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Article

Precise PMU locations on distribution system considering power system disruptions for elegant state estimation

Puvikko Chezhian Vgopal[1,*], Subramanian Srikrishna[1], Ganesan Sivarajan[2], Naveenkumar Kaliyan[3]

[1] Department of Electrical Engineering, Annamalai University, Tamil Nadu 608002, India
[2] Department of Electrical and Electronics Engineering, Government College of Engineering, Tamil Nadu 636011, India
[3] Department of Instrumentation and Control Engineering, Sri Manakula Vinayagar Engineering College, Puducherry 605107, India
*** Corresponding author:** Puvikko Chezhian Vgopal, drpuvikko@yahoo.com

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Abstract: This study presents a novel approach to achieve complete system observability by optimizing the placement of Phasor Measuring Units (PMUs), reducing the risk of fault identification. The process considers both the redundancy and the cost of installation. The proposed solution methodology improves upon existing algorithms by utilizing the Butterfly Optimization Algorithm (BOA), which identifies optimal PMU locations. Resilient fault detection techniques are employed to detect and mitigate disruptions in the power grid swiftly. Addressing transmission line faults, the research integrates a Deep Learning Network (DLN) to enhance the state estimation process during fault conditions. Simulations of fault transients, including LG (Line-to-Ground), LLG (Line-to-Line-to-Ground), and LL (Line-to-Line) faults, are conducted using MATLAB Software. The Neural Network (NN) response is evaluated based on two key hyperparameters—the number of hidden layers and the number of neurons utilized for feature extraction. Results demonstrate the superiority of the proposed method, with approximately 85% fault detection accuracy and a system performance metric of 90%. Additionally, the processing time required for training the network is small in the order of micro seconds.

Keywords: PMU; state estimation; fault detection; optimization; distribution system; machine learning

1. Introduction

1.1. Distribution power system faults

There are numerous encounters observed when the phasor measurement units (PMUs) are located for full network observability. Most of the researchers perceived communication facilities as the most noteworthy feature that affects the PMU procurement and installation costs [1]. The second most substantial issue is the security requirements where the users built an either mission critical or mission-support system that determines voltage stability, the major delinquent over earlier ages that regulates the maximum loadability limit of the buses. If the PMUs are placed on the critical buses, then the Fast Voltage Stability Index (FVSI) [2] is minimized, and the Weak Bus Observability Index (WBOI) [3–5] is maximized. Even though the placement of PMUs offers complete network observability, the cost of placing the PMUs should be condensed because the typical overall cost of PMUs1 ranges from $14,000 to $30,000 [6]. In most developing countries, if the cost of PMU placements at a particular location is high, then it is not conceivable to place the PMUs in the chosen location. Therefore, the cost of placement of PMUs should be less than the overall cost of the connected synchrophasor system outlays. [7]

The precise location of faults is determined using techniques such as fault current analysis, [8] time-domain reflectometry, [9,10] and travelling wave analysis[11,12]. In this study, we use Optimal PMU Placement (OPP) alongside the Butterfly Optimization Algorithm. By incorporating Machine Learning (ML), the fault identification process is further enhanced, providing improved security and reliability in power system management.

1.2. Challenges in present distribution system state estimation

Monitoring multiple buses simultaneously in an active grid is essential for preventing faults [11,12]. This can be achieved by placing PMUs in optimal locations and minimizing the System Maximizing Redundancy Index (SMRI) [13]. While existing fault detection systems simulate and train based on specific scenarios, advanced deep learning and machine learning algorithms offer better detection capabilities. By leveraging these technologies, the grid can be better understood, providing enhanced control and fault prevention. **Figure 1** represents the PMU placements in the Smart grid.

