Comparative Assessment Of Standalone Evolutionary And Hybrid Optimization Techniques For The IEEE 33-Bus Radial Distribution System

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Abstract

This study compares standalone evolutionary algorithms and a hybrid machine learning-evolutionary framework for feeder reconfiguration in the IEEE 33-bus radial distribution system. Using simulations under varying load conditions, the hybrid framework reduced real power loss by 59.34% and improved the minimum bus voltage to 0.982 p.u., outperforming the best standalone optimizer (Grey Wolf Optimization).

Keywords: comparative optimization; IEEE 33-bus feeder; hybrid model; loss reduction; voltage improvement; feeder reconfiguration

1. Introduction

Distribution system reconfiguration is a practical operational strategy for reducing technical losses and improving voltage profile in radial distribution networks [27,28,29]. The switching configuration selected during reconfiguration affects branch currents, bus voltages, feeder loading, and the quality of power delivered to customers. A useful reconfiguration method should therefore provide good loss reduction, acceptable voltage improvement, constraint-compliant switching, and reasonable convergence time. [1,2,3,4]

Standalone evolutionary algorithms have been widely applied to feeder reconfiguration because they can handle nonlinear and constrained search problems. Genetic Algorithm, Particle Swarm Optimization, Differential Evolution, and Grey Wolf Optimization can search large switching spaces without requiring a strictly convex mathematical model. Their limitation is that they may require many repeated load flow evaluations before convergence, especially when the number of candidate switching states increases [5,6,7.8].

Machine learning can help reduce this computational burden by learning patterns from simulated or historical feeder operating states. A trained predictive model can identify promising switching regions, weak voltage buses, high-loss branches, and likely feasible configurations before the final optimization search. This gives the optimizer a smaller and better search space to evaluate [9,10,17].

Recent studies have also shown growing interest in deep learning-aided stochastic reconfiguration, reinforcement learning-based feeder reconfiguration, and machine learning-assisted network reconfiguration [11]-[16]. However, many of these works focus on one method or one operating objective. Fewer studies provide a direct comparison between standalone evolutionary algorithms and a hybrid learning-guided evolutionary framework under the same IEEE 33-bus operating assumptions.

However, many existing studies evaluate standalone optimization methods without clearly assessing how machine learning predictions can reduce search burden, improve convergence, and support practical feeder operation under identical operating conditions [23,24,25,26]. This study addresses this gap by integrating predictive machine learning models with evolutionary optimization and comparing the results systematically. These improvements are relevant to real-time feeder reconfiguration and operational decision support. These improvements demonstrate practical utility for real-time feeder reconfiguration, enabling rapid operator decision support. Recent works

[35,34,33] highlight the benefits of integrating predictive ML with heuristic optimization, but few provide a systematic comparison under identical operating conditions, which this study delivers.

The main contribution of this paper is a consistent comparison of standalone evolutionary algorithms and a hybrid machine learning evolutionary framework for IEEE 33-bus feeder reconfiguration. All methods were assessed using the same network data, load flow procedure, operating conditions, and constraints [32,31,30]. The paper also presents the system architecture, individual model architectures, model training procedure, objective functions, and result generation process. This structure improves clarity and makes the comparison easier to reproduce.

2. Materials and Methods

2.1 Test Network and Load Flow Procedure

The IEEE 33-bus radial distribution system was selected as the benchmark test network. The system consists of 33 buses, 32 normally closed sectionalizing branches, and five normally open tie switches used for reconfiguration studies[20,21,22]. The model used bus data, line resistance and reactance values, active and reactive load demands, sectionalizing switches, tie switches, voltage limits, and branch thermal limits.

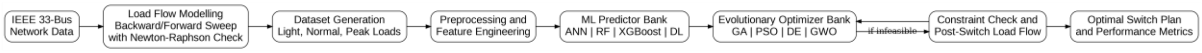

Figure 1. Overall system model architecture

2.2 Objective Functions and Performance Metrics

The optimization objective considered real power loss reduction, voltage deviation reduction, and feasible switch selection. The real power loss objective was computed from branch current and branch resistance values as shown in Equation 1.

$$P\_loss = \Sigma\_(k = 1)\text{^}Nb\ I\_k\text{^}2\ R\_k \quad (1)$$

Voltage deviation was included to encourage voltage profile improvement across the feeder. The voltage deviation term is shown in Equation 2.

