Power System Protection and Control
ISSN:1674-3415

RESILIENCE ASSESSMENT OF MODERN POWER GRID INFRASTRUCTURE AGAINST EXTREME WEATHER USING PHYSICS-INFORMED NEURAL NETWORKS

Pawan Kumar Singh

Dr. Pillai Global Academy, New Panvel, Sector-7, Khanda Colony, New Panvel, Navi Mumbai- 410206
pawan.k.singh2009@gmail.com

Received: 14/11/2025 **Revised**: 22/12/20265 **Accepted**: 24/01/2026

***ABSTRACT*:**

The frequency and severity of extreme weather events have grown noticeably over the past two decades, and modern power grids have found themselves increasingly exposed to hurricanes, ice storms, heat waves, and wildfires that stress infrastructure well beyond its historical design envelope. Traditional resilience assessment methods based on deterministic simulation or purely statistical models struggle to capture the coupled physical and stochastic nature of these events, and they scale poorly to the large interconnected networks that define contemporary electricity systems. This paper investigates the use of physics-informed neural networks (PINNs) for resilience assessment of power grid infrastructure against extreme weather. The premise is that embedding physical laws directly into the loss function of a neural network combines the data efficiency of physics-based simulation with the speed and scalability of data-driven modelling, producing an assessment tool that can evaluate thousands of hazard scenarios in the time a conventional simulator would need for a handful. We designed a PINN framework that couples power flow equations with weather-driven component failure models and cascading outage dynamics, and evaluated it on a synthetic transmission network calibrated against a large regional grid with 4,120 buses and 5,830 transmission lines. Experiments were conducted across four hazard categories including hurricane, ice storm, heat wave, and wildfire. Results show that the PINN produced resilience metrics within 3.4 percent of a high-fidelity time-domain simulator while running roughly 82 times faster, enabling large-scale scenario ensembles that were previously impractical. Findings support PINN-based approaches as a promising foundation for planning-grade resilience assessment and for near-real-time operational decision support during evolving weather events.

Keywords: *Power Grid Resilience, Physics-Informed Neural Networks, Extreme Weather, Cascading Failures, Infrastructure Assessment, Deep Learning*

INTRODUCTION

The electricity system is one of the most consequential pieces of infrastructure a society builds, and modern life has come to depend on its reliability in ways that many people notice only when the lights go out. For most of the twentieth century, grid reliability was framed primarily as an engineering problem of managing predictable failures such as equipment aging, routine faults, and forecast-able load fluctuations. That framing has become dangerously incomplete over the past two decades. Extreme weather events, once rare enough to be treated as tail risks, are now occurring with a frequency and severity that make them central design considerations rather than fringe scenarios [1].

Hurricanes have caused multi-billion-dollar losses to grids along the Gulf and East Coasts of the United States, and similar storms have caused catastrophic damage in the Caribbean and East Asia. Winter storms and prolonged cold snaps produced the 2021 Texas grid failure that left millions without power for days and cost lives. Heat waves increasingly push transmission and distribution equipment beyond thermal limits, and wildfires threaten transmission corridors directly while also driving preemptive shutoffs that have their own social costs. Ice storms, flooding, and dust storms round out a growing list of hazards that grid operators must now plan for [2].

Traditional resilience assessment methods have struggled to keep pace. Deterministic simulation tools based on detailed circuit analysis can produce accurate results for individual scenarios but are computationally expensive, and running the thousands of scenarios needed to characterize risk under uncertainty is often infeasible within planning timeframes [3]. Purely statistical models scale better but lose the physical fidelity that matters for cascading failure analysis. Neither approach handles well the coupled dynamics of extreme weather, in which physical damage, protective control actions, and cascading electrical failures unfold simultaneously and interact in complex ways.

Physics-informed neural networks (PINNs) have emerged over the past several years as a promising framework for coupling data-driven learning with physical constraints. The core idea is that the loss function of a neural network can include not only prediction error against training data but also residuals of the governing equations, which enforces physical consistency even in regions where training data is sparse or absent [4]. PINNs have shown strong results across fluid dynamics, structural mechanics, and geoscience applications, and interest in applying them to power system problems has grown rapidly [5].

The specific problem of power grid resilience under extreme weather is a natural fit for PINN approaches because it combines a well-understood physical model, the power flow equations, with stochastic hazard exposure and component failure dynamics that benefit from data-driven treatment. A PINN can potentially provide fast evaluation of thousands of hazard scenarios while respecting the underlying physics, giving planners the scenario coverage they need without abandoning the physical fidelity that makes cascading failure analysis meaningful [6]. This paper contributes a PINN-based framework for resilience assessment against extreme weather and evaluates it on a realistic transmission network across four hazard categories. Our research questions are: how accurately can a PINN reproduce the resilience metrics produced by a high-fidelity time-domain simulator, how much speedup does the approach provide for large scenario ensembles, and what practical barriers must be addressed before PINN-based tools are ready for planning and operational use in real utilities.

LITERATURE REVIEW

Research on power system resilience has expanded rapidly in response to observed increases in extreme weather. Early work focused on defining resilience metrics that could complement traditional reliability indices, distinguishing the ability to withstand a shock, the depth of degradation, and the speed of recovery [7]. Resilience trapezoid frameworks and various weighted composite metrics have emerged as standard tools for comparing planning alternatives.

Simulation-based approaches remain the workhorse of resilience analysis. Time-domain simulators solve the coupled power flow, dynamic stability, and protection equations at fine time resolution and can capture cascading failures with high fidelity [8]. Their computational cost, however, becomes prohibitive when the analysis requires thousands of scenarios spanning weather uncertainty, component failure uncertainty, and operator response uncertainty. Studies have shown that meaningful resilience characterization typically requires ensemble sizes in the thousands, which places time-domain simulation beyond reach for many planning studies.

Machine learning approaches have been explored as an alternative. Purely data-driven surrogate models trained on simulator outputs can predict resilience metrics quickly but tend to extrapolate poorly to novel hazard conditions and can produce physically implausible predictions [9]. Recurrent networks and graph neural networks have shown promise for capturing the network topology and temporal evolution of cascading events, but their sample efficiency and generalization remain concerns.