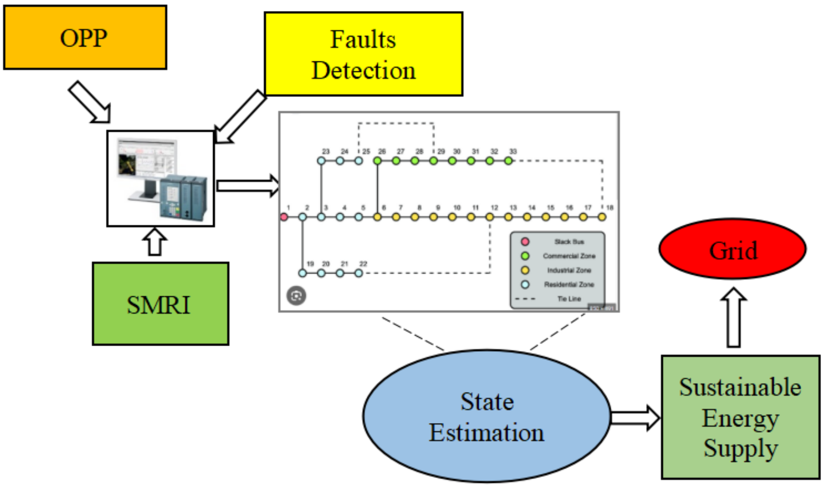

Figure 1. Sustainable PMU placements for smart grid development.

1.3. Research review on distribution system state estimation

This study begins by examining the shortcomings of the traditional Fault Data Self Synchronization (FDSS) algorithm [14], which estimates the initial delay difference at both terminals using zero-crossing time and current polarity. To improve the speed and accuracy of fault detection, we propose a centralized backup protection system combining delta algorithms with the least-squares method [15,16]. PMUs and micro-PMUs [17,18] are emerging technologies that enhance real-time grid monitoring, fault detection, and overall grid safety. Ongoing research focuses on integrating micro-PMUs with control systems for more efficient fault detection.

The research also explores PMU-based Distributed State Estimation (DSE)[19–21] methods, which introduce equality constraints to reduce numerical instability and improve computational efficiency. By integrating machine learning models and advanced optimization techniques, the study seeks to refine PMU placements and enhance the accuracy of fault detection. The **Table 1** depicts the literature survey of the proposed work.

Table 1. Consolidated research review.

Ref	Year	Author	Algorithm/Approaches	Objectives			
				Min OPP	**Resilience and Fault Detection**	**Artificial Neural Network**	**OPP and ML-based Fault detection**
3	2023	Andic, C., et al.	Crow Search Algorithm	Yes	No	No	Absence of Prior Reports
8	2021	Chavez, J. J., et al.	Fault Locator for Transmission Backup Protection	No	Yes	No	
12	2021	F. G. Duque, et al.	Modified Monkey Search Algorithm	Yes	No	No	
13	2023	G. S. Dua, et al.	Fault Detection Technique for Distribution Networks	No	Yes		
18	2023	M. Mukherjee and B. K. S. Roy	Binary Carnivorous Plant Algorithm	Yes	No	No	
22	2023	Pattanaik, V et al.	Artificial Bee Colony Algorithm	Yes	No	No	
23	2006	Peng, J et al.	Tabu Search Algorithm	Yes	No	No	
24	2023	Q. -H. Ngo, et al.	Graph Neural Networks	No	No	Yes	
27	2023	Rezapour, H., et al.	Artificial Intelligence-Based Fault Location Methods	No	Yes	Yes	
28	2021	Sonal and Ghosh, D.	Resilience Assessment of a Distribution System	Yes	Yes	No	
29	2023	Tshenyego, O., et al.	Binary Firefly Algorithm	Yes	No	No	
30	2017	V. Basetti and A. K. Chandel	Taguchi Binary Bat Algorithm	Yes	No	No	
32	2023	Y Raghuvamsi, Kiran Teeparthi, A	State Estimation Uncertainty Issues Using Deep Learning	No	No	Yes	
33	2023	Puvikko et al.	Butterfly Optimization Algorithm	Yes	Yes	Yes	Yes

In addition, various metaheuristic algorithms have been applied to address the challenge of optimizing PMU (Phasor Measurement Unit) placement. These include the Crow Search Algorithm [22], Modified Monkey Search [23], Binary Carnivorous Plant Search Algorithm [24], Artificial Bee Colony Algorithm [25], Tabu Search Algorithm [26], Binary Firefly Algorithm [27], and Taguchi Binary Bat Algorithm [28]. These algorithms are employed to find the best configuration for PMU placement, optimizing the monitoring of power systems.

