



AI-Enabled Condition Monitoring for Predictive Maintenance and Early Anomaly Detection in Renewable-Rich Electric Distribution Systems: A simulation-based proof-of-concept study using the IEEE 33-bus feeder

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Abstract

High penetration of distributed energy resources (DERs) increases the operating variability of distribution systems and complicates the separation of normal renewable-driven changes from developing equipment and network abnormalities. This study presents a reproducible simulation-based condition-monitoring framework intended to support predictive-maintenance research in a renewable-rich radial distribution network. The IEEE 33-bus feeder is solved with a backward-forward sweep load-flow model under stochastic load variation and DER penetration. Four operating classes are generated: normal operation, progressive line-resistance degradation, localized overload, and source-voltage reduction. Each 20-step observation window contains 68 electrical features comprising bus-voltage magnitudes, branch-current magnitudes, net active/reactive power, and feeder losses. Temporal statistical descriptors are used with Random Forest, radial-basis-function support vector machine (RBF-SVM), and HistGradientBoosting classifiers. On an in-distribution (IID) test set, HistGradientBoosting achieved 90.75% accuracy and 90.75% macro-F1, outperforming Random Forest and RBF-SVM. Under a high-DER stress test with 50–70% DER penetration, performance decreased to 83.50% accuracy and 83.58% macro-F1, indicating useful but imperfect generalization. Progressive line degradation was the most difficult condition to distinguish from normal operation, whereas all 100 source-voltage-reduction samples were correctly classified in the simulated IID test set. The findings support the use of feeder physics, temporal feature engineering, and ensemble learning for condition monitoring, while also showing that deployment-oriented predictive maintenance will require field data, higher-fidelity failure models, and explicit adaptation to unseen DER operating regimes.

Keywords

Condition Monitoring, Predictive Maintenance, Distribution System, Anomaly Detection, Machine Learning, Distributed Energy Resources, Smart Grid, IEEE 33-Bus.

INTRODUCTION

Electric distribution systems are becoming more dynamic as photovoltaic generation, battery storage, flexible loads, and other DERs are connected closer to end users. IEEE Std 1547-2018 formalizes interconnection and interoperability requirements for DERs and highlights the importance of operation, abnormal-condition response, power quality, and monitoring in modern distribution networks [1]. At the same time, increased DER penetration can alter feeder voltage profiles, reverse power flows, protection behavior, and operating uncertainty [2], [3]. These changes make traditional threshold-based monitoring less reliable because a measurement deviation can represent either a benign change in operating state or the early signature of equipment stress. Predictive maintenance seeks to move asset management from fixed-interval or reactive maintenance toward condition-informed decisions. Machine learning has become an important enabling technology because it can learn multivariate patterns from sensor data and identify operating states that are difficult to encode with simple rules [4]. In power systems, data-driven fault and anomaly detection has expanded from conventional feature extraction toward deep learning, temporal models, digital-twin concepts, and hybrid physics/data approaches [5]–[7]. Recent work on high-impedance faults also shows that detection performance depends strongly on temporal representation, operating diversity, and robustness to non-fault transients [6], [7]. A central practical challenge is generalization. Models trained under a narrow range of loading and DER conditions may perform well in laboratory data yet deteriorate when the feeder operates outside the training distribution. This study therefore evaluates both an ordinary in-distribution (IID) test set and a high-DER stress set. The work is intended as a transparent proof of concept rather than a claim of field-ready protection performance. The contributions are fourfold: (1) a reproducible IEEE 33-bus simulation based on the classical Baran–Wu benchmark [8], with stochastic loading and DER penetration; (2) a four-class condition-monitoring benchmark that includes progressive line degradation rather than only abrupt faults; (3) a temporal statistical feature representation that can be used with interpretable ensemble classifiers; and (4) an explicit high-DER generalization test designed to quantify performance degradation under operating conditions that differ from the training distribution.

