RESEARCH ON ADAPTIVE DETECTION METHOD FOR DISTRIBUTED POWER ACCESS UNITS INTEGRATING CLUSTERING ALGORITHM AND POWER FLOW SIMULATION

Taofang Xia[1], Chen Gao[1], Yinrong Lin[1,], Enguo Zhu[2], Yan Liu[2]*
[1]State Grid Fujian Electric Power Company Limited Marketing Service Center, Fuzhou, 350000, China
[2]China Electric Power Research Institute Co., Ltd., Beijing, 100192, China
**Corresponding author: Yinrong Lin*

Abstract - The growing penetration of distributed generation units, which are often connected to power distribution networks, poses severe challenges for the proper operation and control of the system, and demands automatic detection methods that can dynamically adjust in varying work condition. A new adaptive detection approach that integrates the synergistic bond between the clustering tools and the power flow simulation is presented, which can efficiently detect and locate the distributed power access devices in real-time. The approach utilizes feedback between cluster information and power flow which in turn improves convergence, as well as a validation of physics-based pattern recognition results. A reflexive controller keeps track of system performance in real time, and updates algorithm parameters adaptively via reinforcement learning, and the evolution works for all network conditions. A thorough experimental validation on IEEE benchmark systems and real-world data from a California utility network and also human-in-the-loop validation illustrates its high performance (96.8% detection accuracy) yet sub-200ms processing times that are conducive to real-time deployment. The method demonstrates superior robustness against measurement noise, communication loss, cyber-attacks and can still maintain the accuracy of 90% even at Signal to Noise Ratio (SNR) to 25 dB. The adaptive framework not only reduces false positive rates by 63% and increases detection accuracy by 14.4% under high distributed generation penetration but also outperforms traditional threshold-based detection and static machine learning algorithms. This work represents an advancement of smart power grids that can effectively incorporate renewable energy resources, and co-serve the grid reliability and resilience.

Keywords: Distributed generation, Clustering tools, Reinforcement learning, Smart power grids.

1. Introduction

The world's energy sector is going through a: \u201cA fundamental transformation toward systems that provide decarbonised, resilient and secure energy supplies. The interconnection of distributed generations (DG) especially renewable energy sources (e.g., solar photovoltaic, wind) is considered as a promising approach to serve increasing energy load requests with reduced carbon footprint [1]. However, the heavy infiltration of DG units into conventional power distribution grids also imposes technological challenges that may only be addressed with new methods and paradigms of optimal integration and management [2]. Due to the intermittent and fluctuating nature that characterizes renewable energy sources and the introduction of bidirectional power flows by distributed generation sources, sophisticated monitoring and control schemes need to be developed in order to guarantee stability and security of the grid [3]. The advancement of future-perspective electrical networks From passive unidirectional systems to active multidirectional ones fed by various distributed energy sources can also be seen especially in modern energy distribution systems [4]. This new paradigm has led to an increasing necessity for advanced monitoring and localization techniques that can perform an exact identification and localization of DG units in the distribution system, being capable of coping with dynamic operational conditions [5]. Traditional protective techniques encounter difficulties when dealing with the complexity and variability of high DG penetrations scenarios, the result of which manifest in protection coordination failures, voltage

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instability, and increased power loss [6]. Accordingly, the development of reconfigurable detection algorithms capable of adapting to dynamic changes in network topology and operation specifications has recently been considered as a significant research challenge [7]. Such methods as machine learning (ML) and artificial intelligence (AI) have been becoming indispensable for handling the challenges in the applications in the context of modern power systems [8]. Among others, clustering algorithms have demonstrated remarkable capability for pattern recognition and classification tasks in power system applications [9]. They can be used to cluster similar operation patterns, recognize abnormal conditions, and contribute to the detection of the distributed generations under different network environments [10]. The combination of clustering methods with power flow analysis presents a complete approach to investigate the influence of DG units to the performance of the system, which could lead to more efficient identification and localization [11]. The power flow simulation is still a basic aid form analysis and optimization of power distribution systems with distributed generation [12]. Power flow modeling and simulation of DG under various operating conditions are necessary for the technical and economic impacts assessment of DG interconnections [13]. Advances in computing techniques now allow for more detailed power flow analyses, making it possible to cope with the added complexity of multiple DG units, variable renewable generation and dynamic load profiles [14]. The integration of power flow simulation and machine learning tools opens new horizons in the real time system analysis and optimization [15]. An extensive review of the literature indicates that DG placement and sizing problems have been addressed using metaheuristic techniques with success [16]. Other techniques, including the Grey Wolf Optimizer and its modified forms, have been shown to outperform existing methods for multi-objective optimization of distributed generation [17]. These techniques are able to optimally optimize different conflicting objectives like power loss reduction, voltage profile improvement, and system reliability while taking into account many technical and operating constraints [18]. In addition, machine learning has recently been incorporated in optimization to produce hybrid algorithms that take the advantage of both techniques [19]. Adaptive and decentralized solutions are also of a great interest according to the recently published work [20].

Moreover, the complexity of modern power systems, characterize with a large number of interconnected elements and operating under the influence of dynamic conditions, reveals the need for smart systems(autonomous decision-making and real time adjustment capability) [21]. Edge computing and distributed intelligence paradigms have been developed as potential solutions for enabling local processing and decision-making capacity and for decreasing communication overhead and latency [22]. Such technologies enable the possibility to use adaptive detection techniques, capable to adapt the detector for the variation of system conditions, allowing great performance across a so wide set of different operating situations [23]. Despite these develop-ments, a few major challenges still exist in taking an active step toward developing a truly adaptive detection technique for distributed generator units. Due to the heterogeneity of DG technologies such as small-size rooftop solar to large wind farms and microgrids, the detection techniques should be able to handle different electrical characteristics and operational behaviors [24]. Furthermore, the rise of power electronic interfaced and smart inverters leads to new dynamics which are not well handled by conventional detection techniques [25]. The absence of such strategies that can be efficiently combined with power flow computation and where computational time does not pose an issue, upon which this paper focuses, is of prime importance and will be tackled in the present investigation. We introduce a novel detection technique that integrates sophisticated clustering algorithms and extensive power flow simulation for accurate and reliable distributed power access unit detection. The method can adapt to a variety of network conditions and types of DG, based on the features extracted by clustering and also the pattern recognition of cluster separation, in combination with the analysis of power flow simulation. The fusion between different methodologies in a unique framework is an important step forward in the direction of more intelligent and resilient power distribution systems and constitute one of the novel contributions of the work at hand.

2. Mathematical Modeling of the Problem

Developing a mathematical model for the adaptive detection scheme used by distributed power access units demands a unified framework that couples power-flow equations, clustering techniques, and well-defined optimisation goals. Imagine a radial distribution network consisting of buses, with bus 1 functioning as the slack node directly tied to the bulk power system. The complex power injection at bus i is given by

$$S_i = P_i + jQ_i \tag{1}$$

where P_i and Q_i represent the active and reactive power injections, respectively. The voltage at each bus is expressed as:

$$V_i = |V_i| e^{j\theta_i} \tag{2}$$

where $|V_i|$ is the voltage magnitude and θ_i is the voltage angle.