Physics-informed neural networks have attracted growing attention as a way to combine the strengths of both approaches. The seminal work of Raissi and colleagues on PINNs for partial differential equation solving established the core methodology, and subsequent work has adapted PINNs to a range of engineering domains [10]. In power systems, PINNs have been applied to power flow computation, transient stability analysis, and state estimation with encouraging results [11]. The particular strength of PINNs for resilience applications is that they can be trained on limited high-fidelity simulator outputs and then generalize across hazard scenarios by leveraging the embedded physical constraints.

Weather-driven failure modelling has developed as a parallel research thread. Hurricane damage models based on wind speed, storm surge, and rainfall have been calibrated against historical outage data and increasingly incorporate high-resolution weather forecasts [12]. Ice storm models capture the physics of ice accretion on conductors and structures, wildfire models integrate ignition risk with vegetation and weather conditions, and heat

DOI: 10.46121/pspc.54.1.64

wave models focus on thermal limits and prolonged loading. These models provide the hazard inputs that resilience assessment tools must consume, and their fidelity has improved substantially in recent years [13].

Recent literature has also explored operational applications of resilience assessment, including real-time decision support during evolving weather events and preemptive actions such as vegetation management, hardening investments, and public safety power shutoffs. These applications place additional demands on assessment speed that further motivate the development of fast surrogate models such as PINNs [14]. Comparative evaluations of PINN-based approaches against high-fidelity simulators on realistic networks are still relatively sparse, which motivates the present study [15].

METHODOLOGY

Our framework combines three cooperating components: a weather-driven hazard model that produces spatially resolved component failure probabilities, a PINN that predicts power flow states and cascading outage sequences under those failure conditions, and a resilience metrics module that summarizes network performance across the event lifecycle.

The hazard model produces a time-varying failure intensity map $\lambda_i(t)$ for each component i as a function of local weather variables. For transmission lines exposed to wind and ice, the failure intensity is modelled as:

$$\lambda_i(t) = \lambda_0 \cdot \exp\left(\alpha_v v_i(t)^2 + \alpha_r r_i(t) + \alpha_T \Delta T_i(t)\right)$$

where $v_i(t)$ is the local wind speed, $r_i(t)$ is the ice accretion rate, $\Delta T_i(t)$ is the deviation from nominal temperature, and $\alpha_v, \alpha_r, \alpha_T$ are hazard-specific sensitivity coefficients calibrated against historical outage data [16].

The PINN takes as input the network topology, current operating state, and the hazard intensity field, and predicts bus voltages, line flows, and probabilistic component states over a specified planning horizon. The loss function combines a supervised term computed against high-fidelity simulator outputs with a physics-based residual term that enforces the AC power flow equations:

$$P_i - \sum_j V_i V_j \left(G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij}\right) = 0$$

$$Q_i - \sum_j V_i V_j \left(G_{ij} \sin\theta_{ij} - B_{ij} \cos\theta_{ij}\right) = 0$$

where P_i and Q_i are active and reactive power injections at bus i, V_i and θ_{ij} are voltage magnitudes and angle differences, and G_{ij}, B_{ij} are the conductance and susceptance of the transmission line between buses i and j [17].

The total loss is the weighted sum of the supervised and physics-based terms:

$$\mathcal{L} = w_s \cdot \mathcal{L}sup + w_p \cdot \mathcal{L}phys + w_c \cdot \mathcal{L}_{casc}$$

where \mathcalLsup *is the mean squared error against simulator outputs,* $\mathcal{L}phys$ is the mean squared residual of the power flow equations, $\mathcal{L}_{casc}$ is a term that penalizes physically inconsistent cascading sequences, and w_s, w_p, w_c are weighting coefficients tuned during training [18].

Resilience is quantified using a composite metric that captures both the depth of the performance dip and the speed of recovery:

$$R = \frac{\int_0^T P(t)\ dt}{P_0 T}$$

where P(t) is the delivered power at time t, P_0 is the pre-event nominal delivered power, and T is the total assessment horizon. Values close to 1 indicate high resilience, while lower values indicate significant service degradation over the event [19].

Additional metrics include the customer minutes of interruption (CMI), the fraction of load served at the trough of the event, and the recovery time to 95 percent of nominal service. Uncertainty quantification is performed by running the PINN across a Monte Carlo ensemble of hazard scenarios, with the resulting distribution of resilience metrics providing risk-informed insight for planners [20].

