**Journal of Emerging Innovations in Engineering (JEIE)**
Volume 2, Number 01, February 2026
ISSN: 3110-3375
Open Access: https://jurnal.sutajaya.org/jeie

# Self-organizing map based adaptive protection scheme for IEEE benchmark networked microgrids: a comprehensive framework for multi-modal operation

Arun Kumar[1*]

Vellore Institute of Technology, Vellore India
*Email: [1]arunkumar.e2023@vitstudent.ac.in*

**Article Info**

*Received December 12th, 2025*
*Revised January 19th, 2026*
*Accepted February 16th, 2026*

***Keywords:***
*Networked microgrids; Self-organizing map; Adaptive protection; IEEE benchmark system; Protection coordination; Distributed generation.*

***DOI:***
https://doi.org/10.65664/jeie.v2i01.17
*Page 43 – 49*

***Correspondent Author:***
*Arun Kumar*
*Email:*
*[1]arunkumar.e2023@vitstudent.ac.in*

## ABSTRACT

Purpose — This study introduced an innovative adaptive protection scheme for networked microgrids (NMGs) utilizing the Self-Organizing Map (SOM) clustering technique, which addressed significant challenges in coordinating protection across multiple microgrids.
Methodology— The SOM-based framework autonomously classified eight distinct NMG operating conditions and adjusted relay settings in real time. The methodology was thoroughly validated on the IEEE benchmark test system for networked microgrids through PSCAD/EMTDC simulations under normal, fault, disturbance, and emergency scenarios.
Findings — The proposed scheme demonstrated a classification accuracy of 94.7% on test data, reduced fault clearing times by an average of 34.3%, decreased miscoordination events by 45%, and enhanced the overall protection reliability index by 10.7% compared to traditional overcurrent protection.
Practical Implications — The framework encompassed hardware specifications, commissioning procedures, and an economic analysis, revealing a 1.75-year payback period, thereby offering a feasible roadmap for real-world implementation.
Originality/Value — This represented the first comprehensive implementation and validation of SOM-based adaptive protection on the standardized IEEE benchmark NMG system, encompassing all major operating modes and transition states within a unified framework.

## INTRODUCTION

The rapid proliferation of distributed energy resources (DERs) and the transition toward smart grid technologies have elevated networked microgrids (NMGs) as a critical architecture for enhancing power system resilience, efficiency, and renewable energy integration. NMGs consist of interconnected clusters of microgrids capable of autonomous or coordinated operation with the main grid, offering improved reliability and economic optimization.

However, protecting NMGs presents challenges that conventional schemes cannot adequately address. Fault current magnitudes vary dramatically across operating modes — from 8–15 kA in grid-connected operation down to 0.5–2.0 kA when inverter-based resources dominate islanded grids (IEEE Power and Energy Society, 2017). Bidirectional power flows, dynamic topology changes, and multiple concurrent operating modes further complicate protection coordination, rendering traditional time-current grading approaches unreliable (Ghadiri & Mazlumi, 2020; Mirsaeidi et al., 2019).

Machine learning techniques have emerged as promising tools for adaptive protection. Among these, the Self-Organizing Map (SOM) — an unsupervised neural network introduced by Kohonen (2001) — offers particular advantages: it classifies high-dimensional operating states without prior labeling, preserves topological structure, operates robustly under noisy conditions, and can be updated online. Ghadiri and Mazlumi (2020) demonstrated SOM's viability in single-microgrid protection; however, no prior work has applied SOM comprehensively to a standardized multi-microgrid benchmark.

This paper fills that gap by presenting and validating a complete SOM-based adaptive protection framework for NMGs using the IEEE benchmark test system (IEEE Power and Energy Society, 2017). The principal contributions are: (i) a novel SOM-based protection architecture tailored for multi-modal NMG operation; (ii) the first comprehensive validation on the IEEE benchmark NMG system covering all relevant operating scenarios; (iii) a systematic eight-class taxonomy of NMG operating states with associated protection setting groups; and (iv) a practical implementation framework including hardware requirements, commissioning procedures, and economic analysis.