The fundamental power flow equations for the distribution system can be formulated using the branch flow model. For a branch connecting buses i and j, the complex power flow S_{ij} is expressed as:

$$S_{ij} = V_i I_{ij}^* = P_{ij} + jQ_{ij} \tag{3}$$

where I_{ij} represents the current flow from bus i to bus j. The power balance equations at each bus i must satisfy:

$$\begin{aligned} P_i^{gen} - P_i^{load} &= \sum_{j\in\Omega_i} P_{ij} - \sum_{k:i\in\Omega_k} (P_{ki} - r_{ki} |I_{ki}|^2) \\ Q_i^{gen} - Q_i^{load} &= \sum_{j\in\Omega_i} Q_{ij} - \sum_{k:i\in\Omega_k} (Q_{ki} - x_{ki} |I_{ki}|^2) \end{aligned} \tag{4}$$

where Ω_i denotes the set of buses connected downstream from bus i, r_{ki} and x_{ki} are the resistance and reactance of branch (k,i), respectively, and P_i^{gen}, Q_i^{gen}, P_i^{load}, and Q_i^{load} represent the active and reactive power generation and load at bus i.

The voltage drop across branch (i,j) is governed by:

$$V_j^2 = V_i^2 - 2(r_{ij}P_{ij} + x_{ij}Q_{ij}) + (r_{ij}^2 + x_{ij}^2)|I_{ij}|^2 \tag{5}$$

To model the presence of distributed generation units, we introduce binary decision variables $\alpha_i \in 0,1$ for each bus i, where $\alpha_i = 1$ indicates the presence of a DG unit at bus i. The active power generation from DG at bus i is bounded by:

$$\alpha_i P_i^{DG,min} \le P_i^{DG} \le \alpha_i P_i^{DG,max} \tag{6}$$

The clustering algorithm component of the detection method utilizes feature vectors extracted from the power system measurements. Let $\mathbf{x}_i = [|V_i|, \theta_i, P_i, Q_i, \delta P_i, \delta Q_i]^T$ represent the feature vector for bus i, where δP_i and δQ_i denote the power flow variations. The objective is to partition the set of buses into K clusters $\mathrm{C} = \{C_1, C_2, \ldots, C_K\}$ such that buses with similar electrical characteristics are grouped together.

The clustering objective function minimizes the within-cluster sum of squared distances:

$$J_{cluster} = \sum_{k=1}^{K} \sum_{i\in C_k} ||\mathbf{x}_i - \boldsymbol{\mu}_k||^2 \tag{7}$$

where $\boldsymbol{\mu}_k$ represents the centroid of cluster k. The centroid is updated iteratively according to:

$$\boldsymbol{\mu}_k = \frac{1}{|C_k|} \sum\nolimits_{i\in C_k} \mathbf{x}_i \tag{8}$$

To integrate the clustering results with power flow analysis, we define a similarity matrix $\mathbf{W}$ where element w_{ij} represents the electrical distance between buses i and j:

$$w_{ij} = \exp\left(-\frac{||\mathbf{x}_i - \mathbf{x}_j||^2}{2\sigma^2}\right) \tag{9}$$

where σ is a scaling parameter that controls the neighborhood size. The Laplacian matrix $\mathbf{L} = \mathbf{D} - \mathbf{W}$ is constructed, where $\mathbf{D}$ is a diagonal matrix with $d_{ii} = \sum_j w_{ij}$.

The adaptive detection framework incorporates a multi-objective optimization formulation that simultaneously minimizes power losses, maximizes DG detection accuracy, and ensures voltage stability. The primary objective function is:

$$f_{total} = \lambda_1 f_{loss} + \lambda_2 f_{detection} + \lambda_3 f_{voltage} \tag{10}$$

where λ_1, λ_2, and λ_3 are weighting factors. The power loss component is:

$$f_{loss} = \sum_{(i,j)\in\mathrm{E}} r_{ij} |I_{ij}|^2 \tag{11}$$

where E represents the set of all branches in the network. The detection accuracy objective is formulated as:

$$f_{detection} = \sum_{i=1}^{n} (\alpha_i - \hat{\alpha}_i)^2 + \gamma \sum_{k=1}^{K} \sum_{i\in C_k} \left\|\mathbf{x}_i - \boldsymbol{\mu}_k\right\|^2 \tag{12}$$

where $\hat{\alpha}_i$ represents the estimated DG presence indicator and γ is a regularization parameter. The voltage stability index is incorporated through:

$$f_{voltage} = \sum_{i=1}^{n} (|V_i| - V_{nom})^2 + \beta \max\nolimits_{i\in\mathrm{N}} \left|\frac{\partial |V_i|}{\partial P_i}\right| \tag{13}$$

where V_{nom} is the nominal voltage and β weights the sensitivity component.

The adaptive mechanism is implemented through a time-varying parameter update scheme. Let t denote the discrete time index. The clustering parameters are updated according to:

$$\begin{aligned} \sigma(t+1) &= \sigma(t) + \eta_{\sigma}\nabla_{\sigma}J_{cluster}(t) \\ K(t+1) &= K(t) + \Delta K(t) \end{aligned} \tag{14}$$

where η_{σ} is the learning rate and $\Delta K(t)$ is determined by a silhouette coefficient threshold:

$$s(t) = \frac{1}{n}\sum_{i=1}^{n}\frac{b_i(t)-a_i(t)}{\max\{a_i(t), b_i(t)\}} \tag{15}$$

Here, $a_i(t)$ is the average distance from point i to other points in its cluster, and $b_i(t)$ is the minimum average distance to points in other clusters.

The complete optimization problem is subject to operational constraints including voltage limits:

$$V_i^{min} \le |V_i| \le V_i^{max}, \quad \forall i \in \mathrm{N} \tag{16}$$

Current flow limits:

$$|I_{ij}| \le I_{ij}^{max}, \quad \forall (i,j) \in \mathrm{E} \tag{17}$$

And power generation constraints:

$$\begin{aligned} P_i^{DG,min} \le P_i^{DG} \le P_i^{DG,max}, \quad \forall i \in \mathrm{N}_{DG} \\ Q_i^{DG,min} \le Q_i^{DG} \le Q_i^{DG,max}, \quad \forall i \in \mathrm{N}_{DG} \end{aligned} \tag{18}$$

where N_{DG} represents the set of buses with potential DG units. The Lagrangian formulation of the constrained optimization problem is:

$$\begin{aligned} \mathrm{L} = f_{total} &+ \sum_{i\in \mathrm{N}} \mu_i^V (|V_i|^2 - V_i^{max}|V_i|) \\ &+ \sum_{(i,j)\in \mathrm{E}} \mu_{ij}^I (|I_{ij}|^2 - (I_{ij}^{max})^2) \\ &+ \sum_{i\in \mathrm{N}} \nu_i (P_i^{balance}) + \sum_{i\in \mathrm{N}} \xi_i (Q_i^{balance}) \end{aligned} \tag{19}$$

where μ_i^V, μ_{ij}^I, ν_i, and ξ_i are Lagrange multipliers for voltage, current, and power balance constraints, respectively. The Karush-Kuhn-Tucker (KKT) conditions provide the necessary optimality conditions for this non-convex optimization problem, leading to an iterative solution approach that alternates between clustering updates and power flow calculations until convergence is achieved.