$$\Delta V = \Sigma\_(i = 1)\text{^}Nb\ (V\_ref - V\_i)\text{^}2 \quad (2)$$

Data normalization was performed before model training so that features with large numerical ranges did not dominate the training process. Min-Max normalization was applied as shown in Equation 3.

$$x\_norm = (x - x\_min) / (x\_max - x\_min) \quad (3)$$

The predictive models were evaluated using mean square error, root mean square error, and decision accuracy. The error equations are shown in Equations 4 and 5.

$$MSE = (1/n)\ \Sigma\_(i = 1)\text{^}n\ (y\_i - \hat{y}\_i)\text{^}2 \quad (4)$$

$$RMSE = sqrt(MSE) \quad (5)$$

Decision accuracy was computed as the percentage of test cases or repeated optimization runs in which the predicted or selected switching decision agreed with the validated feasible switching label, satisfied all radiality, voltage, and thermal constraints, and achieved loss reduction within the accepted tolerance of the best feasible solution obtained from repeated simulation runs. This definition allowed machine learning and optimization decisions to be compared using the same feasibility-based decision measure.

$$Accuracy = (N\_correct / N\_total) \times 100\% \quad (6)$$

Table 1. Dataset preparation and model training configuration

Item	Description
Test network	IEEE 33-bus radial distribution system with 33 buses, 32 sectionalizing branches, and five tie switches
Dataset source	Load flow simulations generated from the IEEE 33-bus feeder model and repeated switching scenarios
Operating scenarios	Light load 50%, normal load 100%, and peak load 125%
Primary load flow method	Backward/Forward Sweep method for radial feeder analysis
Validation method	Newton-Raphson load flow check, repeated simulation runs, and post-reconfiguration feasibility assessment
Input features	Bus voltage magnitudes, branch currents, active and reactive load demand, feeder loading, switch states, losses, and voltage deviation
Target outputs	Power loss level, voltage condition, switching suitability, and feasible reconfiguration decision
Preprocessing	Data cleaning, duplicate removal, interpolation, Min-Max normalization, and feature engineering
Training and testing split	70% training and 30% testing/validation with cross-validation checks
Operational constraints	Radiality, voltage limits of 0.95 to 1.05 p.u., thermal limits, power balance, and switch operation limits
Evaluation metrics	Real power loss reduction, minimum voltage, iteration count, computation time, MAE, MSE, RMSE, and decision accuracy

2.3 Machine Learning Model Development

Four machine learning models were developed to support feeder operating condition prediction and switching decision support. Their role was to learn nonlinear relationships among load demand, bus voltages, branch currents, losses, and switch states. The outputs were used to screen candidate switching states before the evolutionary search stage.

