spatio-T ✓
Case 2 −A	Uniform health H=2, no asset health variability	Health ✗	T–L ✓	Spatio-T ✓
Case 3 −B	Independent T/L failures, no tower–line coupling	Health ✓	T–L ✗	Spatio-T ✓
Case 4 −C	Uniform wind, no spatio-temporal dynamics	Health ✓	T–L ✓	Spatio-T ✗

Resilience Metrics

EDNS	VaR_{95}	$CVaR_{95}$
Expected Demand Not Served Mean DNS across all Monte Carlo trials (MW)	Value-at-Risk (95th pct.) Worst-case DNS level not exceeded in 95% of runs	Conditional VaR (95th pct.) Mean DNS in the extreme 5% tail, captures rare catastrophic events

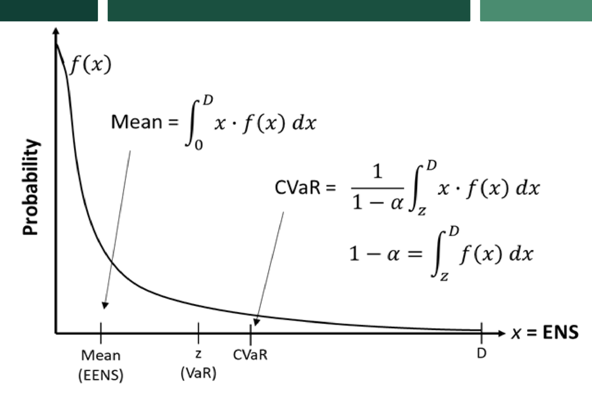


Fig. 4: Statistical risk metrics derived from the Monte Carlo DNS ensemble

Results: Tower-Line Interaction Effect

Crossover ~5 km: **interactive < independent PoF** (mutual tower support)

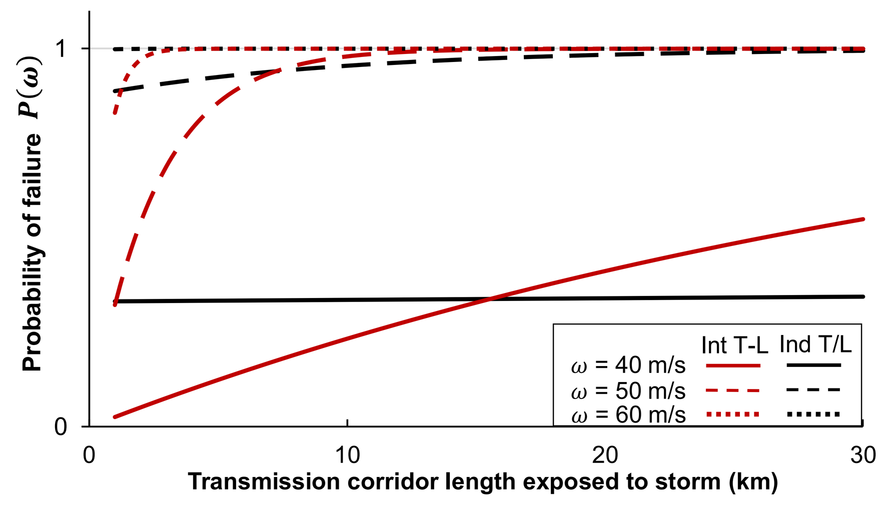


Fig. 5 Corridor failure probability vs. storm-exposed length: interactive vs. independent

Results: Demand-Loss Distribution (Health)

Case 1 (Variable H)
>1300 MW max loss
Fewer loss events (15% exceed 10 MW) but higher severity, tail risk driven by aged assets.

Case 2 (Uniform H=2)
723 MW max loss
More frequent but milder losses (37% exceed 10 MW). Masks catastrophic tail risk.