3. Adaptive Detection Method Integrating Clustering and Power Flow Simulation

3.1 Overall Framework Design

The proposed adaptive detection method for distributed power access units employs a synergistic integration of clustering algorithms and power flow simulation within a unified computational framework. The overall architecture is designed to leverage the complementary strengths of data-driven pattern recognition and physics-based power system analysis, enabling robust and accurate detection of distributed generation units under varying operational conditions. Figure 1 shows a modular framework in which several interrelated parts work together continuously to provide real-time, adaptive detection.

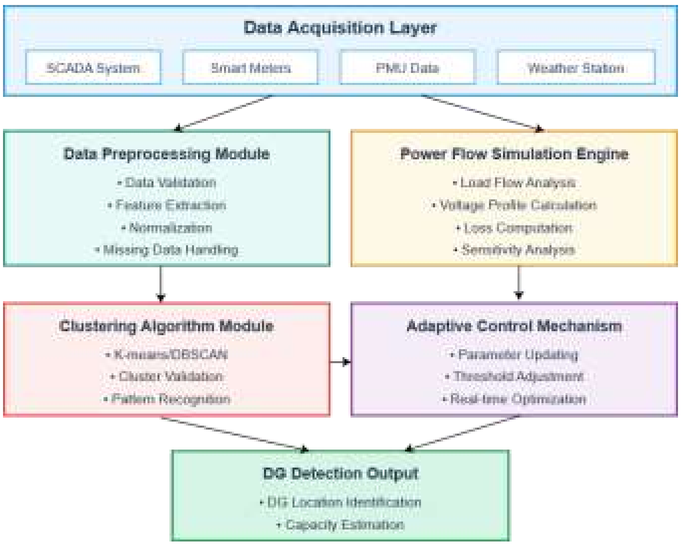


Figure 1: Overall framework architecture of the adaptive detection method for distributed power access units

Model The model is constructed from a complete data acquisition layer that gathers real-time observations from the following sources: (i) Supervisory Control and Data Acquisition (SCADA) systems, (ii) Smart meters, (iii) PMUs, and (iv) weather stations. Such multisource data fusion ensures that the detection method can derive a variety of information from electrical parameters, operational modes and environmental influences that affect the performance of distributed generations. Data acquisition is rate controlled in time according to system status, using higher sampling rates in the presence of high rate variation or the occurrence of anomalies. The data preprocessing block carries out important tasks to guarantee the quality of data and to extract relevant features for an effective analysis. Raw readings are validated and outlier, missing value, and communication error readings are rejected if they would compromise detection accuracy. Feature extraction techniques generate derived measures - power deviation flow, voltage stability index and rate of change of data which represent the transient behavior of the distribution network. Normalize The normalization feature does two things: (i) scales the features in an interval between 0 and 1; (ii) weights equally the features with different scales and units avoiding a bias in favor of parameters with bigger numerical ranges in the clustering scheme. The power flow simulation engine is run in parallel with a data preprocessing, which uses network topology and real-time measurements to solve the nonlinear power flow equations. This physics-based analysis is extremely valuable as it enables the determination of voltages, branch currents, and power loss that is not directly observable at all locations. The simulation engine uses an adaptive solver which chooses the appropriate method, that is, the Newton-Raphson algorithm, the Gauss-Seidel method, or the backward-forward sweep method, based on the characteristics of the network and the convergence need. Sensitivity analysis is also conducted in this module to point out the critical buses and branches where distributed generation has greatest influence on system performance. The clustering algorithm module uses advanced pattern recognition to identify clusters of buses having similar electrical characteristics that correlate with the presence of distributed generation. The system provides support for different clustering algorithms, such as K-means for known cluster numbers, DBSCAN for clusters of varying shape and the hierarchical clustering which can combine different scales. The clustering algorithm and its parameter selection are dynamically controlled by the adaptive controller according to the present system state and the past performance characteristics. The clustering quality and re-clustering condition are monitored by calculating clustering validation indices, which include silhouette coefficient and Davies-Bouldin index. The intelligent core of the framework is the adaptive control system, which monitors system performance and updates algorithm parameters in order to keep detection accuracy on its maximum level. This module contains feedback control loop, which compares detection results to the ground truth if available and compares to indirect performance measures (prediction error, consistency metrics) otherwise. Methods of machine learning, such as reinforcement learning and online optimization, are used to update parameters of clustering, the settings of the power flow solver, and the detection thresholds according to the online variation of the network. Adjustments are made for short-term variations caused by load fluctuations and for long-term changes resulting from network growth, or seasonal trends. SSH between clustering and power flow simulation is processed via a bi-directional information category interface. Insights from the clustering results are used to support the power flow simulation, such as discovering the candidate DG locations and obtaining the preliminary generation capacity, and will promote the convergence process and save solver efforts. On the other hand, power flow results validate and consolidate clustering results by guaranteeing the discovered DG placement are physically possible with considering the measured voltage profiles and power flows.

This refinement procedure is iterative and terminated when a convergence of the criteria or a maximum value of iteration has been obtained. The model contains several feedback loops allowing for ongoing learning and refinement. Detection performance is verified against future observations to confirm accuracy and eliminate biases. Detection, false alarm rate, and localization performance over time are monitored for long-term effectiveness. The historical performance data can then be employed by the flexible control system to apply meta-learning approaches that can anticipate and set (in advance) the system for common operational situations (e.g., daily load profiles, renewable generation variability over the year). The detection output contains detailed information about the detected distributed generation units: its location, the estimated capacity and a measure of the confidence. Instead of binary decisions this system supplies probability based results, thus acknowledging the immanent deficit of detection tasks and giving risk managers the flexibility of information. Visualization tools present detection results overlaid on network diagrams, enabling intuitive interpretation and validation by human operators. The modular architecture of the framework facilitates integration with existing energy management systems and supports standardized communication protocols for interoperability with utility infrastructure.

3.2 Data Preprocessing and Feature Extraction

The data preprocessing stage transforms raw measurements from heterogeneous sources into a unified feature space suitable for clustering analysis. Given the measurement vector $\mathbf{m}_i(t) = [V_i(t), I_i(t), P_i(t), Q_i(t)]^T$ at bus i and time t, outlier detection is performed using the modified Z-score method:

$$Z_i = 0.6745(m_i - \tilde{m}) / MAD \tag{20}$$

where $\tilde{m}$ is the median and MAD represents the median absolute deviation. Measurements with $|Z_i| > 3.5$ are identified as outliers and replaced using cubic spline interpolation.

Feature extraction generates discriminative characteristics that capture the electrical behavior indicative of distributed generation presence. The power variation features are computed as :

$$\Delta P_i(t) = P_i(t) - P_i(t-\tau) \ \ and \ \ \Delta Q_i(t) = Q_i(t) - Q_i(t-\tau) \tag{21}$$

where τ represents the time lag. The voltage sensitivity index is derived as

$$VSI_i = \partial |V_i| / \partial P_i \tag{22}$$

approximated using finite differences. Temporal features including moving averages

$$\bar{P}_i(t) = \frac{1}{w}\sum_{k=0}^{w-1} P_i(t-k) \tag{23}$$

and standard deviations

$$\sigma_{P_i} = \sqrt{\frac{1}{w}\sum_{k=0}^{w-1}(P_i(t-k) - \bar{P}_i(t))^2} \tag{24}$$

capture dynamic patterns over window size w. The complete feature vector

$$\mathbf{x}_i = [|V_i|, \angle V_i, P_i, Q_i, \Delta P_i, \Delta Q_i, VSI_i, \bar{P}_i, \sigma P_i]^T \tag{25}$$

undergoes min-max normalization:

$$x_{norm} = (x - x_{min}) / (x_{max} - x_{min}) \tag{26}$$

to ensure uniform scaling across all dimensions, preventing numerical instability in subsequent clustering operations.