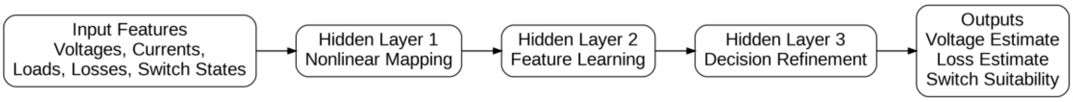

Figure 2. Artificial Neural Network architecture

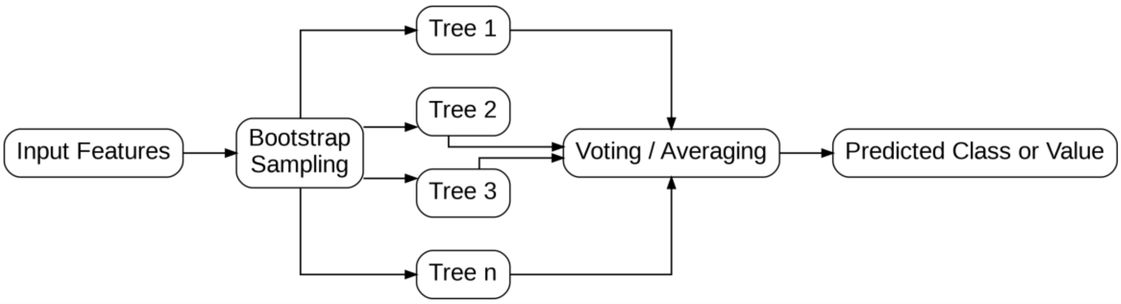

Figure 3. Random Forest architecture

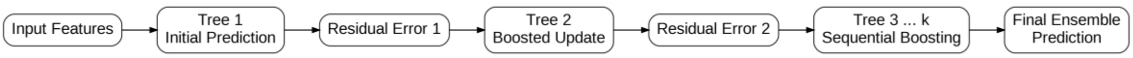

Figure 4. XGBoost architecture

Figure 5. Deep learning model architecture

Table 2. Training summary of the machine learning models

Model	Accuracy (%)	MAE	MSE	RMSE	Key training setting	Training time (s)
ANN	93.42	0.024	0.012	0.109	120 epochs, backpropagation, sigmoid activation	18.4
Random Forest	95.18	0.019	0.009	0.095	150 trees, bootstrap aggregation	15.7
XGBoost	97.36	0.012	0.005	0.071	85 boosting iterations, learning rate 0.10	12.6
Deep Learning	98.54	0.008	0.003	0.055	100 epochs, Adam optimizer, ReLU activation	21.3

Table 3. Model hyperparameters and optimization settings

Note: Hyperparameter values were selected through preliminary simulation trials and literature-guided settings, then kept constant across all comparative runs to ensure fair evaluation. The same stopping criteria, load flow tolerance, and constraint checks were applied to all evolutionary methods. These hyperparameter values were determined through preliminary simulation trials and literature guidance to ensure fair comparisons.

Algorithm or model	Key settings used in the study
Genetic Algorithm	Population size 50, crossover rate 0.80, mutation rate 0.10, maximum iterations 50, elitist replacement
Particle Swarm Optimization	Swarm size 30, inertia weight 0.70, acceleration constants c1 = 1.50 and c2 = 1.50, maximum iterations 50
Differential Evolution	Population size 40, mutation factor 0.80, crossover rate 0.90, maximum iterations 50
Grey Wolf Optimization	Wolf pack size 30, linearly decreasing control parameter, maximum iterations 50
Artificial Neural Network	Input features from feeder data, three hidden layers of 32, 16, and 8 neurons, sigmoid activation, learning rate 0.001, batch size 32, 120 epochs
Random Forest	150 trees, maximum depth 10, bootstrap sampling, feature subset selection at each split
XGBoost	85 estimators, maximum depth 6, learning rate 0.10, subsampling ratio 0.80, regularized gradient boosting
Deep Learning	Dense layers of 64, 32, and 16 neurons, ReLU activation, dropout 0.20, Adam optimizer, learning rate 0.001, batch size 32, 100 epochs

2.4 Evolutionary Optimization Models

Each optimization algorithm represented a candidate feeder switching configuration as a feasible or near-feasible search solution. Fitness evaluation was performed by load flow analysis. Candidate solutions that violated radiality, voltage, thermal, or power balance constraints were penalized and rejected during the search.