The remainder of this paper is structured as follows. Section 2 describes the IEEE benchmark NMG system and its protection challenges. Section 3 presents the SOM-based protection methodology. Section 4 details the simulation study design. Section 5 reports and analyses the results. Section 6 concludes with practical implications and future research directions.

## IEEE Benchmark Networked Microgrid System

### System Architecture and Components

The IEEE benchmark test system for networked microgrids (IEEE Power and Energy Society, 2017) comprises four interconnected microgrids (MG1–MG4), each capable of autonomous or networked operation. Voltage levels span 33 kV (main grid), 11 kV (microgrid distribution), and 400/230 V (end-user). Each microgrid hosts solar PV (1–2.5 MW), wind turbines (1.5–2.5 MW), battery energy storage (2–4 MWh), and optionally diesel or CHP backup generation, resulting in 60–80% renewable penetration. Peak demands range from 3.8 to 4.5 MW per microgrid at power factors between 0.85 and 0.95 lagging. Microgrids are connected via tie-lines, individual points of common coupling (PCCs) to the main grid, and an IEC 61850-compliant communication network.

### Operating Modes and Protection Challenges

Three primary operating modes exist for each microgrid: (1) grid-connected mode, with high fault current availability (8–15 kA) and conventional overcurrent coordination applicable; (2) islanded mode, where inverter current limiting constrains fault currents to 0.5–2.0 kA and voltage/frequency-based elements become essential; and (3) networked mode, with variable fault currents (2–8 kA) depending on the real-time topology. The combination of these modes across four microgrids produces a complex state space that must be managed continuously by the protection system.

Conventional inverse-time overcurrent relays, set for a fixed topology and fault current level, suffer systematic miscoordination as operating conditions change. Field studies have reported margin violations exceeding 12% of event records in comparable systems, motivating the adaptive approach presented here.

### Existing Protection Architecture

The benchmark system employs a three-level protection hierarchy: primary directional overcurrent relays (50/51) and distance elements (21) at Level 1; time-delayed overcurrent, under/over-voltage, and frequency relays at Level 2; and emergency load-shedding and intentional islanding schemes at Level 3. Baseline primary settings use a 1.25 × I_rated pickup with IEC standard-inverse curves and 200–400 ms coordination intervals — settings optimised for grid-connected operation and inadequate for islanded or transition states.

.

# RESEARCH METHODS

## SOM-Based Adaptive Protection Methodology

### SOM Algorithm and Feature Vector

The SOM maps a d-dimensional input vector $x(t)$ onto a two-dimensional neuron grid whose weights $w_{ij}(t)$ are updated competitively. The Best Matching Unit (BMU) is identified as BMU = $(i,j)$ argmin $\|x(t)-wij(t)\|$, and weights are updated according to $w_{ij}(t+1) = w_{ij}(t) + \alpha(t)\cdot h_{ij,BMU}(t)\cdot[x(t) - w_{ij}(t)]$, where $\alpha(t) = \alpha_0\cdot\exp(-t/\tau_1)$ is the decaying learning rate and $h_{ij,BMU}(t) = \exp(-d^2_{ij,BMU}/2\sigma^2(t))$ is the Gaussian neighbourhood function with decaying radius $\sigma(t) = \sigma_0\cdot\exp(-t/\tau_2)$.

The 24-element feature vector x contains: (a) RMS voltage magnitudes and unbalance factors at critical buses; (b) RMS feeder currents and sequence components; (c) active/reactive power flows and power factors; (d) frequency deviation $\Delta f$ and rate-of-change of frequency (ROCOF); (e) binary DER operational indicators and circuit-breaker positions; and (f) energy storage state-of-charge. All elements are normalised to [0, 1] using min-max scaling, and a moving-average pre-filter reduces measurement noise. The vector is computed every fundamental-frequency cycle (50 ms).

### Network Architecture and Training

A 12×12 rectangular SOM (144 neurons, periodic boundary conditions) was selected after ablation studies balancing classification resolution against computational cost. Training employed 35,000 samples (70% of the 50,000-sample dataset) with parameters $\alpha_0 = 0.8$, $\sigma_0 = 6.0$, $\tau_1 = \tau_2 = 1000$, and 5,000 epochs; convergence was reached at epoch 3,847. The remaining samples were split 20/10% for validation and test. Training required 45.7 minutes on an Intel i7-10700K workstation; real-time classification takes 1.2 ms per cycle.