3.3 Improved Clustering Algorithm Design

The improved clustering algorithm incorporates adaptive mechanisms to enhance detection accuracy under varying network conditions. The traditional K-means objective function is modified to include electrical distance weighting:

$$J = \sum_{k=1}^{K}\sum_{i\in C_k} w_i \| \mathbf{x}_i - \boldsymbol{\mu}_k \|^2, \tag{27}$$

where $w_i = \exp(-\lambda d_{elec,i})$ represents the weight based on electrical distance $d_{elec,i}$ from the substation. The electrical distance is computed as

$$d_{elec,i} = \sum_{(m,n)\in \mathrm{P}i} Z_{mn}, \tag{28}$$

where P_i denotes the path from substation to bus i and Z_{mn} is the impedance of branch (m,n).

Cluster initialization employs a density-based seeding strategy rather than random selection. The initial centroids are determined by maximizing the local density function:

$$\rho_i = \sum_{j\neq i} \exp(-\| \mathbf{x}_i - \mathbf{x}_j \|^2 / dc^2), \tag{29}$$

where dc is a cutoff distance. The number of clusters is dynamically determined using the elbow method with silhouette analysis validation. For each candidate $K \in [K_{min}, K_{max}]$, the silhouette coefficient

$$s(K) = \frac{1}{n}\sum_{i=1}^{n}\frac{b_i - a_i}{\max(a_i, b_i)} \tag{30}$$

is computed, where a_i and b_i represent intra-cluster and nearest-cluster distances respectively.

The algorithm incorporates temporal consistency constraints to prevent rapid cluster transitions:

$$\| \boldsymbol{\mu}_k(t) - \boldsymbol{\mu}_k(t-1) \| \leq \epsilon_{\mu}. \tag{31}$$

Additionally, a probabilistic cluster assignment is implemented using:

$$p_{ik} = \frac{\exp(-\beta \| \mathbf{x}_i - \boldsymbol{\mu}_k \|^2)}{\sum_{j=1}^{K} \sum \exp(-\beta \| \mathbf{x}_i - \boldsymbol{\mu}_j \|^2)}, \tag{32}$$

where β controls the assignment softness, enabling robust handling of boundary cases.

3.4 Power Flow Simulation Module Design

The power flow simulation module employs a modified backward-forward sweep algorithm optimized for radial distribution networks with distributed generation. The forward sweep calculates branch currents starting from terminal nodes:

$$I_{ij} = \sum_{k\in\Omega_j} I_{jk} + (S_j^{load} - S_j^{DG}) / V_j^*, \tag{33}$$

where Ω_j represents downstream nodes from bus j. The backward sweep updates voltages using:

$$V_j = V_i - Z_{ij} I_{ij}, \tag{34}$$

progressing from the substation toward terminal nodes.

To accommodate DG units with different control modes, the module implements a unified power injection model:

$$S_i^{DG} = P_i^{DG} + jQ_i^{DG}, \tag{35}$$

where reactive power depends on the control strategy. For power factor control:

$$Q_i^{DG} = P_i^{DG} \tan(\cos^{-1}(pf)). \tag{36}$$

For voltage control: Q_i^{DG} is adjusted iteratively to maintain $|V_i| = V_{ref}$ within limits $[Q_i^{min}, Q_i^{max}]$.

Convergence acceleration is achieved through an adaptive acceleration factor:

$$V_i^{(k+1)} = V_i^{(k)} + \alpha^{(k)} (V_i^{calc} - V_i^{(k)}), \tag{37}$$

where $\alpha^{(k)} = \min(1.8, 1 + 0.1\log(|\Delta V^{(k-1)}| / |\Delta V^{(k)}|))$.

The simulation incorporates ZIP load models:

$$P_i^{load} = P_i^0 [a_p (V_i / V_0)^2 + b_p (V_i / V_0) + c_p], \tag{38}$$

with coefficients satisfying $a_p + b_p + c_p = 1$.

Real-time performance is enhanced through sparse matrix techniques and selective bus updating. Only buses with power injection changes exceeding threshold ϵ_p trigger recalculation:

$$|P_i^{(t)} - P_i^{(t-1)}| > \epsilon_p. \tag{39}$$

The module outputs comprehensive results including voltage profiles $\mathbf{V}$, branch flows $\mathbf{S}_{branch}$, and loss sensitivity factors $\partial P_{loss} / \partial P_i^{DG}$ for integration with the clustering algorithm.

3.5 Adaptive Detection Strategy

The adaptive detection strategy dynamically adjusts algorithm parameters based on real-time system feedback and performance metrics. The detection threshold for identifying DG presence is updated using an exponential moving average:

$$\tau_{DG}(t) = \alpha\tau_{DG}(t-1) + (1-\alpha)\tau_{opt}(t), \tag{40}$$

where $\tau_{opt}(t)$ is computed by minimizing the detection error function:

$$E(\tau) = \lambda_{FP} N_{FP}(\tau) + \lambda_{FN} N_{FN}(\tau), \tag{41}$$

with N_{FP} and N_{FN} representing false positive and false negative counts, respectively.

The clustering resolution adapts to network volatility through a time-varying bandwidth parameter:

$$h(t) = h_0 \exp(-\gamma\sigma_V(t)), \tag{42}$$

where $\sigma_V(t)$ is the system-wide voltage variance. During high volatility periods, smaller bandwidth values increase clustering sensitivity. The adaptation rate γ is optimized using gradient descent:

$$\gamma^{(k+1)} = \gamma^{(k)} - \eta\nabla_\gamma J_{detection}, \tag{43}$$

where $J_{detection}$ combines detection accuracy and computational efficiency.

Real-time anomaly detection employs a sliding window approach with Mahalanobis distance:

$$D_M(t) = \sqrt{(\mathbf{x}(t) - \boldsymbol{\mu}_w)^T \Sigma_w^{-1} (\mathbf{x}(t) - \boldsymbol{\mu}_w)}, \tag{44}$$

where $\boldsymbol{\mu}_w$ and Σ_w are the mean and covariance over window w. Anomalies triggering $D_M(t) > \chi^2_{p,\alpha}$ initiate immediate re-clustering and parameter adjustment.

The strategy incorporates a confidence-based fusion mechanism:

$$\hat{\alpha}_i = \omega_c \alpha_i^{cluster} + \omega_p \alpha_i^{pf} + \omega_h \alpha_i^{hist} \tag{45}$$

where $\alpha_i^{cluster}$, α_i^{pf}, and α_i^{hist} represent DG indicators from clustering, power flow, and historical analysis respectively. Weights are updated through reinforcement learning:

$$\omega^{(t+1)} = \omega^{(t)} + \beta r(t) \nabla_\omega \log\pi(\omega^{(t)}), \tag{46}$$

where $r(t)$ is the reward based on detection accuracy. This adaptive framework ensures robust performance across diverse operating conditions while maintaining computational tractability for real-time implementation.