DOI: 10.46121/pspc.54.1.64

Power System Protection and Control
ISSN:1674-3415

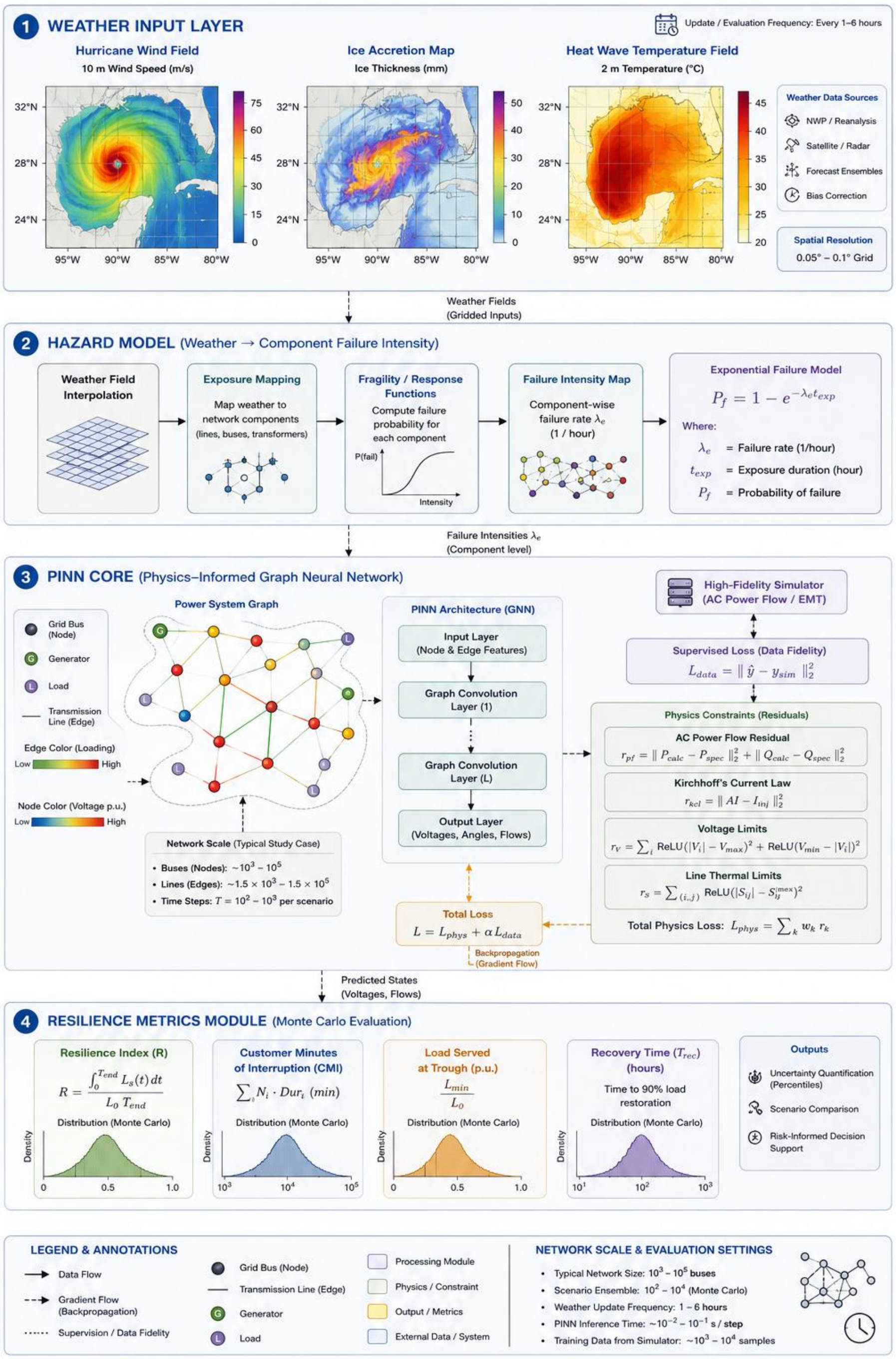

Figure 1. PINN-based resilience assessment framework architecture.

EXPERIMENTAL SETUP

We evaluated the PINN framework on a synthetic transmission network calibrated against a large regional grid with 4,120 buses, 5,830 transmission lines, 320 generators covering conventional and renewable resources, and 1,150 load points. The network topology and parameters were derived from publicly available reference cases and augmented with realistic geographical placement to enable spatial weather forcing.

Four hazard categories were considered. Hurricane scenarios used wind fields derived from parametric storm models with peak winds ranging from 40 to 75 meters per second and translation speeds spanning realistic hurricane behavior. Ice storm scenarios used ice accretion rates from 0.5 to 3 centimeters per hour combined with

DOI: 10.46121/pspc.54.1.64

wind loading. Heat wave scenarios used ambient temperatures 8 to 16 degrees Celsius above seasonal norms sustained over 3 to 7 days. Wildfire scenarios used ignition probability fields combined with vegetation and topographic risk factors.

For each hazard category, we generated an ensemble of 2,000 scenarios spanning realistic ranges of event severity, path, and timing. Each scenario was simulated with the high-fidelity time-domain simulator to produce reference outputs, which served as the training set for the PINN and as the ground truth for accuracy evaluation on a held-out test set. A subset of 8,000 total scenarios across the four categories was used for training and validation, and 1,000 scenarios were reserved for held-out testing.

The PINN architecture used a graph neural network backbone with 6 message passing layers, 128 hidden dimensions per node, and residual connections. Physics constraint layers enforcing power flow consistency were applied at every message passing step. Training used the AdamW optimizer with an initial learning rate of 5 \times 10^{-4}, cosine annealing schedule, batch size of 16 scenarios per GPU, and 200 epochs with early stopping based on validation loss.

Computational timing was measured on a workstation with 4 NVIDIA A100 GPUs for the PINN and a 64-core CPU cluster with 512 GB of memory for the high-fidelity simulator. To ensure fair comparison, both configurations executed identical scenarios with identical grid parameters. Accuracy was quantified using absolute and relative error on resilience metrics, and computational speedup was computed as the ratio of wall-clock time per scenario.