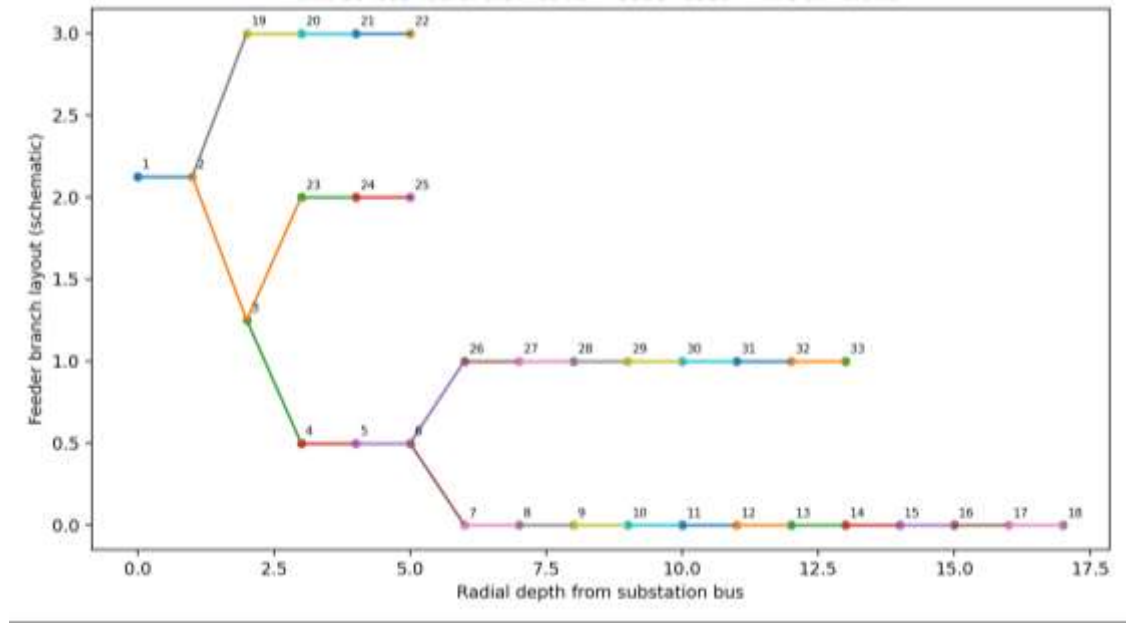
Related Work and Research Gap

Predictive-maintenance research has established that machine-learning performance depends not only on classifier selection but also on the quality of sensing, labeling, feature construction, and validation methodology [4]. In power distribution systems, fault detection has increasingly adopted neural networks and temporal deep-learning architectures because voltage and current waveforms contain time-dependent fault signatures [5]. Silva et al. combined wavelet features with an evolving neural network for high-impedance-fault detection and showed the importance of adaptation when fault patterns drift [6]. More recent work has used temporal convolution, attention mechanisms, and confidence checking to improve fault detection and interpretability [7].

Digital-twin and data-driven monitoring concepts are also being investigated for resilience and predictive grid management [3]. Prior reviews by Rana [9] and Nuruzzaman and Rana [10] synthesize AI-driven fault detection/predictive maintenance and IoT/SCADA-based condition monitoring, respectively. Broader DER-integration work has emphasized the operational implications of increasing distributed resources [11], while IEEE Std 1547.2-2023 provides application guidance for DER interconnection and interoperability [12]. However, two gaps remain relevant to practical deployment. First, many studies emphasize abrupt short-circuit or high-impedance faults, while slower changes such as conductor or connection degradation can be subtle and easily confused with normal load/DER variability. Second, performance is often reported under a test distribution that closely resembles the training data. The present study directly evaluates both of these issues.

Test System and Simulation Method

The benchmark network is the classical 33-bus radial distribution feeder introduced by Baran and Wu [8]. The feeder operates at 12.66 kV and contains 32 branches. The nominal active and reactive load totals are approximately 3.715 MW and 2.300 MVar, respectively. A 10-MVA base is used for per-unit calculations. The implemented base case produces a minimum bus voltage of approximately 0.904 p.u. and active-power loss of approximately 211 kW, consistent with the expected behavior of the benchmark.

Fig. 1. Schematic topology of the IEEE 33-bus radial feeder used in the simulation

A backward-forward sweep algorithm is used for each operating point. For a bus j , the injected current is computed from $I_j = \text{conjugate}(S_j / V_j)$. Branch currents are accumulated from downstream buses toward the source, and voltages are then updated in the forward direction using $V_j = V_i - Z_{ij} I_{ij}$. Branch active-power loss is calculated as the sum of $|I_{ij}|^2 R_{ij}$. DER is modeled as aggregate unity-power-factor active-power injection at buses 6, 18, 25, and 30 with allocation weights of 0.20, 0.20, 0.30, and 0.30, respectively. In this study, DER penetration is defined as total DER active-power injection divided by the feeder nominal active load; it therefore represents an aggregate operating parameter rather than a detailed inverter or battery-storage dynamic model.