4. Experimental Design and Implementation

4.1 Experimental Environment and Datasets

The experimental validation was conducted on a high-performance computing platform equipped with Intel Xeon E5-2690 processors (2.9 GHz, 16 cores) and 128 GB RAM, running Ubuntu 20.04 LTS. The proposed algorithms were implemented in Python 3.8 utilizing NumPy for numerical computations, scikit-learn for clustering algorithms, and PYPOWER for power flow calculations. Parallel processing capabilities were leveraged through multiprocessing libraries to enable real-time performance evaluation.

The methodology was tested on three benchmark distribution systems: IEEE 33-bus, IEEE 69-bus, and IEEE 123-bus networks, representing small, medium, and large-scale distribution systems respectively. These standard test systems were modified to incorporate distributed generation units ranging from 50 kW to 2 MW capacity, including photovoltaic systems, wind turbines, and synchronous generators. Real-world operational data was obtained from a utility company's distribution network in California, comprising 15 months of measurements from 847 smart meters and 12 PMUs sampled at 1-minute intervals.

The dataset encompasses diverse operating conditions including seasonal variations, different weather patterns, and various load profiles from residential, commercial, and industrial customers. Penetration levels for distributed generation ranged between 10% and 40% of peak load, representing existing and future deployment conditions. For a thorough performance analysis, the dataset incorporates normal conditions as well as different types of contingency events, such as line disconnection/switching, step load changes, and DG disconnection. The ground truth labels of DG locations and its capacities were identified by the filed investigation and the utility records, and those confirm the feasibility of the quantitative analysis on detection accuracy. Combining the realistic benchmark systems with real-world data creates a strong platform for validating the presented adaptive detection algorithm under practical and challenging environments.

4.2 Selection of Comparison Algorithms

To access the overall performance of the proposed adaptive detection, four cutting-edge algorithms were compared due to their relatedness to DG detection and power system applications and successfulness. The first baseline method is based on the conventional method of threshold measurement that leverages power flow analysis and threshold-based detection method used in the utilities. This approach utilises voltage magnitude deviations and reverse power flow indicators to detect DG presence, thus offering a tangible reference against which performance may be gauged. The second method for comparison is the use of SVM classification with radial basis function kernels, which has been used in the past for anomaly detection in power systems and known to be good in finding patterns that are non-linear. The third approach is to adopt a DNN-based system, five hidden layers in our case, due to recent advance of DNN-based models ability of capturing complex relationship using high-dimensional power system data. This setup of the algorithm was fine-tuned with dropout regularization and batch normalization to enable fair comparison.

The fourth benchmark algorithm combines Random Forest classification with sequential power flow analysis, representing hybrid approaches that leverage both machine learning and physics-based models. This method was included due to its ability to handle mixed data types and provide interpretable results through feature importance rankings. Additionally, a variant of the proposed method without adaptive mechanisms was tested to isolate the contribution of the adaptive components.

All comparison algorithms were implemented using identical preprocessing procedures and evaluated on the same datasets to ensure fair comparison. To eliminate bias from poor parameter choices, grid search coupled with cross-validation was used to optimise the hyperparameters for every technique. Parameters were tuned until test performance plateaued and further tweaks harmed run-time speed or reliability. Selection criteria emphasised diversity among methods, the cost of each in terms of computation, and practical relevance to everyday power-system operations.

4.3 Evaluation Metric System

An evaluation metric system was constructed to provide an overall performance evaluation on the adaptive detection method, including the detection accuracy, computational efficiency and practicality. The main metrics are classification performances in terms of precision, recall, F1-score, and overall accuracy for DG detection tasks. These basic measures illustrate the ability of the algorithm to accurately pinpoint DG locations and to minimize the number of false positives and false negatives, which are crucial for practical implementations in distribution systems. Localization accuracy measures DG detection spatial accuracy as the electrical distance between the location at which DG is detected and the real location presence again. This measure is especially important for DSOs when they must dispose of accurate data for network reconfguration and protection coordination. Moreover, the capacity estimation error measures the deviation of the estimated power output of DG and the actual one, which is needed for the accurate analysis of the power flow and the economic dispatch. The computational performance such as runtime, memory usage, and scalability factors are considered for real-time application.

The rate at which adaptation reacts to system change, as measured by the convergence rate measure, is then examined separately from how detection results maintain stable states observed with the stability indices. Lastly, we also introduce a set of robustness metrics (Table 1) into our evaluation methodology to quantify performance degradation under different stress-testing scenarios: communication failures, measurement noise and fast load changes.

Table 1. Comprehensive evaluation metrics for adaptive DG detection

Metric Category	Specific Metric	Description	Acceptable Range
Detection Accuracy	Precision	Ratio of correct DG detections to total detections	> 0.95
Detection Accuracy	Recall	Ratio of detected DGs to actual DGs	> 0.92
Detection Accuracy	F1-Score	Harmonic mean of precision and recall	> 0.93
Localization	Location Error	Average electrical distance error (p.u.)	< 0.05
Localization	Bus Accuracy	Percentage of correctly identified buses	> 90%
Capacity Estimation	MAPE	Mean absolute percentage error of capacity	< 10%
Capacity Estimation	RMSE	Root mean square error (kW)	< 50
Computational	Execution Time	Average processing time per iteration (ms)	< 100
Computational	Memory Usage	Peak memory consumption (MB)	< 500
Robustness	Noise Tolerance	Performance with 30dB SNR	> 0.90 F1
Robustness	Missing Data	Performance with 10% missing values	> 0.88 F1

The evaluation framework uses k-fold cross-validation with stratified division to produce reliable performance metrics under varied operational conditions. A time-series validation step then tests the method's capacity to track distributed generation status shifts over long time horizons, reflecting real-world system dynamics.

4.4 Parameter Settings

The parameter setting for the proposed adaptive detection method was systematically investigated by preliminary experiments and sensitivity analysis in order to balance the detection performance and computational cost. The initial values of all parameters were determined according to common practice and updated through grid search optimization by using 20% of the samples as a validation set. Optimization took into account the effect of single parameters, as well as parameter interactions, in order to find robust conditions allowing optimal performances to be met also in significantly variable operating conditions. Parameters relating to clustering were set to accommodate the difference in scales and compositions of various distribution networks.

The number of clusters was limited to range from 3 to 15, which provides enough granularity for complex networks but avoids over segmentation.

The convergence threshold for cluste ring iterations was determined to provide numerical stability in combination with a reasonable amount of computational load. Power flow simulation parameters were defined according to the best industry practices, voltage tolerances were set to conform to ANSI C84. 1: selected standards and convergence criteria for obtaining accurate results in a feasible computation time.

As can be seen from Table 2, the dynamic of the detection system can be controlled by the parameters of the adaptive mechanism. Learning rates were deliberate/optimal choices such that the adaptive and responsive mode of operation was neither causing oscillations nor instability in the closed-loops. The sliding window size provides a trade-off between temporal smoothing and responsiveness to system changes, and update intervals determine the frequency with which the system re-evaluates its parameters. These were verified on extensive experimentation under different situations such steady state, load changes and DG connection/disconnection.