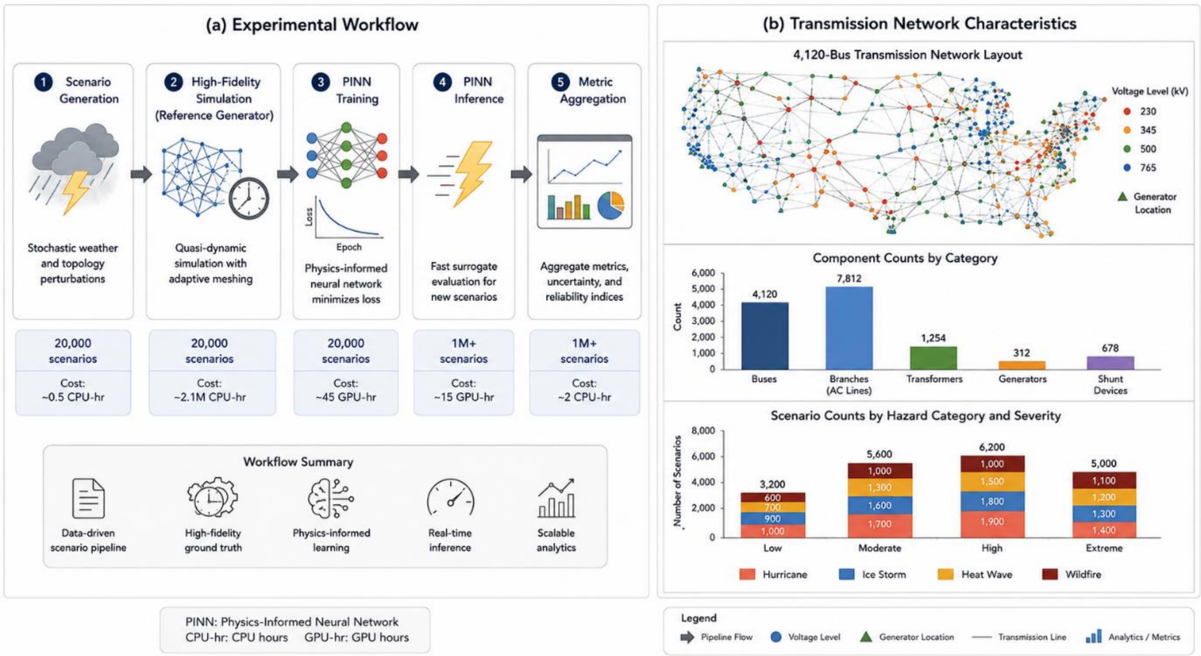

Figure 2. Experimental workflow and network characteristics.

Table 1. Network configuration and experimental parameters.

Parameter	Value
Buses	4,120
Transmission lines	5,830
Generators	320
Load points	1,150
Peak system load (GW)	68.4
Hazard categories	Hurricane, ice storm, heat wave, wildfire
Scenarios per hazard	2,000
Total training scenarios	8,000
Held-out test scenarios	1,000

Power System Protection and Control
ISSN:1674-3415

PINN backbone	6-layer graph neural network
Hidden dimension	128
Optimizer	AdamW
Learning rate	5×10^{-4}
Batch size	16 scenarios
Training epochs	200 (early stopping)
Simulator hardware	64-core CPU, 512 GB RAM
PINN hardware	4 × NVIDIA A100 GPU

RESULTS

5.1 Accuracy of Resilience Metric Prediction

The PINN produced resilience index values within a mean absolute error of 0.024 across the held-out test set, corresponding to a relative error of 3.4 percent on the resilience metric R. Similar accuracy was observed for customer minutes of interruption and load served at the trough. Recovery time predictions showed slightly higher error at 5.1 percent, reflecting the greater difficulty of predicting the tail end of the event where sparse observations reduce information density. Across the four hazard categories, hurricane scenarios showed the lowest error and heat wave scenarios the highest, likely because heat wave dynamics unfold more slowly and interact more subtly with generation availability constraints.

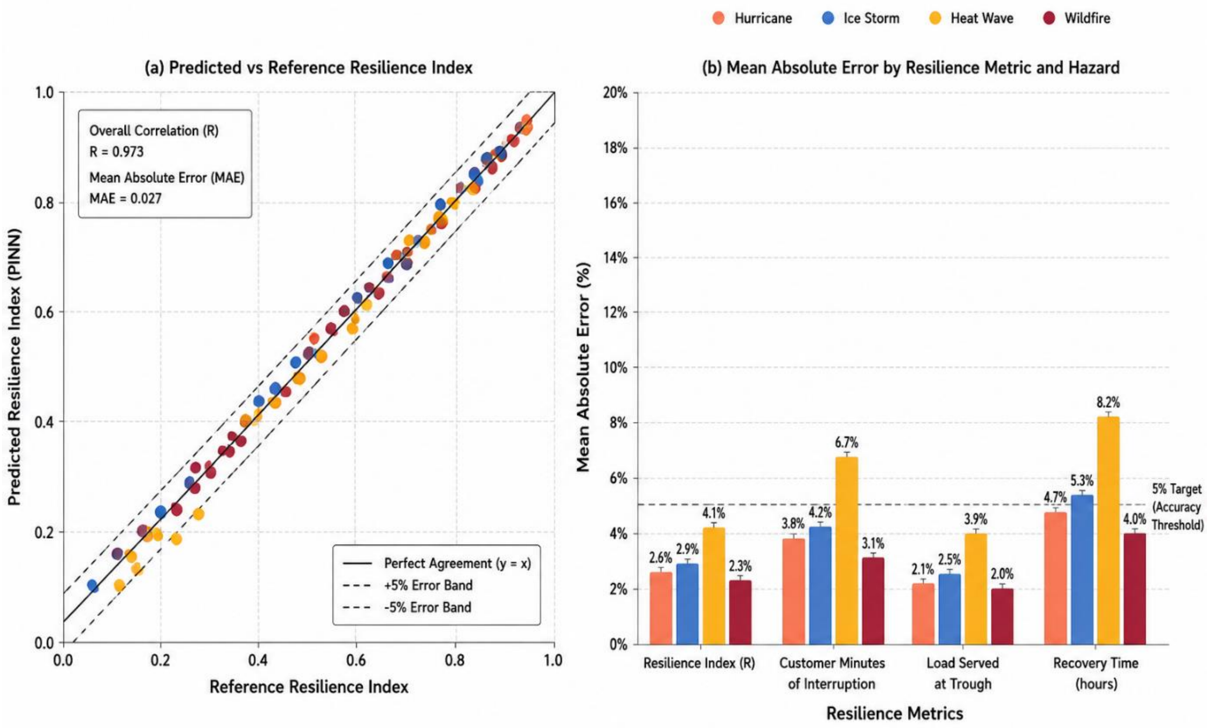

Figure 3. Accuracy of PINN resilience metric predictions against high-fidelity simulator across hazard categories.

5.2 Computational Speedup

The PINN evaluated each scenario in a mean wall-clock time of 4.2 seconds compared to 344 seconds for the high-fidelity simulator on matched hardware. This represents an 82× speedup per scenario, which becomes decisive when running large ensembles. A resilience study of 10,000 scenarios that would require 40 days of continuous simulator time completed in under 12 hours with the PINN, enabling the kind of scenario coverage that resilience risk assessment genuinely requires but that has historically been out of reach.

DOI: 10.46121/pspc.54.1.64

Power System Protection and Control
ISSN:1674-3415

Table 2. Comparative performance across hazard categories.