Parameter	Value / range
System	IEEE 33-bus radial feeder
Base voltage	12.66 kV
Base power	10 MVA
Nominal load	3.715 MW + j2.300 MVar
DER buses	6, 18, 25, 30
Training DER range	0–50% of nominal active load
High-DER stress range	50–70%
Observation length	20 time steps
Electrical channels	68 per time step
Classes	Normal, degradation, overload, source-voltage reduction

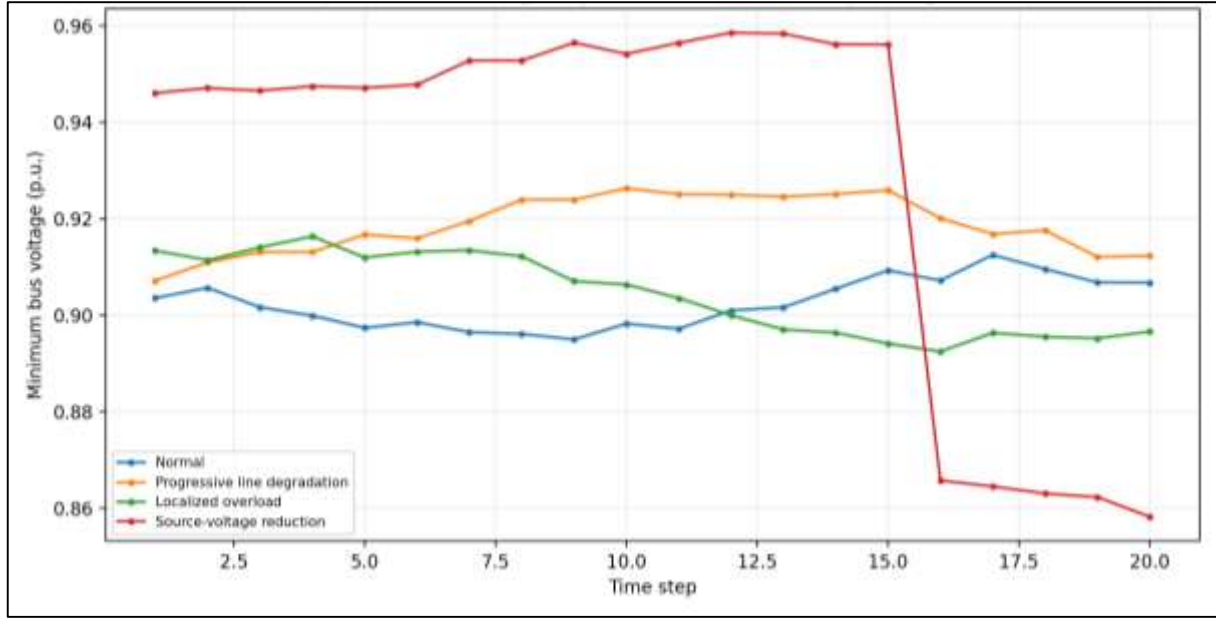
Scenario Generation and Feature Engineering

For every observation window, the base load multiplier is randomized between approximately 0.78 and 1.12 and modulated by a smooth temporal variation. DER output is also varied over the window to represent renewable-driven operating changes. Small measurement noise is added to bus voltages and branch currents.

Progressive line degradation is represented by a gradual increase in the resistance of one selected branch, reaching 1.65–3.00 times its nominal value by the end of the observation window. This abstraction is intended to emulate an incipient resistive defect such as a degrading connection or conductor condition; it is not an electromagnetic-transient model of a specific physical failure mechanism. Localized overload is generated by increasing demand at a selected downstream bus by

approximately 150–500 kW on the 10-MVA base, with a randomized reactive component. Source-voltage-reduction events are generated by lowering the slack-bus magnitude to approximately 0.90–0.955 p.u. during the latter part of the observation window. Because the simulation uses abstract steady-state time steps rather than cycle-resolved durations, the term source-voltage reduction is used instead of a standards-based voltage-sag classification.

Fig. 2. Representative minimum-bus-voltage trajectories for the four simulated operating states.