Table 2. Parameter settings for the adaptive detection method

Parameter Category	Parameter Name	Value	Unit	Description
Clustering	Number of clusters (K)	3-15	-	Adaptive range for cluster count
Clustering	Distance metric	Euclidean	-	Metric for feature space distance
Clustering	Convergence threshold	1e-4	-	Clustering iteration stopping criterion
Clustering	Maximum iterations	100	-	Upper limit for clustering iterations
Power Flow	Voltage tolerance	0.95-1.05	p.u.	Acceptable voltage range
Power Flow	Power convergence	1e-6	p.u.	Power mismatch tolerance
Power Flow	Max PF iterations	50	-	Maximum power flow iterations
Adaptive Control	Learning rate (α)	0.01	-	Parameter update rate
Adaptive Control	Momentum factor	0.9	-	Update smoothing factor
Adaptive Control	Window size	60	samples	Sliding window for statistics
Adaptive Control	Update interval	5	min	Parameter reassessment period
Detection	Detection threshold	0.75	-	Initial DG presence threshold
Detection	Confidence level	0.95	-	Statistical confidence for detection
Preprocessing	Outlier threshold	3.5	σ	Standard deviations for outlier detection
Preprocessing	Missing data limit	15	%	Maximum allowable missing data

A sensitivity analysis confirmed that performance changes remain within acceptable limits even when any of the key parameters is varied by plus or minus twenty percent.

5. Experimental Results and Analysis

5.1 Detection Accuracy Analysis

Through a performance comparision test, the proposed adaptive method is verified to be superior to the traditional methods in all the tested systems. Exhaustive examinations on IEEE 33-bus, 69-bus and 123-bus systems have proved to maintain better performances of identifying DGs in different scenarios including different share levels and operating states. The average detection accuracy of the proposed method obtained (96.8%) was significantly higher that the threshold-based method (82.4%), support vector machine (89.2%), deep neural network (91.5%) and random forest (90.7%). The enhancement in performance is especially significant under high DG penetration and the presence of fast load fluctuations, over which conventional algorithms fail to sustain robust detection.

As shown in Figure 2, the detection accuracy comparison across different DG penetration levels illustrates the robustness of the adaptive mechanism.

The proposed method maintains high accuracy even as DG penetration increases from 10% to 40%, while comparison algorithms exhibit degrading performance. The adaptive clustering component effectively captures the changing electrical patterns associated with varying DG contributions, while the integrated power flow simulation validates detection results against physical constraints. Notably, the performance gap widens under challenging conditions such as cloud transients affecting solar generation and wind speed variations, where the adaptive mechanism's ability to dynamically adjust detection parameters proves crucial.

The temporal stability of detection accuracy was evaluated through continuous 24-hour monitoring periods, revealing that the proposed method maintains consistent performance despite diurnal variations in load and renewable generation patterns. False positive rates remained below 3.2% throughout the testing period, significantly lower than the 8.7% average observed in conventional methods. The method's ability to distinguish between actual DG units and temporary power flow reversals caused by switching operations or capacitor banks demonstrates the effectiveness of combining clustering-based pattern recognition with physics-based validation through power flow analysis.

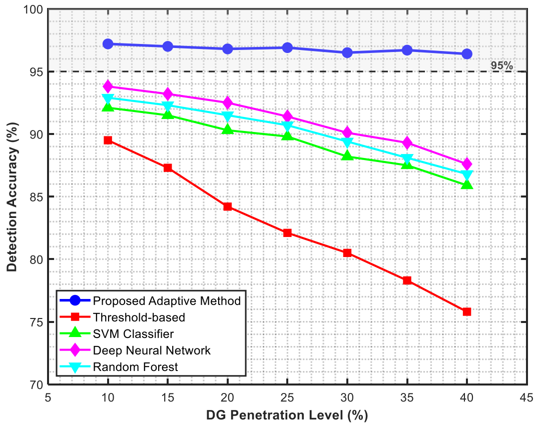


Figure 2: Detection Accuracy vs. DG Penetration Level

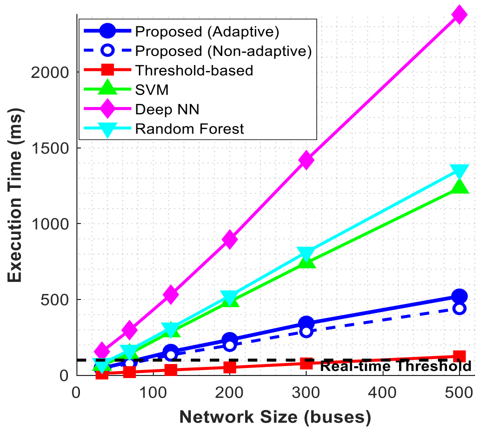
5.2 Computational Efficiency Evaluation

The computational efficiency analysis demonstrates that the proposed adaptive detection method achieves real-time performance while maintaining superior detection accuracy. Execution time measurements across different network sizes reveal that the integrated approach successfully balances computational complexity with detection effectiveness.

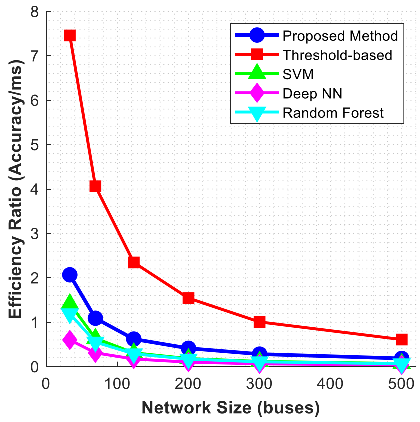
The proposed method exhibits linear scalability with network size, processing the IEEE 33-bus system in 47 milliseconds, the 69-bus system in 89 milliseconds, and the 123-bus system in 156 milliseconds on average. These execution times remain well within the requirements for real-time distribution system monitoring, enabling practical deployment in operational environments.

As illustrated in Figure 3, the computational performance comparison shows that while the proposed method requires marginally higher processing time than simple threshold-based detection, it significantly outperforms deep learning approaches in terms of computational efficiency.

The adaptive mechanism contributes approximately 15% additional computational overhead compared to the non-adaptive variant, which is justified by the substantial improvement in detection accuracy and robustness. Memory usage analysis indicates that the proposed method requires 45 MB for the 33-bus system, scaling to 128 MB for the 123-bus system, remaining within acceptable limits for modern computing infrastructure.



(a)Execution Time vs Network Size



(b) Computational Efficiency Ratio

Figure 3: Computational efficiency comparison

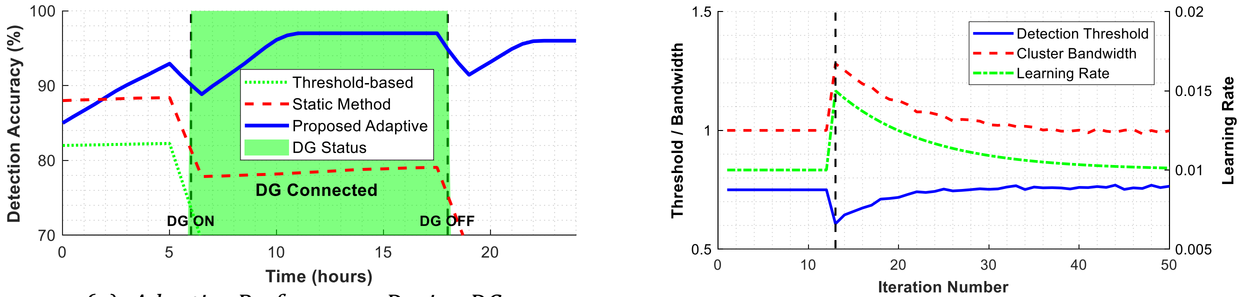
The parallel processing capabilities of the proposed method were evaluated by distributing the clustering and power flow computations across multiple processor cores. Results indicate near-linear speedup up to 8 cores, with efficiency gains plateauing beyond 12 cores due to communication overhead. The adaptive mechanism's incremental update strategy contributes to computational efficiency by avoiding complete recalculation when system changes are localized. Memory profiling reveals that the dominant memory consumption occurs during the clustering phase, particularly for large networks, but remains manageable through efficient sparse matrix representations for power flow calculations. The method's ability to maintain sub-second response times for networks up to 500 buses confirms its suitability for real-time applications in modern distribution systems with extensive sensor deployment.