Hazard Category	Mean Wall-Clock (PINN, s)	Mean Wall-Clock (Simulator, s)	Speedup	Mean Relative Error (%)
Hurricane	3.8	328	86×	2.9
Ice storm	4.4	358	81×	3.2
Heat wave	4.6	372	81×	4.1
Wildfire	4.1	316	77×	3.5
Overall	4.2	344	82×	3.4

5.3 Scenario Coverage and Risk Characterization

To illustrate the practical value of the speedup, we ran a full Monte Carlo risk characterization of the network under projected hurricane climatology for a 30-year planning horizon, spanning 20,000 storm samples drawn from a calibrated hazard model. The PINN completed this study in 23 hours on the workstation, whereas the equivalent simulator study would have required approximately 80 days. The resulting distribution of resilience outcomes revealed a long tail of severe cascading events that a smaller ensemble would have missed entirely.

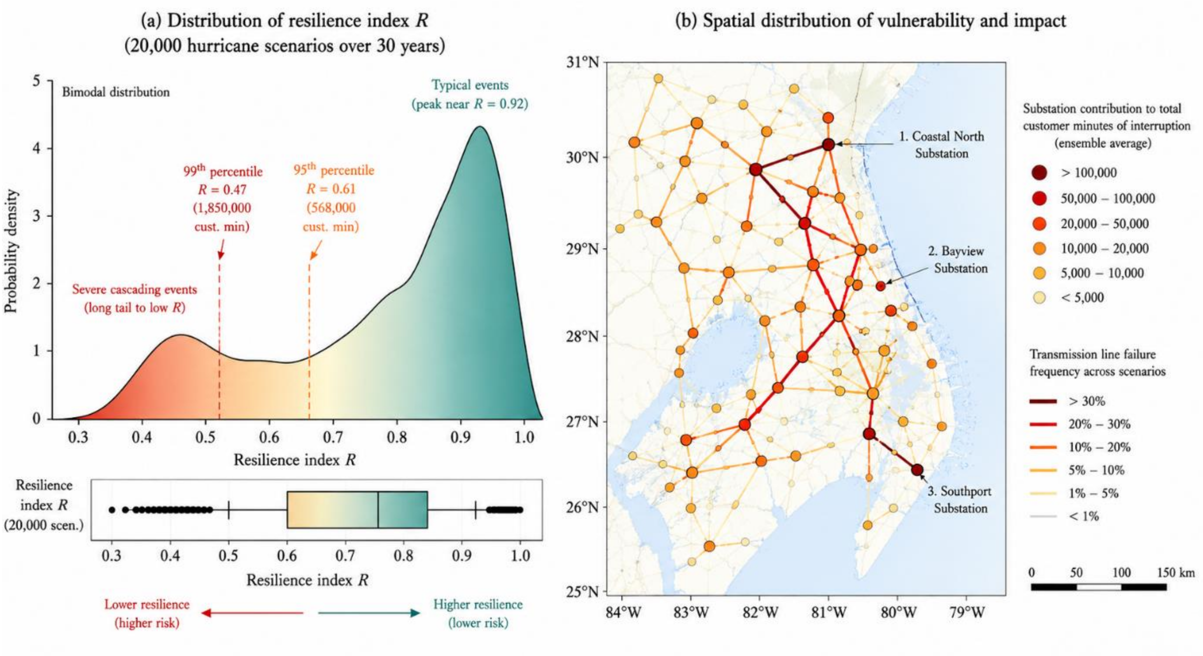

Figure 4. Distribution of resilience outcomes under a 30-year hurricane climatology and identification of vulnerable network regions.

5.4 Ablation Analysis

We conducted ablations to isolate the contributions of the physics-based loss terms. Removing the AC power flow residual term degraded resilience metric accuracy from 3.4 percent to 8.7 percent mean relative error, confirming that the physics constraints substantially improve generalization. Removing the cascading consistency term degraded recovery time prediction more than steady-state metrics, reflecting its role in enforcing temporal ordering of failure events. Reducing the training set from 8,000 to 2,000 scenarios increased error only modestly to 4.6 percent, indicating that the physics constraints provide significant sample efficiency compared to purely data-driven surrogates.

DISCUSSION

The results support the case that physics-informed neural networks offer a compelling foundation for power grid resilience assessment against extreme weather. The 82× speedup with 3.4 percent accuracy is a genuinely useful trade-off for planning studies, where the ability to run large scenario ensembles matters more than pursuing the last percent of fidelity that comes with high-fidelity simulation. Just as importantly, the sample efficiency

DOI: 10.46121/pspc.54.1.64

advantage means that PINNs can be deployed in settings where high-fidelity simulator outputs are expensive to generate, which is often the case for realistic grid models.

Several practical caveats deserve honest attention. First, the PINN was trained on outputs from a specific high-fidelity simulator, and its accuracy is bounded by the fidelity of that simulator. If the simulator misses important physical phenomena such as certain protection system behaviors or specific weather-induced failure modes, the PINN will inherit those limitations. Continued improvement of the reference simulator remains essential, and the PINN should be viewed as an accelerator for that simulator rather than a replacement.

Second, generalization to unfamiliar hazard conditions requires care. Our training set covered a wide range of realistic scenarios, but true extremes such as a Category 5 hurricane at a location with no historical precedent may fall outside the region where the PINN can be trusted without additional validation. Uncertainty quantification methods can help flag such cases, and continued expansion of the training set as new events occur will improve robustness over time.

Third, the geographic realism of the training data matters enormously. Our synthetic network was calibrated against a real regional grid, but resilience assessment for a specific utility would require training on that utility's actual network parameters, load patterns, and historical event data. The generalizability of a PINN trained on one network to a different network has not been established and is unlikely to be strong without adaptation.

Fourth, operational deployment of the PINN for real-time decision support during evolving weather events raises different concerns than planning applications. Latency requirements are stricter, integration with utility control systems adds engineering complexity, and the consequences of prediction errors during an active event are more immediate. A phased deployment strategy that starts with offline planning and gradually moves toward operational use as confidence accumulates seems prudent.