1.4. Research hiatus

Despite advancements in power system monitoring, achieving optimal power system resilience remains a significant challenge, particularly in radial networks. The methods discussed in this paper address critical limitations in current fault location and PMU placement techniques. Traditional fault detection approaches often fail to fully influence the potential of deep learning. This research aims to fill these gaps by optimizing PMU placement and enhancing fault detection using machine learning models.

1.5. Problem statement

This research addresses the gaps in current fault detection methods by providing a comprehensive framework for improving power system resilience. By using deep learning methods and optimizing PMU placement, authors are targeting to improve fault detection and system monitoring, particularly in radial networks.

1.6. Motivation and objectives

The primary objectives of this study are:

- To determine optimal PMU placements in radial networks for improved observability and control.
- To enhance machine learning models for accurately locating and classifying faults.
- To ensure quick fault detection and system recovery through deep learning models, minimizing downtime.
- Ultimately, to strengthens the power system's resilience, enabling it to withstand and recover from faults.

1.7. Organization of the work

The organization of this paper is carried out as follows. Section 2 describes the recent research works related to the OPP and metaheuristics. The proposed methodology is explained in Section 3 as a BOA. Section 4 is enclosed with a performance analysis of the proposed system 4 and the overall conclusion of the proposed algorithm is given in Section 5.The functioning flow chart of the proposed method as shown in **Figure 2**.

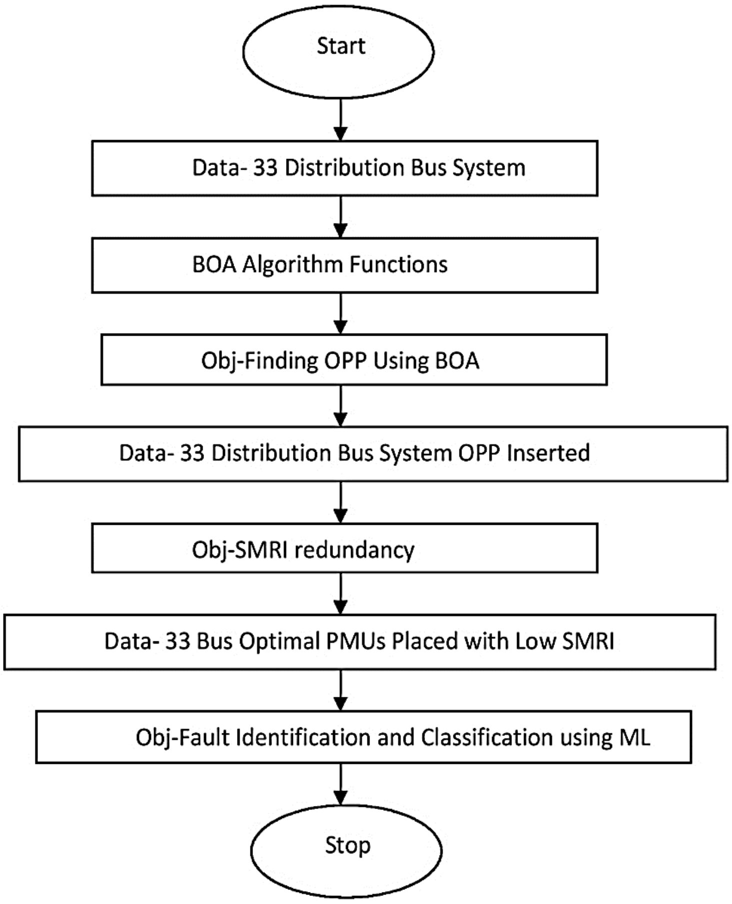

Figure 2. Flow chart: Functioning of the current method.