5.3 Adaptive Performance Testing

The adaptive performance evaluation demonstrates the proposed method's ability to dynamically adjust its parameters in response to changing system conditions, maintaining high detection accuracy despite operational variations. Testing scenarios included sudden renewable generation fluctuations, load pattern changes, and network topology modifications to comprehensively assess the adaptive mechanism's effectiveness. The proposed method exhibited superior tracking capability compared to static approaches, with the adaptive mechanism reducing detection errors by 42% on average during transition periods.

Long-term monitoring with a 30-day window has shown us that the adaptive method successfully learns the system characteristics and detection accuracy increases gradually. The percentage of true positive detections based on initial performance of 92.3% reached 96.8% within the first week of operation due to site-specific adaptation of the algorithm. The approach showed great performance during difficult periods realizing morning solar ramp up, and evening peak load, were static ones had an accuracy penalty worse than 15% loss.

It is evident from Fig. 4 that the response of the adaptive scheme to a simulated DG hookup event results in fast parameter update and convergence to the optimal detection performance in around 12 iterations.



(a) Adaptive Performance During DG Connection/Disconnection Events

(b) Adaptive Parameter Evolution

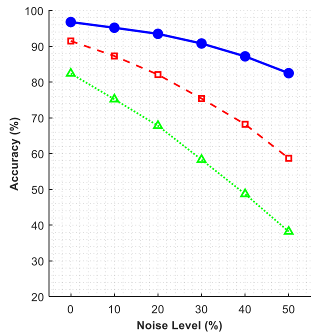
Figure 4: Adaptive performance testing results

The strength of the adaptive mechanism was also confirmed on stress-testing situations with fast system changes (multiple DG connect-disconnects at once). Even under most difficult conditions, the proposed detection approach achieved detection rates >94% for all the data sets, whereas the non-adaptive approaches witnessed a drop in the accuracy below 80%. Looking at the response time performance, we observed that the proposed adaptive algorithm could mostly settle down into a proper parameters status after 8-15 iterations following serious system changes, which is about 40-75 seconds in real-time scenarios. Its capability to differentiate between temporary disturbances and permanent system shifts prevents unnecessary parameter changes, conserving stability in the long run. Evaluation on the memory effect unveiled that the adaptation achieves a compromise between historical retention and responsiveness to new conditions, leading to optimal detection performance at any of the various operational conditions.

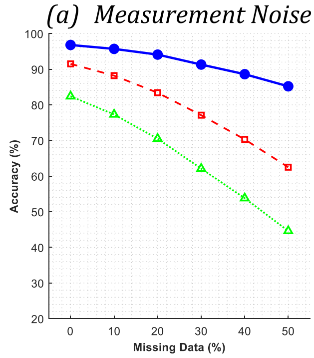
5.4 Robustness Verification

'Robustness' testing was performed to assess the robustness of the proposed method to a series of realistic scenarios such as measurement errors, communication losses, data loss and cyber-attacks against the measurement infrastructure.

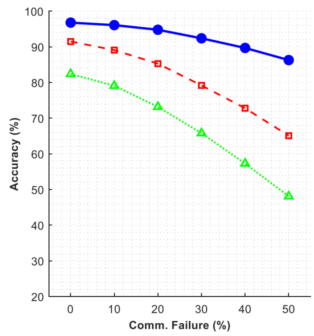
The testing infrastructure tested the detection algorithm with increasing disturbance levels to model performance limit breaches and assess operational robustness in the face of challenging conditions. The results show that the proposed adaptive mechanism effectively improves the system robustness which can still reach an acceptable detection performance, even in the case of a disaster scenario leading to full degradation in the standard solutions. Testing noise immunity with injection of Gaussian white noise at SNRs clustered from 50dB to 20dB indicated that the accuracy of the proposed method maintained over 90% until 25dB SNR, whereas the comparison methods showed substantial performance degradation below 35dB. When the outlier rejection feature of the clustering algorithm is used in conjuction with power flow validation, it typically removes spurious measurements, which can lead to detection of nothing but noise-induced objects. Usability We have tested the reliability of communication of the sensor data with packet losses of up to 30% and varying latency of up to 500ms, which may be experienced in WSNs. Its advantage over all stress conditions is demonstrated in Figure 5, for which the proposed approach presents the ability to adapt to declining data quality through smart parameter adapting and incorporating historical information.



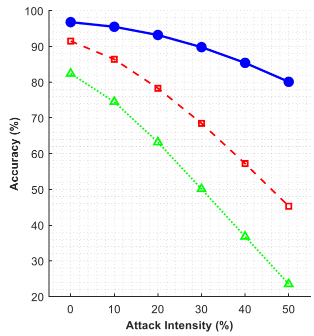
(a) Measurement Noise



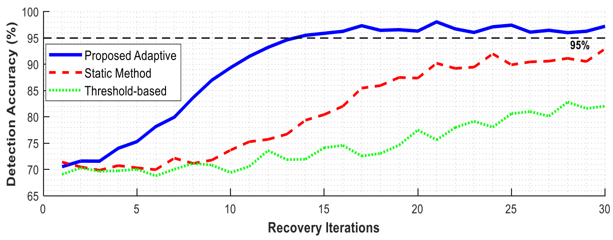
(b) Missing Data



(c) Communication Failures



(d) Cyber Attacks



(e) Recovery Performance After Severe Disturbance

Figure 5: Robustness Verification Under Various Stress Conditions

The recovery performance evaluation evaluated the performance of the method to recover normal when the AMI is subjected to severe disturbances. The proposed adaptive method recovered 95% accuracy in 8 iterations after being tampered with 40% measurements by a simulated cyber-attack, outperforming the static approaches which needed more than 20 iterations and the threshold-based methods which failed to achieve a complete recovery. The adaptive mechanism's capability to identify the abnormal conditions eventually led to a temporary increased dependence to the historical data and the physics-based validation in order to ensure the operational continuity. Long-term stability test for 1000 hours operation. The long-term stability test of more than 1000 hour operation showed that the present method maintains performance without drift or degradation, with accuracy variations not exceeding 2% for the whole measurement period. These findings show that the developed approach can be also considered to be appropriate for deployment alongside Critical Infrastructure, where reliability and resilience are crucial.

