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PHYSICS-GUIDED RESIDUAL LEARNING FOR FAST VOLTAGE-SECURITY SCREENING IN DISTRIBUTION NETWORKS

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Research Motivation

- Fast screening requires repeated power-flow calculations across variable loading and PV generation.

- Pure neural surrogates may demand substantial training data and degrade outside sampled operating points.

- A small voltage bias near 0.95 p.u. can change the operational classification.

Research Objective

- Predict minimum feeder voltage and total active power loss.
- Combine inexpensive linearized distribution-flow physics with a compact neural correction.
- Compare against the physics-only baseline and direct neural regression.

Core Physics-Guided Idea

$$\hat{y} = y_{LDF} + f_\theta(z)$$

- Compute linearized distribution-flow estimate y_{LDF} from the operating point.
- Learn the residual between AC power flow and this inexpensive baseline.
- At inference: correct the physical estimate instead of predicting the entire mapping from scratch.

Benchmark and Data

- 33-bus radial feeder; 12.66 kV and 100 MVA bases.
- 5,200 sampled loading and photovoltaic scenarios; fixed 2,000-scenario test set.
- Training-set sizes: 200, 500, 1,000 and 2,500 scenarios.
- Photovoltaic injections at buses 6, 18, 25 and 30.

Learning Setup

- Residual network: two tanh hidden layers with 48 and 24 units.
- Direct neural comparison: two tanh hidden layers with 64 and 32 units.
- Standardized features and targets; Adam, L2 regularization, early stopping.
- Low-voltage decision rule: $V_{min} < 0.95$ p.u.

Nominal Test Results — 1,000 Training Scenarios

Method	Vmin MAE (p.u.)	Loss MAE (kW)	Class accuracy
Linearized physics	0.002788	15.738	99.15%
Direct neural	0.001276	5.011	99.35%
Physics-guided residual	0.000072	0.573	99.95%

Improvement over Direct Neural Learning

Smaller prediction errors with a simpler correction task

- 94.38% reduction in minimum-voltage MAE.
- 88.57% reduction in active-loss MAE.
- Physics baseline captures first-order network behavior; neural network focuses on nonlinear approximation error.

Sample Efficiency

Training cases	Direct V MAE	Residual V MAE	Residual loss MAE
200	0.002394	0.000192	1.642 kW
500	0.001672	0.000121	1.113 kW
1,000	0.001276	0.000072	0.573 kW
2,500	0.000873	0.000051	0.440 kW

Voltage-Limit Classification

- 2,000 test cases; 1,748 true low-voltage cases.
- 1,747 true positives, 1 false negative, 0 false positives and 252 true negatives.
- Precision: 100%; recall: 99.94%; overall accuracy: 99.95%.
- The remaining false negative occurs very close to the 0.95 p.u. threshold.

Near-Limit Example

- True AC minimum voltage at bus 33: 0.949982 p.u.
- Linearized baseline predicts 0.951027 p.u.
- Residual model predicts 0.950059 p.u.—much closer, but still just above the security threshold.
- Use a guard band and run full AC power flow near the decision boundary.

Recommended Hybrid Screening

- Predicted Vmin > 0.955 p.u.: accept the screening result.
- 0.945–0.955 p.u.: run full AC power flow.
- Predicted Vmin < 0.945 p.u.: flag low voltage.
- Unseen features or topology changes: rerun full analysis and revalidate/retrain.

Sensitivity to Parameter Mismatch

Impedance scale	Vmin MAE (p.u.)	Loss MAE (kW)	Class accuracy
0.95	0.004415	10.303	96.75%
1.00	0.000072	0.573	99.95%
1.05	0.004450	10.420	97.90%
1.10	0.008950	21.082	95.40%

Limitations and Future Research

- Findings apply to one balanced radial benchmark with simulated data.

- Topology changes, incorrect line parameters, noise and larger reverse-flow conditions require evaluation.

- Extend to unbalanced three-phase feeders, switching topologies and uncertainty-aware guard bands.

Conclusions

Approximate physics → learned correction → safeguarded screening

• A low-cost physical approximation and a compact residual neural network complement each other.

• At 1,000 training samples: 0.000072 p.u. voltage MAE and 0.573 kW loss MAE.

• 99.95% voltage classification accuracy—but a solver fallback remains vital near security limits.