### Operating-Condition Classification and Setting Groups

SOM clustering identifies eight classes: Class 1 — Grid-Connected Normal (GCN); Class 2 — Grid-Connected Heavy Load (GCHL); Class 3 — Islanded Single MG (ISM); Class 4 — Islanded Multiple MG (IMM); Class 5 — Networked Normal (NN); Class 6 — Networked Emergency (NE); Class 7 — Transition Grid-to-Island (TGI); and Class 8 — Transition Island-to-Grid (TIG). Each class is mapped to a dedicated protection setting group (Table 1), enabling automatic relay reconfiguration within one fundamental cycle of the classification decision.

**Table 1.** Protection Setting Groups by Operating Class

| Class | Description | Pickup (× I_rated) | TMS | Curve Type | Additional Elements |
|---|---|---|---|---|---|
| 1–2 | Grid-Connected | 1.25 | 0.15–0.30 | IEC Normal Inverse | Directional overcurrent |
| 3–4 | Islanded | 1.10 | 0.05–0.15 | IEC Extremely Inverse | Voltage (0.8–1.2 pu), Freq (±1.5 Hz) |
| 5–6 | Networked | 0.90–1.30 (adaptive) | Comms-assisted | Adaptive | Peer-to-peer coordination |
| 7–8 | Transition | 1.05 | 0.02–0.10 | Fastest Available | PSB, OOS, synchrocheck |

### System Integration Architecture

The framework operates on three tiers. At the device level, numerical relays (ARM Cortex-A9, 512 MB RAM) execute the pre-trained SOM in firmware, perform feature extraction, and apply the selected setting group. At the microgrid level, a bay controller aggregates local measurements and coordinates intra-microgrid settings via IEC 61850 GOOSE messaging with sub-10 ms latency. At the network level, a SCADA-integrated coordination engine handles inter-microgrid communication, updates the SOM with new training data, and provides a monitoring dashboard. Redundant fibre and wireless links ensure protection continuity under single-link failures.

### Simulation Environment

Electromagnetic transient simulations were performed in PSCAD/EMTDC v4.6 with a 50 µs time step. The SOM was implemented in MATLAB R2022a (Neural Network Toolbox) and interfaced via co-simulation. Communication latencies of 10–50 ms were modelled using OPNET Modeler. All component models were validated against manufacturer data and IEC test-case benchmarks.

### Test Case Categories

Four test categories were defined. Category A (Normal Operation) covers 24-hour operational cycles in all three operating modes, including load/generation variations and planned topology changes. Category B (Fault Conditions) includes symmetrical three-phase, single line-to-ground (SLG), phase-to-phase, and evolving faults at 12 network locations with fault resistances from 0 to 50 Ω. Category C (System Disturbances) addresses large motor starting (6 × I_rated), capacitor bank switching, and generation unit tripping. Category D (Emergency Scenarios) covers unplanned islanding, planned maintenance islanding, and dynamic network reconfiguration. In total, more than 200 simulation scenarios were executed.

## RESULTS AND DISCUSSION

### SOM Classification Performance

The trained network achieved a quantization error of 0.031 and a topographic error of 0.012, confirming good topological preservation. The silhouette coefficient of 0.783 and Davies-Bouldin index of 0.156 indicate well-separated, compact clusters. Table 2 summarises per-class classification performance on the held-out test set.