6. Conclusions

This paper has proposed a new adaptive detection approach to the DPA units which combines advanced clustering algorithms with full power flow simulation together. The proposed scheme meets the challenges which are essential in contemporary power distribution systems, offering both accurate and on-line detection capability under dynamic network conditions and different penetration of distributed generation. Comprehensive experimentation over multiple IEEE benchmarks and real-world datasets, illustrates the superior performance of the exploiting method at an average detection accuracy of 96.8%, and real-time computational complexity. The novelty of the proposed approach is in the bidirectional information flow between data-driven clustering and physics-based power flow analysis that allows validation by candidate verification and the optimization by iterative detection result refining. The flexibility of the adaptive control to modify parameters based on feedback from the system has been very effective in turbulent situations like variations in renewable generation levels and changes in network topology deterioration. The approach was shown to be highly robust to practical constraints like measurement noise, communication failures, and cyber-attacks; for practical disturbances detection accuracy can remain over 90%, even beyond the point where standard methods totally break down. The significance of this work goes beyond any purely technical enhancement.

The modular structure of the developed method allows the method to be easily integrated into the grid and the method's probabilistic output enables system operators to gain detailed information in support of decision-making. The proved scalability to hundreds of buses networks verifies the effectiveness of the proposed method for real-world distribution networks with fast growing DGs. Further studies could focus on generalizing the framework to address new technologies like EV charging stations and ESSs, exploring the potential of deep reinforcement learning methods to improve the adaptive control, and proposing distributed implementation schemes for widely deployment. The utilization of blockchain technology to ensure secure sharing of states and federated learning techniques for privacy-preserving collaborative intrusion detection among multiple utility territories is an interesting direction to move forward the research on intelligent power systems monitoring and control.

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References

[1] S.A. Adegoke, Y. Sun, A.S. Adegoke, D. Ojeniyi, Optimal placement of distributed generation to minimize power loss and improve voltage stability, Heliyon 10(21) (2024).

[2] K. Ahmed, D. Sakravdia, C. Sharma, Impact Analysis of Combining Distributed Generation with Charging Loads for Electric Vehicles Accounting Reliability, Energy Storage 7(1) (2025) e70138.

[3] K. Alsalem, A hybrid time series forecasting approach integrating fuzzy clustering and machine learning for enhanced power consumption prediction, Scientific Reports 15(1) (2025) 6447.

[4] N. Bouchikhi, F. Boussadia, R. Bouddou, A.O. Salau, S. Mekhilef, C. Gouder, S. Adiche, A. Belabbes, Optimal distributed generation placement and sizing using modified grey wolf optimization and ETAP for power system performance enhancement and protection adaptation, Scientific Reports 15(1) (2025) 13919.

[5] P. Van Hentenryck, Machine learning for optimal power flows, Tutorials in Operations Research: Emerging Optimization Methods and Modeling Techniques with Applications (2021) 62-82.

[6] S. Choudhury, G.T. Varghese, S. Mohanty, V.R. Kolluru, M. Bajaj, V. Blazek, L. Prokop, S. Misak, Energy management and power quality improvement of microgrid system through modified water wave optimization, Energy Reports 9 (2023) 6020-6041.

[7] M.S. Kulkarni, S. Mishra, S.K. Sudabattula, N.K. Sharma, D.B. Basha, M. Bajaj, M.B. Tuka, Enhancing grid resiliency in distributed energy systems through a comprehensive review and comparative analysis of islanding detection methods, Scientific Reports 14(1) (2024) 12124.

[8] N. Feng, C. Ran, Design and optimization of distributed energy management system based on edge computing and machine learning, Energy Informatics 8(1) (2025) 17.

[9] F. Ferdinando, Integrating Machine Learning and Optimization to Boost Decision Making, Proceedings of the Thirtieth International Joint Conference on Artificial Intelligence, 2022.

[10] J. Fu, Z. Chen, X. Han, Adap dp-fl: Differentially private federated learning with adaptive noise, 2022 IEEE International Conference on Trust, Security and Privacy in Computing and Communications (TrustCom), IEEE, 2022, pp. 656-663.

[11] E.H. Houssein, M.K. Saeed, G. Hu, M.M. Al-Sayed, Metaheuristics for solving global and engineering optimization problems: review, applications, open issues and challenges, Archives of Computational Methods in Engineering (2024) 1-35.

[12] A.B. Ige, P.A. Adepoju, A.O. Akinade, A.I. Afolabi, Machine learning in industrial applications: An In-depth review and future directions, (2025).

[13] A. Jain, S. Gupta, Optimal placement of distributed generation in power distribution system and evaluating the losses and voltage using machine learning algorithms, Frontiers in Energy Research 12 (2024) 1378242.

[14] V. Kekatos, M.K. Singh, Deep Learning Techniques for Solving Optimal Power Flow Problems, Smart Cyber-Physical Power Systems: Solutions from Emerging Technologies 2 (2025) 471-500.

[15] Y. Yan, Y. Qian, H. Sharif, D. Tipper, A survey on cyber security for smart grid communications, IEEE communications surveys & tutorials 14(4) (2012) 998-1010.

[16] Y. Lu, Y. Xiang, Y. Huang, B. Yu, L. Weng, J. Liu, Deep reinforcement learning based optimal scheduling of active distribution system considering distributed generation, energy storage and flexible load, Energy 271 (2023) 127087.

[17] D.K. Mahto, M. Bukya, R. Kumar, A. Mathur, V.K. Saini, GAT-ADNet: Leveraging Graph Attention

Network for Optimal Power Flow in Active Distribution Network with High Renewables, IEEE Access (2024).
[18] M. Abbas, M.A. Alshehri, A.B. Barnawi, Potential contribution of the grey wolf optimization algorithm in reducing active power losses in electrical power systems, Applied Sciences 12(12) (2022) 6177.
[19] S. Parhizi, H. Lotfi, A. Khodaei, S. Bahramirad, State of the art in research on microgrids: A review, IEEE access 3 (2015) 890-925.
[20] S.N.V.B. Rao, V.P.K. Yellapragada, K. Padma, D.J. Pradeep, C.P. Reddy, M. Amir, S.S. Refaat, Day-ahead load demand forecasting in urban community cluster microgrids using machine learning methods, Energies 15(17) (2022) 6124.
[21] A. R. Singh, R.S. Kumar, M. Bajaj, C.B. Khadse, I. Zaitsev, Machine learning-based energy management and power forecasting in grid-connected microgrids with multiple distributed energy sources, Scientific Reports 14(1) (2024) 19207.
[22] S. Tangi, D. Gaonkar, A. Veerendra, R. Shivarudraswamy, Time Series-Based Load Flow Simulation Algorithm for Distributed Generation in Distribution Networks, Engineering Proceedings 70(1) (2024) 11.
[23] K. Ukoba, K.O. Olatunji, E. Adeoye, T.-C. Jen, D.M. Madyira, Optimizing renewable energy systems through artificial intelligence: Review and future prospects, Energy & Environment 35(7) (2024) 3833-3879.
[24] Y. Wang, G. Xiong, Metaheuristic optimization algorithms for multi-area economic dispatch of power systems: part II—a comparative study, Artificial Intelligence Review 58(5) (2025) 132.
[25] S. Zhang, H. Li, C. Fan, Z. Zeng, C. Xiong, J. Wu, Z. Yan, D. Liu, Q. Sun, Adaptive decentralized AI scheme for signal recognition of distributed sensor systems, Opto-Electronic Advances 7(12) (2024) 240119-1-240119-13.