Each time step contains 32 non-source bus-voltage magnitudes, 32 branch-current magnitudes, total net active and reactive power, and feeder active/reactive losses. To preserve temporal information while enabling efficient ensemble learning, five descriptors are calculated for every channel across the 20-step window: mean, standard deviation, minimum, maximum, and end-to-start change. This produces a 340-element temporal feature vector for classification.

Machine-Learning Models and Evaluation

Three classifiers are compared: Random Forest, RBF-SVM, and HistGradientBoosting. A fixed random seed of 123 is used for dataset generation and model initialization. The Random Forest uses 600 trees with square-root feature sampling and class balancing. The RBF-SVM uses $C = 5$ with gamma set to the scikit-learn scale convention. HistGradientBoosting uses 350 boosting iterations, learning rate 0.07, 31 maximum leaf nodes, and L2 regularization of 0.1. Hyperparameters were selected conservatively for the proof-of-concept experiment rather than through exhaustive optimization. The training set contains 1,800 windows (450 per class).

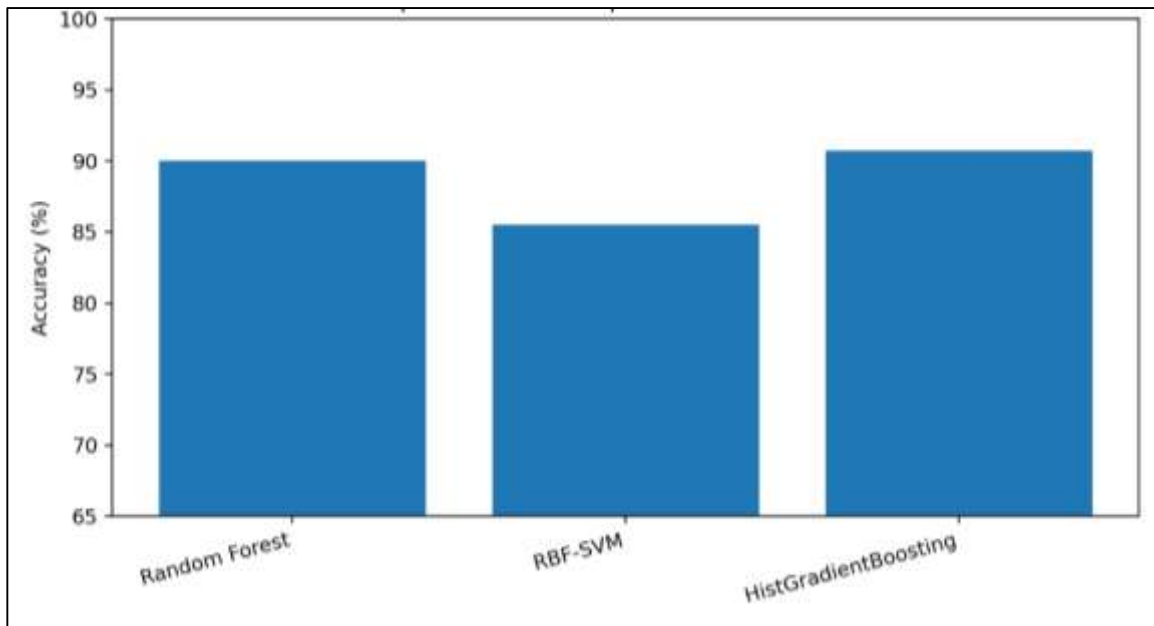
Results

Model	Evaluation set	Accuracy (%)	Macro precision (%)	Macro recall (%)	Macro F1 (%)
Random Forest	IID test	90.00	90.13	90.00	89.96
Random Forest	High-DER stress	78.50	79.36	78.50	78.55
RBF-SVM	IID test	85.50	86.47	85.50	85.43
RBF-SVM	High-DER stress	72.75	72.69	72.75	69.91
HistGB	IID test	90.75	91.00	90.75	90.75
HistGB	High-DER stress	83.50	83.83	83.50	83.58

The IID test set contains 400 windows (100 per class), and the high-DER stress set contains another 400 windows. Per-channel normalization statistics are computed from the training set only; the temporal summary features are then used for model fitting and evaluation.