**Table 2.** Per-Class Classification Accuracy on Test Set

| Class | Description | Precision (%) | Recall (%) | F1-Score (%) |
|---|---|---|---|---|
| 1 | Grid-Connected Normal | 97.2 | 96.8 | 97.0 |
| 2 | Grid-Connected Heavy Load | 94.1 | 95.3 | 94.7 |
| 3 | Islanded Single MG | 96.5 | 94.7 | 95.6 |
| 4 | Islanded Multiple MG | 93.8 | 92.4 | 93.1 |
| 5 | Networked Normal | 92.6 | 93.9 | 93.2 |
| 6 | Networked Emergency | 89.7 | 91.2 | 90.4 |
| 7 | Transition Grid-to-Island | 88.3 | 87.6 | 87.9 |
| 8 | Transition Island-to-Grid | 90.1 | 89.4 | 89.7 |
| Overall | — | — | — | 94.7 |

The most frequent misclassifications occur between Classes 7 and 8 (transition states), which share similar transient signatures. Steady-state classes (1–5) achieve F1-scores above 93%, confirming robust discrimination between the most operationally critical conditions. The overall test accuracy of 94.7% meets the design target of ≥ 90% and is achieved with a 1.2 ms real-time inference time — well within one protection operating cycle.

### Fault Detection and Clearing Performance

Table 3 compares fault clearing times between the proposed SOM-based scheme and conventional fixed-setting overcurrent protection across key fault types and operating modes.

**Table 3.** Fault Clearing Time Comparison (ms)

| Fault Type | Operating Mode | Conventional (ms) | SOM-Based (ms) | Improvement (%) |
|---|---|---|---|---|
| 3-Phase | Grid-Connected | 120 | 78 | 35.0 |
| 3-Phase | Islanded | 180 | 125 | 30.6 |
| 3-Phase | Networked | 150 | 95 | 36.7 |
| SLG | Grid-Connected | 140 | 89 | 36.4 |
| SLG | Islanded | 220 | 145 | 34.1 |
| SLG | Networked | 170 | 108 | 36.5 |
| Phase-Phase | Grid-Connected | 125 | 82 | 34.4 |
| Phase-Phase | Islanded | 195 | 135 | 30.8 |
| Average | — | 162.5 | 107.1 | 34.3 |

The SOM-based scheme reduces average fault clearing times by 34.3%, with the largest gains in networked and islanded modes where conventional settings are most mismatched. The minimum coordination margin improves from 45 ms (conventional) to 156 ms (SOM-based), eliminating the risk of catastrophic simultaneous relay operation that was present in 12.4% of conventional test cases.

**Protection Coordination and Reliability**

Overall protection selectivity improves from 87.6% to 96.8% (+9.2 percentage points). Dependability — the probability of correct operation for in-zone faults — increases from 94.3% to 98.7%, and security — the probability of no false operation — from 91.8% to 97.2%. The composite reliability index (product of dependability and security) rises from 0.866 to 0.959, a 10.7% improvement. Miscoordination events across all 200+ test scenarios are reduced by 45% compared to the conventional baseline.

For high-resistance SLG faults, detection success rates are 100% (0–5 Ω), 96.8% (5–25 Ω), and 89.2% (25–50 Ω), with a false positive rate below 2.1%. During the most challenging scenario — simultaneous unplanned islanding of all four microgrids — the SOM correctly sequences through Classes 1 → 7 → 6 → 4 in 2.5 seconds, triggering only 15.3% load shedding and maintaining frequency deviation within ±2.1 Hz.

Computational Scalability

The total real-time processing pipeline (feature extraction 8.3 ms, SOM classification 1.2 ms, setting calculation 3.7 ms, plus 15–45 ms communication latency) yields an average end-to-end response of 28.2 ms, comfortably within the 100 ms target. Scalability analysis shows O(n^1.12) growth in classification time with network size, enabling extension to 16-microgrid networks with a classification time of 4.9 ms per cycle. Offline retraining time scales at O(n^1.67), requiring approximately 4 hours for a 16-MG system — feasible for periodic overnight retraining.

**Economic Assessment**

Implementation cost for a four-microgrid deployment is estimated at US $667,000, covering digital relay upgrades ($12,000 per device), communication infrastructure ($45,000 per MG), a central monitoring system ($85,000), and commissioning ($25,000). Annual benefits of $382,000 arise from reduced outage costs ($125,000), avoided equipment damage ($85,000), maintenance savings ($32,000), power-quality improvements ($67,000), and ancillary service revenues ($45,000). This yields a simple payback period of 1.75 years and a net present value of $2.1 M over 10 years at a 6% discount rate, confirming strong economic viability.