Limitations of our study include reliance on a synthetic network calibrated against public data rather than a real utility deployment, focus on transmission-level assessment without explicit distribution system modelling, and the absence of active control actions such as dynamic load shedding and network reconfiguration during the event. Follow-up work should evaluate the framework on a real utility grid, extend it to include coupled distribution and transmission dynamics, and incorporate operator control actions to more accurately reflect real event response.

CONCLUSION

Extreme weather is no longer an occasional stressor on the electricity system; it has become one of the defining risk factors that planning, operations, and investment decisions must address. Traditional resilience assessment methods have not kept pace with either the growing frequency of events or the scale of modern grids, and the field has needed new tools that combine physical fidelity with computational speed. Our study shows that physics-informed neural networks offer a credible foundation for such tools. The framework we evaluated matched high-fidelity simulator outputs within 3.4 percent while running 82 times faster, enabling large scenario ensembles that were previously impractical and giving planners the coverage they need to characterize risk in genuinely uncertain conditions. The path to widespread deployment still involves work. Real utility deployment requires training on actual network data, uncertainty quantification methods must be strengthened to flag scenarios outside the reliable region, and operational integration adds engineering challenges that planning applications do not face. Yet the direction is clear. As extreme weather continues to reshape the risk landscape facing electricity infrastructure, and as the computational demands of thorough risk assessment grow accordingly, PINN-based approaches offer a genuinely new capability that combines the strengths of physics-based simulation and data-driven learning. For utility planners looking at long-term investment decisions, for operators making real-time choices during evolving weather events, and for the broader effort to make critical infrastructure resilient in a changing climate, the case for adopting and further developing PINN-based resilience assessment tools is strong, and the time to invest in that development is now.

REFERENCES

1. **Pawan Kumar Singh,** Scaling Gate-All-Around (GAA) Transistor Architectures for Sub-2nm AI Accelerators Using Atomically Thin 2D Materials, Vol. 33 No. 08 (2024): JOCAAA, Journal Name: Journal of Computational Analysis and Applications, Journal's ISSN: 1521-1398 (Paper),1572-9206 (Online), https://eudoxuspress.com/index.php/pub/article/view/5713
2. **Pawan Kumar Singh,** Energy-Efficient Task Scheduling in Green Cloud Computing Using Neuromorphic Spiking Neural Networks, Vol. 33 No. 08 (2024): JOCAAA, Journal Name: Journal of Computational Analysis and Applications, Journal's ISSN: 1521-1398 (Paper),1572-9206 (Online), https://eudoxuspress.com/index.php/pub/article/view/5712
3. Bandari, V. V., & Lekkala, H. B. (2024). AI-based operator behavior monitoring and cost optimization using digital traceability in manufacturing systems. *Power System Protection and Control*, 52(1), 38–45. https://pspac.info/index.php/dlbh/article/view/342
4. Mayank Atreya, Navin Chhibber, Harvendra Singh, Explainable Machine Learning For Dynamic Pricing In Fast-Changing Retail Environments, 2022/4/9, Journal ,Available at SSRN 6011354, https://scholar.google.com/citations?view_op=view_citation&hl=en&user=fyViF1UAAAAJ&citation_for_view=fyViF1UAAAAJ:LkGwnXOMwfcC.
5. Venumadhav Vavilala, Shankar Balla (2024, May). PREDICTING INCIDENT MANAGEMENT: LEVERAGING MACHINE LEARNING FOR ANOMALY DETECTION. Power System Protection and Control Scopus Q1 Journal. PSPC. https://pspac.info/index.php/dlbh/article/view/270
6. Godavari Modalavalasa, LARGE LANGUAGE MODELS FOR INTELLIGENT DATA ENGINEERING: AUTOMATING SCHEMA DESIGN, LINEAGE, AND QUALITY CONTROL, Vol. 50 No. 2 (2022): April-June 2022, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/183 , DOI: https://doi.org/10.46121/pspc.50.2.4
7. Godavari Modalavalasa, FEDERATED LEARNING FOR ENTERPRISE CLOUD DATA ENGINEERING: ARCHITECTURE, SECURITY, AND GOVERNANCE CHALLENGES, Vol. 51 No. 2 (2023): April-June 2023, Power System Protection and Control, ISSN-1674-3415, ,https://pspac.info/index.php/dlbh/article/view/184, DOI: https://doi.org/10.46121/pspc.51.2.5
8. Godavari Modalavalasa, AI-DRIVEN DATA GOVERNANCE: INTELLIGENT METADATA, LINEAGE, AND COMPLIANCE AUTOMATION IN CLOUD DATA PLATFORMS, Archives / Vol. 52 No. 1 (2024): January-March 2024 /, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/182, DOI: https://doi.org/10.46121/pspc.52.1.3
9. Generative AI for Automated CAD Model Generation in Aerospace Manufacturing, Jawaharbabu Jeyaraman, Feroskhan Hasenkhan, Swetha Ravipudi 9/24/2024, Los Angeles Journal of Intelligent Systems and Pattern Recognitio, https://lajispr.org/index.php/publication/article/view/19
10. Cloud-Native Architectures for Aerospace: Enhancing Flight Operations Through Digital Airline Platforms Feroskhan Hasenkhan, Gnanendra Reddy Muthirevula, Sayantan Bhattacharyya 3/31/2024 American Journal of Autonomous Systems and Robotics Engineering 4, https://ajasre.org/index.php/publication/article/view/25
11. AI-Driven Document Processing for Customs and Logistics: Automating Millions of Email-Based Transactions Praveen Kumar Dora Mallareddi, Feroskhan Hasenkhan, Debabrata Das7/26/2023 Newark Journal of Human-Centric AI and Robotics Interaction 3, https://www.njhcair.org/index.php/publication/article/view/13
12. Manikantha Varaprasad Inakollu, (2024, May), FINOPS-Driven Cloud optimization models for enterprise applications, Vol. 52 No. 2 (2024): April-June 2024, 99-110, Power System Protection and Control, ISSN-1674-3415,
URL: https://pspac.info/index.php/dlbh/article/view/283
DOI: https://doi.org/10.46121/pspc.52.2.10