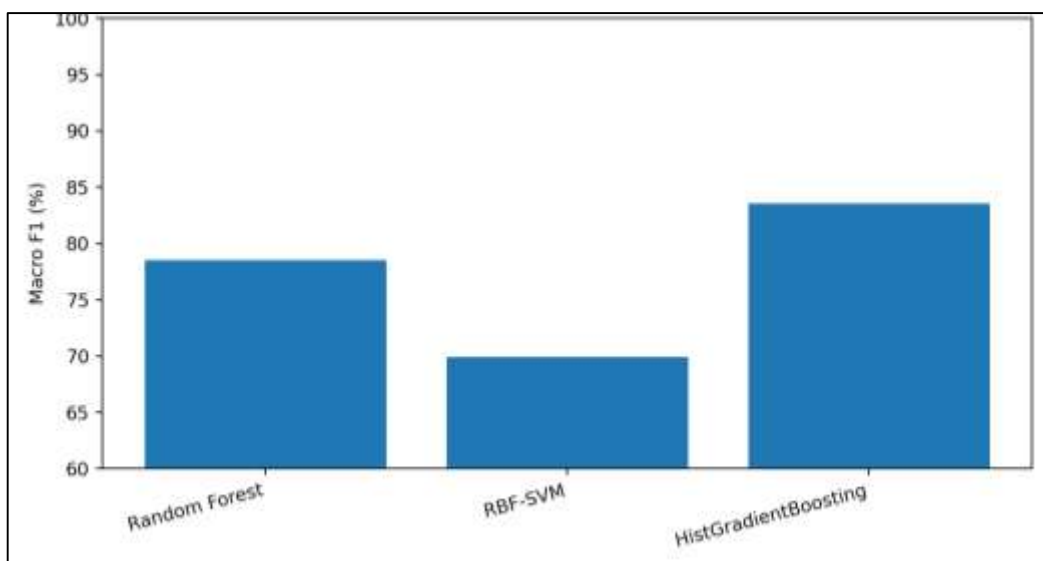
Performance is assessed using overall accuracy and macro-averaged precision, recall, and F1-score. Macro averaging is used so that each class contributes equally to the reported score. Confusion matrices are examined to identify which operating states are most difficult to distinguish. HistGradientBoosting produced the highest IID accuracy (90.75%) and macro-F1 (90.75%). Random Forest was close behind at 90.00% accuracy and 89.96% macro-F1, whereas RBF-SVM reached 85.50% accuracy. These results indicate that non-linear tree-based ensembles were well suited to the temporal summary representation used in this study.

Fig. 3. Classification accuracy on the IID test set.



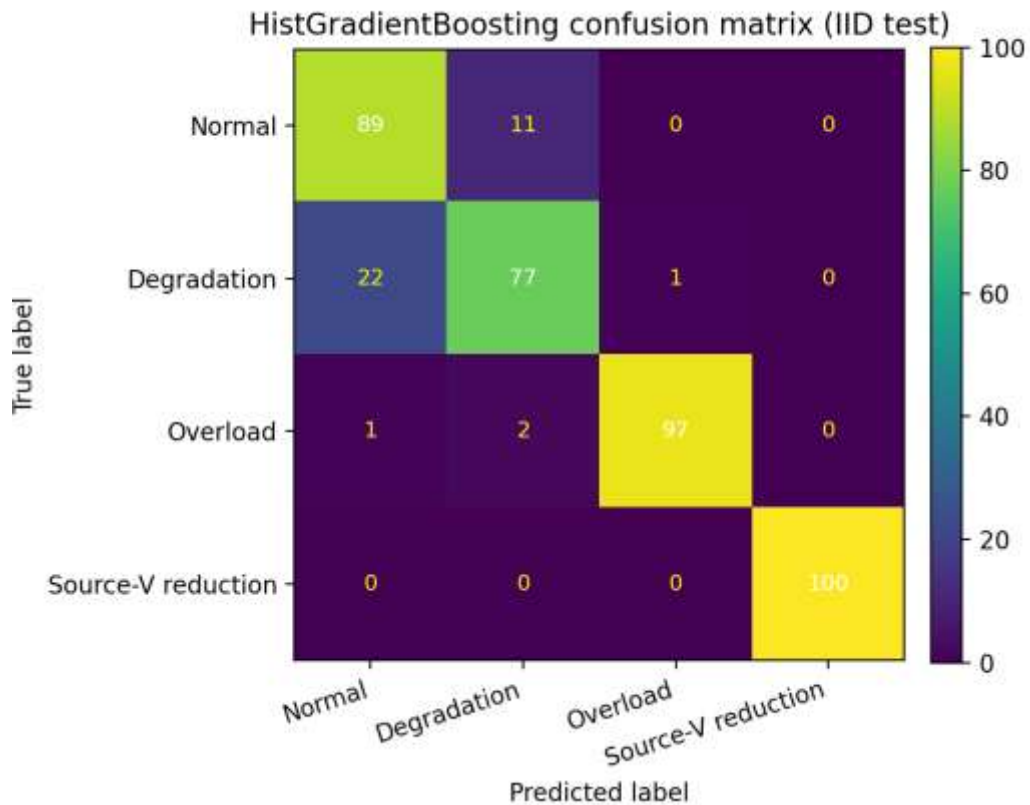
The high-DER stress test reduced the performance of all models. HistGradientBoosting retained the strongest performance at 83.50% accuracy and 83.58% macro-F1.