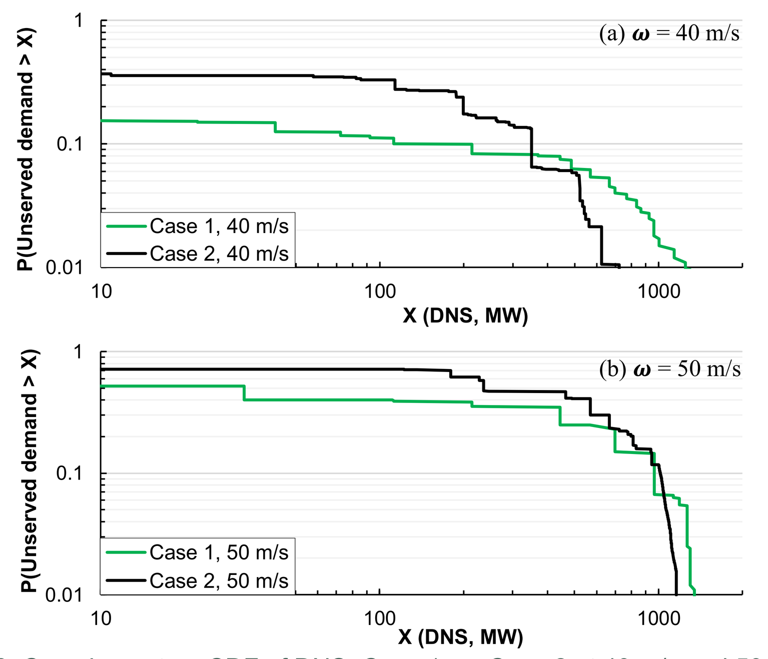


Fig. 6: Complementary CDF of DNS: Case 1 vs. Case 2 at 40 m/s and 50 m/s

Results: Quantitative Comparison

EDNS, VaR_{95} and $CVaR_{95}$ (MW), Case 1 vs Case 2, fixed trajectory storm

Metric	Case	40 m/s	50 m/s	60 m/s
EDNS (MW)	Case 1	121.6	442.8	1051.4
	Case 2	83.2	328.0	986.1
VaR_{95} (MW)	Case 1	656.3	1265.1	1272.8
	Case 2	518.6	1065.5	1272.8
$CVaR_{95}$ (MW)	Case 1	986.0	1278.1	1290.8
	Case 2	596.5	1130.0	1290.8

−32% EDNS underestimate at 40 m/s, peaks at moderate intensity

< 1% Converges at 60 m/s, catastrophic saturation masks differences

Conclusions

1 Asset health is the most critical assumption

−18% EDNS *when health variability omitted*

Omitting health variability produces systematically optimistic estimates, especially at moderate intensities. CNAIM scores provide a practical, data-ready basis.

2 Tower-line structural coupling must be included

+17% EDNS *when coupling excluded*

Independent assumptions both under- and over-predict risk depending on corridor length. Interaction provides mutual support at typical ~5 km spans.

3 Spatio-temporal dynamics: scenario-critical, ensemble-stable

~2% EDNS *difference over large ensembles*

Attack angle and trajectory drive large variation in individual scenarios but average out across the ensemble. Critical for worst-case planning, not mean-risk.

4 Modelling complexity should match the application context

Moderate *Intensity, highest sensitivity*

Tailored fragility models add most value at moderate events. Under catastrophic extremes, systemic network vulnerability dominates and simpler models carry reduced penalty.

Key Insight: Tailored fragility modelling is most valuable at moderate hazard intensities. Under extreme events, network topology and systemic overload dominate all individual modelling assumptions.

Acknowledgement

Supported by the UK EPSRC, Supergen Energy Networks Hub (EP/S00078X/2).

References

1. Ofgem, "Final report on the review into the networks' response to Storm Arwen," 2022.
2. IEEE Task Force on Methods for Analysis and Quantification of Power System Resilience, " The Definition and Quantification of Resilience," Tech. Rep. IEEE PES-TR65, 2018.