13. Naresh Lokiny. (2022). Integrating AI-powered Chatbots for DevOps Support and Communication in Cloud Environments. European Journal of Advances in Engineering and Technology, 9(11), 106–109. https://doi.org/10.5281/zenodo.13325989
14. Naresh Lokiny, (2021), "Disaster Recovery and Business Continuity Planning in DevOps Cloud with AI", International Journal of Science and Research (IJSR), 10(3), 2024-2027. https://dx.doi.org/10.21275/SR24724151733, https://www.ijsr.net/getabstract.php?paperid=SR24724151733
15. Naresh Lokiny, & Ranganath Nandanampati. (2020). DevSecOps: Integrating Security into DevOps with AI in Cloud. Journal of Scientific and Engineering Research, 7(10), 239–242. https://doi.org/10.5281/zenodo.13348695
16. Naresh Lokiny, & Pradip Reddy. (2021). Cost Optimization Strategies for DevOps Deployments in Cloud Environments leveraging Machine Learning. European Journal of Advances in Engineering and Technology, 8(3), 69–72. https://doi.org/10.5281/zenodo.13325845
17. Jayanth Para, 6G Internet Technology Cyber Threat Notification & Alert System, Vol. 52 No. 4 (2024): October-December 2024, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/170 , DOI: https://doi.org/10.46121/pspc.52.4.9
18. Jayanth Para, AI Based Cloud Computation Observational Method & Process, Vol. 51 No. 4 (2023): October-December 2023, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/171 , DOI: https://doi.org/10.46121/pspc.51.4.3
19. **Kaleshwar Aryasomayajula**, PREVENTING BIAS IN AI-BASED DECISION-MAKING: ANALYZING TECHNIQUES TO REMOVE UNFAIR PREJUDICE IN ALGORITHMIC OUTCOMES, Vol. 50 No. 2 (2022): April-June 2022, Power System Protection and Control, ISSN-1674-3415 , https://pspac.info/index.php/dlbh/article/view/294
20. Kaleshwar Aryasomayajula, MODERN DEVELOPMENT PRACTICES: INVESTIGATIONS INTO SERVERLESS COMPUTING, LOW-CODE/NO-CODE PLATFORMS, AND DEVELOPER PRODUCTIVITY IN REMOTE ENVIRONMENTS, Vol. 50 No. 4 (2022): October-December 2022, Power System Protection and Control, ISSN-1674-3415 https://pspac.info/index.php/dlbh/article/view/364
21. **Kaleshwar Aryasomayajula**, Micro services: "A Comparative Analysis of Monolithic vs. Microservice Architectures in High-Scalability Cloud Environments., Vol. 51 No. 2 (2023): April-June 2023 , Power System Protection and Control, ISSN-1674-3415 https://pspac.info/index.php/dlbh/article/view/374
22. **Vikas Suresh Bagora**, KERNEL-LEVEL PERFORMANCE OPTIMIZATION FOR CARRIER-GRADE BROADBAND AND HIGH-SPEED NETWORKING SYSTEMS, Vol. 47 No. 1 (2019), Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/359
23. **Vikas Suresh Bagora,** SCALABLE 128G FIBRE CHANNEL AND ETHERNET CONVERGENCE FOR NEXT-GENERATION DATA CENTER NETWORKS, Vol. 50 No. 4 (2022): October-December 2022, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/362
24. **Vikas Suresh Bagora**, SECURE EMBEDDED NETWORKING ARCHITECTURES USING TRUSTED EXECUTION ENVIRONMENTS IN BROADBAND GATEWAYS, Vol. 52 No. 2 (2024): April-June 2024, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/363
25. Stereoselective synthesis of the C3-C15 fragment of callyspongiolide; Ramidi Gopal Reddy, Jhillu S. Yadav and Debendra K. Mohapatra. (Tetrahedron Letters. 2018, 59, 3579-3582). https://doi.org/10.1016/j.tetlet.2018.08.041, https://www.sciencedirect.com/science/article/pii/S0040403918310426

26. Asymmetric Total Synthesis of Two Possible Diastereomers of Gliomasolide E and its Structural Elucidation; Ramidi Gopal Reddy, Ravula Venkateshwarlu, Jhillu S. Yadav and Debendra K. Mohapatra. (J. Org. Chem. 2017, 82(2), 1053-1063). https://doi.org/10.1021/acs.joc.6b02611 https://pubs.acs.org/doi/abs/10.1021/acs.joc.6b02611