Fig. 4. Macro-F1 on the high-DER generalization stress test.



Random Forest decreased to 78.50% accuracy, while RBF-SVM decreased to 72.75%. The decrease confirms that renewable operating regimes outside the training distribution can materially affect classifier performance even when the underlying feeder topology is unchanged. The IID confusion matrix for HistGradientBoosting shows that source-voltage reduction was the easiest class, with all 100 test samples identified correctly. Localized overload was also well separated, with 97 of 100 samples classified correctly. The principal ambiguity occurred between normal operation and progressive line degradation: 11 normal samples were labeled as degradation, while 22 degradation samples were labeled as normal. This is physically plausible because modest resistance growth can be masked by load and DER variability during the early part of the observation window.

Fig. 5. Confusion matrix for HistGradientBoosting on the IID test set



Discussion

The results support three technical observations. First, the most useful condition-monitoring problem is not always the easiest classification problem. Abrupt source-voltage reduction and overload create pronounced signatures, whereas progressive degradation is subtle and therefore more representative of the challenge that motivates condition-based and predictive maintenance. Second, temporal statistical descriptors provide a compact alternative to raw-sequence deep learning when the dataset is moderate in size. Third, high-DER generalization should be treated as a first-class validation requirement rather than an optional sensitivity analysis.

The performance gap between IID and high-DER tests also argues against reporting a single accuracy value as evidence of deployment readiness. In a real feeder, inverter control modes, weather-driven PV ramps, topology changes, regulator actions, capacitor switching, measurement errors, and load composition can all shift the data distribution. Model adaptation, domain generalization, and uncertainty estimation are therefore important future extensions.

Limitations

This study is intentionally limited to a simulation-based proof of concept. The backward-forward sweep model is a steady-state representation and does not reproduce electromagnetic transients, harmonics, arc physics, protection-device dynamics, inverter control loops, battery state-of-charge dynamics, or unbalanced phase behavior. DER is represented as aggregate unity-power-factor active

injection rather than device-level inverter or storage dynamics. The degradation model is a resistive proxy and should not be interpreted as a validated physical model of a specific asset failure. No field measurements were used. The reported results therefore establish computational feasibility for condition monitoring, not field-ready protection or predictive-maintenance performance.

Conclusion

A reproducible AI-enabled condition-monitoring framework was evaluated on a renewable-rich IEEE 33-bus distribution feeder. HistGradientBoosting achieved 90.75% IID accuracy and 83.50% accuracy under a high-DER stress test. The dominant classification difficulty was the separation of normal behavior from progressive line degradation, while overload and source-voltage reduction were detected with substantially higher reliability. The study demonstrates that temporal feature engineering combined with ensemble learning can support condition-monitoring research relevant to predictive maintenance in distribution systems, but also shows that performance degrades when DER operating conditions move outside the training regime. Future work should use higher-fidelity failure models, real SCADA/AMI or power-quality measurements, uncertainty-aware detection, and hardware-in-the-loop validation.

Data and Code Availability

The data used in this study are synthetic and were generated from the IEEE 33-bus simulation workflow described in the manuscript. Code used for scenario generation, model training, metric calculation, and evaluation is available from the author upon reasonable request. Any public repository associated with a journal submission should include the final scripts, dependency versions, and only the outputs corresponding to the reported experiment.

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