**Comparison with Related Work**

Existing adaptive protection schemes for NMGs typically rely on communication-assisted overcurrent coordination (Zeineldin et al., 2006) or fixed offline setting groups (Oudalov & Fidigatti, 2009), neither of which provides real-time multi-modal classification. Communication-dependent schemes degrade when link availability drops below 95%, whereas the SOM-based framework falls back gracefully to locally stored class settings. Compared to the ANN-based approach of Ghadiri and Mazlumi (2020) on a single-microgrid platform, the proposed method extends coverage to four interconnected microgrids, adds explicit modelling of transition states (Classes 7–8), and validates on a standardised benchmark enabling reproducible comparison.

## CONCLUSION

This paper has presented, implemented, and comprehensively validated a Self-Organizing Map based adaptive protection scheme for IEEE benchmark networked microgrids. The SOM automatically classifies eight distinct operating conditions covering grid-connected, islanded, networked, and transient states, and maps each to an optimised protection setting group that is applied in real time within one power-frequency cycle.

Simulation results on the IEEE benchmark NMG system demonstrate 94.7% classification accuracy, 34.3% reduction in average fault clearing times, 45% fewer miscoordination events, and a 10.7% improvement in the composite reliability index relative to conventional fixed-setting overcurrent protection. The framework is computationally efficient, scalable to larger networks, robust to communication degradation, and economically attractive with a 1.75-year payback period.

Future work will investigate deep-learning enhancements for improved transition-state discrimination, federated learning to enable distributed SOM retraining without centralising sensitive operational data, hardware-in-the-loop validation on physical relay platforms, and extension to multi-energy system environments where electricity, heat, and gas networks interact. Standardisation pathways through IEC 61850 extensions and IEEE microgrid protection guidelines are also identified as key near-term research priorities.

## REFERENCES

Coffele, F., Booth, C., & Dysko, A. (2015). An adaptive overcurrent protection scheme for distribution networks. IEEE Transactions on Power Delivery, 30(2), 561–568.

Ghadiri, A., & Mazlumi, K. (2020). Adaptive protection scheme for microgrids based on SOM clustering technique. Applied Soft Computing, 88, 1–15. https://doi.org/10.1016/j.asoc.2019.106062

IEEE Power and Energy Society. (2017). IEEE standard for the specification of microgrid controllers (IEEE Std 2030.7-2017). IEEE.

IEEE Standards Association. (2018). IEEE standard for interconnection and interoperability of distributed energy resources with associated electric power systems interfaces (IEEE Std 1547-2018). IEEE.

IEEE Power and Energy Society. (2011). IEEE guide for design, operation, and integration of distributed resource island systems with electric power systems (IEEE Std 1547.4-2011). IEEE.

Jayawarna, N., Wu, X., Zhang, Y., Jenkins, N., & Barnes, M. (2006). Stability of a microgrid. In Proceedings of the 3rd IET International Conference on Power Electronics, Machines and Drives (pp. 316–320). IET.

Kohonen, T. (2001). Self-organizing maps (3rd ed.). Springer.

Mahat, P., Chen, Z., Bak-Jensen, B., & Bak, C. L. (2011). A simple adaptive overcurrent protection of distribution systems with distributed generation. IEEE Transactions on Smart Grid, 2(3), 428–437.

Mirsaeidi, S., Dong, X., & Wang, C. (2019). Towards hybrid AC/DC microgrids: Critical analysis and classification of protection strategies. Renewable and Sustainable Energy Reviews, 107, 229–241.

Oudalov, A., & Fidigatti, A. (2009). Adaptive network protection in microgrids. International Journal of Distributed Energy Resources, 5(3), 201–226.

Sortomme, E., Venkata, S. S., & Mitra, J. (2010). Microgrid protection using communication-assisted digital relays. IEEE Transactions on Power Delivery, 25(4), 2789–2796.

Zeineldin, H. H., Abdel-Galil, T., El-Saadany, E. F., & Salama, M. M. A. (2006). Protective relay coordination for micro-grid operation using particle swarm optimization. In Proceedings of the IEEE Large Engineering Systems Conference on Power Engineering (pp. 152–157). IEEE.