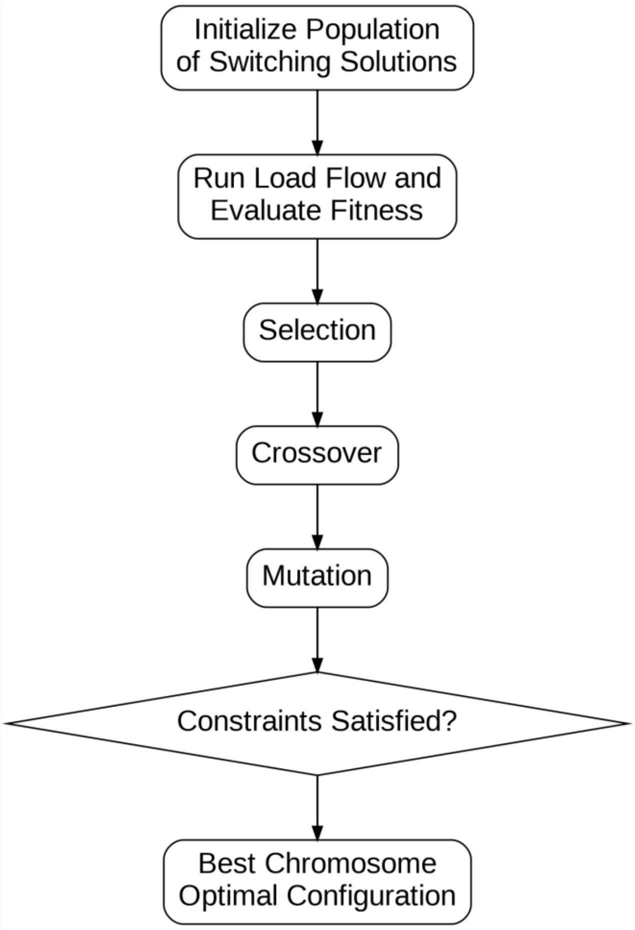

Figure 6. Genetic Algorithm workflow

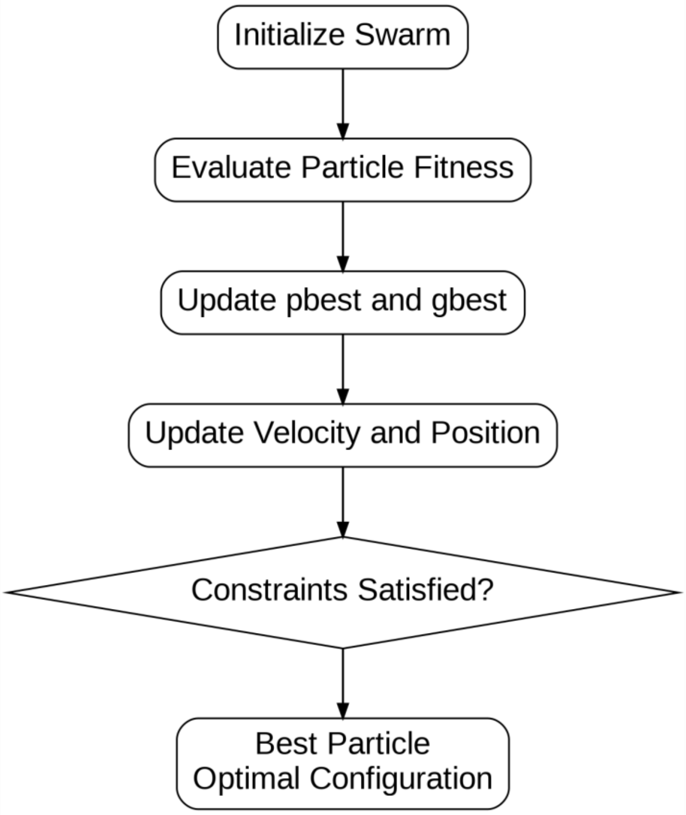

Figure 7. Particle Swarm Optimization workflow

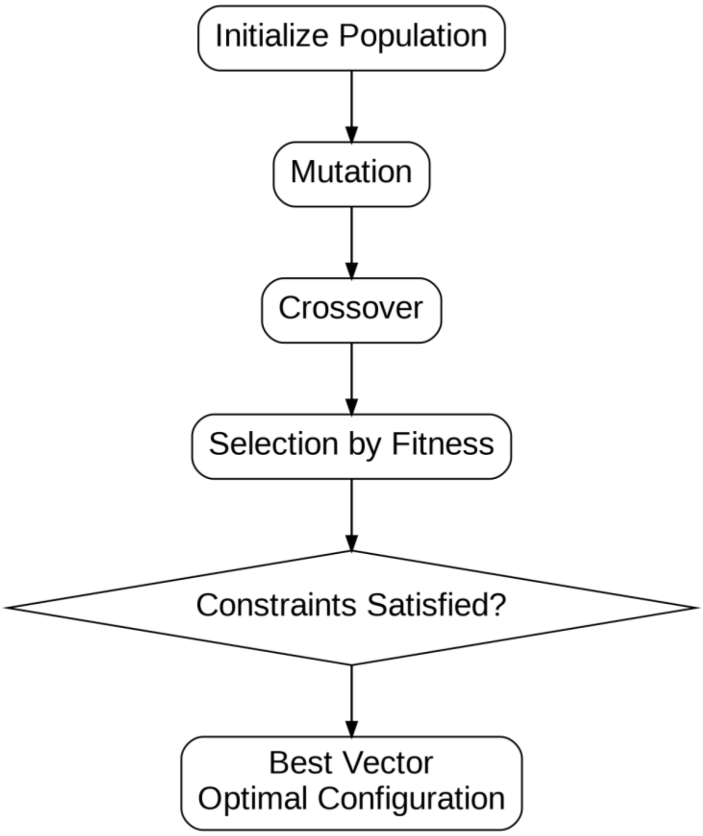

Figure 8. Differential Evolution workflow

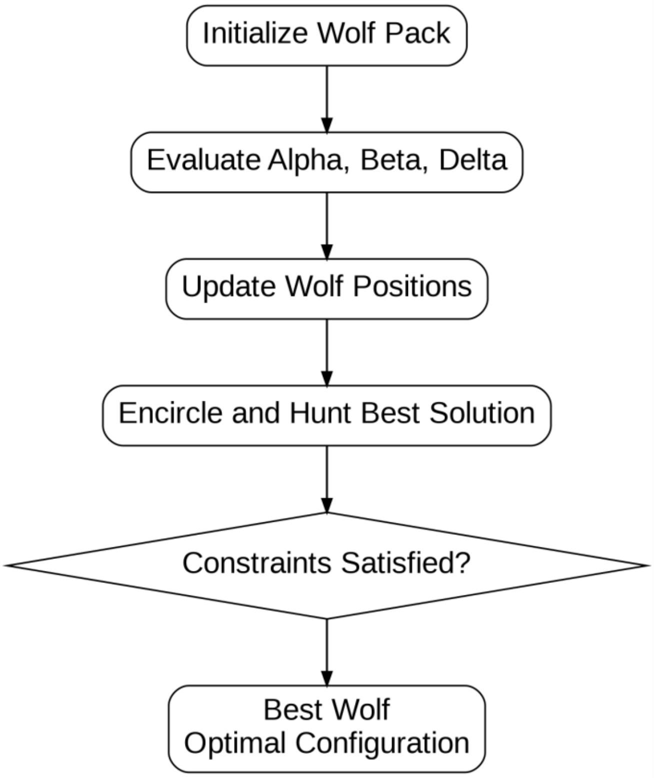

Figure 9. Grey Wolf Optimization workflow

2.5 Hybrid ML-Evolutionary Framework

The hybrid framework integrated machine learning prediction and evolutionary optimization. The machine learning layer first predicted feeder operating conditions and switching suitability. The prediction output reduced the search space by removing poor or infeasible switching candidates before the final optimization stage. The evolutionary optimizer then searched the reduced candidate space and selected the best feasible switching configuration after load flow validation.

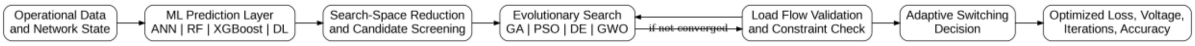

Figure 10. Hybrid ML-evolutionary architecture

The training and result generation procedure followed a single sequence for all methods. This helped ensure that the observed performance differences were caused by algorithmic behaviour rather than by inconsistent input data or evaluation conditions.

Figure 11. Training and evaluation procedure

2.6 Validation and Reproducibility Procedure

The validation process was designed to ensure that the reported results were caused by algorithmic performance rather than inconsistent simulation settings. First, the base case load flow result was established using the original IEEE 33-bus feeder configuration. Second, post-reconfiguration load flow analysis was repeated for every selected switching state. Third, infeasible candidates were rejected when