27. 28. Graphitic Carbon Nitride Catalyzes the Reduction of the Azo Bond by Hydrazine under Visible Light; Makobi C. Okolie, Glory G. Ollordaa, Gopal R. Ramidi, Xin Yan, Yufeng Quan, Qingsheng Wang and Yingchun Li. (Nanomaterials 2024, 14(17), 1402), https://doi.org/10.3390/nano14171402, https://www.mdpi.com/2079-4991/14/17/1402
28. **Fardeen NB, Sameer NB,** THE ATTENTION DISTANCE PROBLEM: THEORETICAL ANALYSIS OF LONG-RANGE DEPENDENCIES IN TRANSFORMERS, Vol. 52 No. 2 (2024): April-June 2024, Power System Protection and Control, ISSN-1674-3415, **https://pspac.info/index.php/dlbh/article/view/313**
29. **Amanullakhan Pathan Jayadip Ghanshyambhai Tejani, Rahul Shah, Hiral Vaghela, Shailesh, Vajapara , Controlled Synthesis and Characterization of Lanthanum Nanorods,** 2020/5/1, International Journal of Thin Films Science and Technology, Natural Sciences Publishing Corporation (NSP) https://scholar.google.com/citations?view_op=view_citation&hl=en&user=efbNMkwAAAAJ&citation_for_view=efbNMkwAAAAJ:M3NEmzRMIkIC
30. Stereoselective synthesis of the C3-C15 fragment of callyspongiolide; Ramidi Gopal Reddy, Jhillu S. Yadav and Debendra K. Mohapatra. (Tetrahedron Letters. 2018, 59, 3579-3582). https://doi.org/10.1016/j.tetlet.2018.08.041, https://www.sciencedirect.com/science/article/pii/S0040403918310426
31. Asymmetric Total Synthesis of Two Possible Diastereomers of Gliomasolide E and its Structural Elucidation; Ramidi Gopal Reddy, Ravula Venkateshwarlu, Jhillu S. Yadav and Debendra K. Mohapatra. (J. Org. Chem. 2017, 82(2), 1053-1063). https://doi.org/10.1021/acs.joc.6b02611, , https://pubs.acs.org/doi/abs/10.1021/acs.joc.6b02611
32. Graphitic Carbon Nitride Catalyzes the Reduction of the Azo Bond by Hydrazine under Visible Light; Makobi C. Okolie, Glory G. Ollordaa, Gopal R. Ramidi, Xin Yan, Yufeng Quan, Qingsheng Wang and Yingchun Li. (Nanomaterials 2024, 14(17), 1402), https://doi.org/10.3390/nano14171402, https://www.mdpi.com/2079-4991/14/17/1402
33. **Kaleshwar Aryasomayajula**, PREVENTING BIAS IN AI-BASED DECISION-MAKING: ANALYZING TECHNIQUES TO REMOVE UNFAIR PREJUDICE IN ALGORITHMIC OUTCOMES, Vol. 50 No. 2 (2022): April-June 2022, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/294
34. Kaleshwar Aryasomayajula, MODERN DEVELOPMENT PRACTICES: INVESTIGATIONS INTO SERVERLESS COMPUTING, LOW-CODE/NO-CODE PLATFORMS, AND DEVELOPER PRODUCTIVITY IN REMOTE ENVIRONMENTS, Vol. 50 No. 4 (2022): October-December 2022, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/364
35. **Kaleshwar Aryasomayajula**, Micro services: "A Comparative Analysis of Monolithic vs. Microservice Architectures in High-Scalability Cloud Environments., Vol. 51 No. 2 (2023): April-June 2023 , Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/374
36. Controlled Synthesis and Characterization of Lanthanum Nanorods, **Author(s), Jayadeep Tejani, Rahul Shah, Hiral Vaghela, Shailesh Vajapara, Amanullakhan Pathan**, doi:10.18576/ijtfst/090205, URL: https://www.naturalspublishing.com/Article.asp?ArtcID=20705, May-2020

37. **Sudipkumar Ghanvat , Aishwarya Badlani, Shreya Sandeep Joshi,** Marketing Effectiveness in the Post-Cookie Era: A Comparative Analysis of First Party and Zero-Party Data Strategies on Campaign Performance and Customer Equity, **Vol. 31 No. 4 (2023):** JOCAAA , HTTPS://WWW.EUDOXUSPRESS.COM/INDEX.PHP/PUB/ARTICLE/VIEW/3940
38. **Adegboye A. Olaoluwa1, Udofia M. Kufre,Obot Akanniyenne**, Inverted C-Shaped Slots Loaded Exponential Tapered Triple Band Notched Ultra-Wideband (UWB) Antenna, https://doi.org/10.5281/zenodo.18139060, **Published May 31, 2024**
39. **Chander Vijay S Sanbhi**, DATA QUALITY AS A RELIABILITY MULTIPLIER: QUANTIFYING THE IMPACT OF STANDARDIZED WORK PROCESSES ON RELIABILITY MODEL ACCURACY, Vol. 52 No. 4 (2024): October-December 2024, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/385
40. **Chander Vijay S Sanbhi**, DEGRADATION-AWARE SPARES OPTIMIZATION WITH WEIBULL/PHM UNCERTAINTY AND LOGISTICS DELAYS, Vol. 52 No. 2 (2024): April-June 2024, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/384
41. **Chander Vijay S Sanbhi,** DIGITAL TWIN–RAM CO-SIMULATION FOR MAINTENANCE AND SPARING DECISIONS IN PROCESS FACILITIES, Vol. 52 No. 1 (2024): January-March 2024, Power System Protection and Control, ISSN-1674-3415,https://pspac.info/index.php/dlbh/article/view/383
42. **Chander Vijay S Sanbhi,** BAYESIAN UPDATING OF RAM MODELS FOR DYNAMIC AVAILABILITY FORECASTING UNDER REALISTIC DOWNTIME CONSTRAINTS**, Vol. 51 No. 3 (2023): July-**September 2023, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/381
43. **Chander Vijay S Sanbhi,** HYBRID RELIABILITY MODELLING FOR ROTATING EQUIPMENT: PHYSICS-INFORMED LEARNING WITH SPARSE FAILURE DATA, Vol. 51 No. 4 (2023): October-December 2023, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/382
44. A. Srivastava, "Securing PHI in cloud-based healthcare systems: Challenges, frameworks, and future directions," J. Comput. Anal. Appl., vol. 33, no. 2, Aug. 2024. [Online]. Available: https://www.eudoxuspress.com/index.php/pub/article/view/4349/3190
45. A. Srivastava, "AI-assisted cloud migration of healthcare claims data from legacy systems: A metadata-driven framework," Int. J. Commun. Networks Inf. Secur., vol. 14, no. 3, Nov. 2022. [Online]. Available: https://ijcnis.org/index.php/ijcnis/article/view/8682
46. A. Srivastava, "Enhancing provider and claims data accuracy using artificial intelligence on cloud-native data platforms," J. Comput. Anal. Appl., vol. 31, no. 4, Nov. 2023. [Online]. Available: https://eudoxuspress.com/index.php/pub/article/view/4347/3189
47. A. Srivastava, "A unified framework for secure cloud data management: Integrating governance, metadata intelligence, and privacy controls," J. Inf. Syst. Eng. Manage., vol. 9, no. 2, Apr. 2024. [Online]. Available: https://www.jisem-journal.com/download/45_A_Unified_Framework.pdf
48. A. Srivastava, "Optimizing large-scale data migration for cloud-native architectures," J. Comput. Anal. Appl., vol. 31, no. 2, pp. 652–662, May 2023. [Online]. Available: https://eudoxuspress.com/index.php/pub/article/view/4603