radiality, voltage, thermal, or power balance constraints were violated. Fourth, all algorithms were evaluated under the same loading scenarios, objective function, and maximum iteration limit. Finally, the hybrid result was compared against the best standalone result to confirm the performance gain in loss reduction, voltage improvement, convergence speed, and computation time.

3. Results and Discussion

3.1 Base Case Result

The base case load flow analysis produced 202.67 kW real power loss and 135.14 kVAr reactive power loss. The minimum voltage was 0.913 p.u. at Bus 18. This confirmed that the original network condition had weak voltage buses and considerable technical losses before reconfiguration.

3.2 Optimal Switching Configuration

The hybrid framework selected the switching configuration shown in Table 4. The selected configuration was validated by post-reconfiguration load flow. The final network preserved radiality and satisfied the voltage and thermal limits. This means that the switching decision was not accepted only because it reduced losses; it was accepted because it produced a feasible radial operating state.

Table 4. Optimal switching configuration obtained from the hybrid framework

Switch type	Switch number	Final status
Sectionalizing switch	S7	Closed
Sectionalizing switch	S14	Closed
Sectionalizing switch	S28	Closed
Tie switch	T33	Closed
Tie switch	T35	Closed
Tie switch	T37	Open

3.3 Comparative Performance of the Optimization Methods

The same test system, load flow model, operating conditions, objective function, and constraints were used for all compared methods. The comparison therefore reflects the behaviour of the algorithms under a common evaluation condition.

Table 5. Comparative analysis of optimization methods

Method	Loss reduction (%)	Minimum voltage (p.u.)	Iterations	Accuracy (%)
Genetic Algorithm	30.26	0.947	42	93.42
Particle Swarm Optimization	36.73	0.956	31	95.18
Differential Evolution	40.21	0.961	28	97.36
Grey Wolf Optimization	43.54	0.968	24	98.54
Hybrid ML-Evolutionary Model	59.34	0.982	16	99.12

Table 6. Computation time comparison

Method	Computation time (s)
Genetic Algorithm	18.4
Particle Swarm Optimization	15.2
Differential Evolution	13.8
Grey Wolf Optimization	12.4
Hybrid ML-Evolutionary Model	8.7

Table 5 shows that Grey Wolf Optimization was the best standalone method, with 43.54% real power loss reduction and 0.968 p.u. minimum voltage. The hybrid model improved real power loss reduction to 59.34%, which represents a 15.80 percentage point improvement over Grey Wolf Optimization. It also reduced the iteration count from 24 to 16. Table 6 confirms that the hybrid framework required the lowest computation time at 8.7 s, compared with 12.4 s for Grey Wolf Optimization and 18.4 s for Genetic Algorithm. These results support the claim that predictive search-space reduction improved both solution quality and computational efficiency.

3.4 Voltage Profile Improvement

Voltage improvement was observed across the weak and representative buses after hybrid reconfiguration. The most notable improvement occurred at Bus 18, where the voltage increased from 0.913 p.u. to 0.982 p.u.

Table 7. Hybrid voltage profile improvement

Bus	Base voltage (p.u.)	Hybrid voltage (p.u.)
Bus 5	0.975	0.989
Bus 10	0.956	0.984
Bus 15	0.944	0.983
Bus 18	0.913	0.982
Bus 20	0.918	0.981
Bus 25	0.927	0.983
Bus 30	0.936	0.985
Bus 33	0.942	0.986

3.5 Discussion

The hybrid model outperformed the standalone methods because the machine learning stage reduced the number of low-quality switching candidates passed to the optimizer. This lowered the number of unnecessary load flow evaluations and allowed the evolutionary search to focus on promising feasible regions. The improvement in computation time shows that the hybrid model did not simply improve the final result; it also improved the route taken to reach the result.

The standalone methods also showed useful behaviour. Genetic Algorithm gave a clear improvement over the base case but converged more slowly because crossover and mutation required many candidate evaluations. Particle Swarm Optimization improved convergence through collective particle movement, but it can lose diversity when particles move too quickly toward the same region. Differential Evolution produced stable convergence because mutation and crossover preserve population diversity. Grey Wolf Optimization produced the strongest standalone result because its leadership hierarchy gives a practical balance between exploration and exploitation, helping it avoid premature convergence better than the other standalone methods in this study.

The practical implication is that standalone algorithms may be adequate for offline planning studies, while the hybrid model is more suitable when faster operational decision support is required. A distribution utility can use the hybrid framework as a screening layer that identifies feasible switching actions before operator approval or automated implementation. This can help operators prioritize low-loss, voltage-secure, and constraint-compliant switching decisions under changing load conditions.

4. Limitations of the Study

The study was based on IEEE 33-bus benchmark simulations. Real utility feeder data were not fully used for field validation. Switching transients, protection coordination, communication delays, and the economic cost of switching operations were not modelled. The study also did not test scalability on larger practical feeders or hardware-in-the-loop distribution management systems. Future work should validate the framework with real feeder data, larger networks, distributed energy resources, and online operator-in-the-loop implementation.

5. Conclusion

This paper compared standalone evolutionary optimization methods and a hybrid machine learning-evolutionary framework for IEEE 33-bus feeder reconfiguration. The paper presented the system architecture, model architectures, dataset preparation, hyperparameter settings, validation procedure, and comparative results. The hybrid framework achieved the best overall performance by combining predictive learning with evolutionary search. The results confirm that machine learning can reduce search burden and improve feeder reconfiguration outcomes when it is integrated with constraint-checked evolutionary optimization.

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