2. Formulation of the distribution system state estimation

In an N-bus power system configuration equipped with *m* voltage and current phasor measurements, the relationship between these measurements and the system state vector can be expressed through a nonlinear matrix equation [29]. This equation reflects the interaction between the measured data and the internal variables of the system.

The following nonlinear equation describes the relationship:

$$\delta Z = \begin{bmatrix} \delta Z_1 \\ \delta Z_2 \\ \cdot \\ \cdot \\ \cdot \\ \delta Z_m \end{bmatrix} = \begin{bmatrix} h_1(\ddot{x}_1, \ddot{x}_2, \ldots\ldots \ddot{x}_n) \\ h_2(\ddot{x}_1, \ddot{x}_2, \ldots\ldots \ddot{x}_n) \\ \cdot \\ \cdot \\ \cdot \\ h_m(\ddot{x}_1, \ddot{x}_2, \ldots\ldots \ddot{x}_n) \end{bmatrix} + \begin{bmatrix} e_{r1} \\ e_{r2} \\ \cdot \\ \cdot \\ \cdot \\ e_{rm} \end{bmatrix} = h(\ddot{x}) + e_r \tag{1}$$

where *h* represents the nonlinear measurement function, *x* denotes the state vector, and *r* represents measurement errors. When the system is fully observable, the rank of the Jacobian matrix *H* matches the size of the state vector. In this context, the Weighted Least Squares (WLS) [30] state estimation method is commonly employed to minimize the weighted sum of the squares of the measurement residuals. Each residual is weighted according to its associated error covariance.

The WLS objective function is expressed as:

$$J(x) = (\delta Z - \mathrm{h}(\ddot{x}))^{T} R^{-1} (\delta Z - \mathrm{h}(\ddot{x})) \tag{2}$$

The Gain matrix is constructed by combining the Jacobian matrix (*H*) and the error covariance matrix (*R*) measurement. The covariance matrix is presumed to have a diagonal structure, with the variances of measurements occupying its diagonal entries. This results in the formation of the Gain Matrix as follows:

$$J\left(x^{k}\right) = H^{T} R^{-1} \tag{3}$$

Its where $H = \frac{\partial \mathrm{h}(\ddot{x})}{\partial x} = \begin{bmatrix} \frac{\partial \mathrm{h}_1(\ddot{x})}{\partial x_1} & \cdots & \frac{\partial \mathrm{h}_1(\ddot{x})}{\partial x_n} \\ \vdots & \ddots & \vdots \\ \frac{\partial \mathrm{h}_m(\ddot{x})}{\partial x_1} & \cdots & \frac{\partial \mathrm{h}_m(\ddot{x})}{\partial x_n} \end{bmatrix}$ is the Jacobian matrix, and *R* is the diagonal matrix with a value $\epsilon_{\mathrm{i}}^{2}$, where $\begin{bmatrix} \epsilon_{\mathrm{i}}^{2} & \cdots & . \\ \vdots & \ddots & \vdots \\ . & \cdots & \epsilon_{\mathrm{m}}^{2} \end{bmatrix}$ is the standard deviation of the error associated with i^{th} measurement. *m* is the number of measurements, and *n* is the number of state variables.

2.1. Objective function-1: Optimal PMU placement

The objective of the OPP problem is to determine the minimum number of PMUs needed to achieve full system observability. This objective can be formulated as a nonlinear optimization problem within the WLS framework: [31,32]

$$WLS_x = min \sum_{i=1}^{N} W_i * X_i^2 \tag{4}$$

subject to the constraint that each bus is observed by at least one PMU:

$$\sum_{\mathrm{i}=1}^{\mathrm{N}} X_{\mathrm{i}} \geq 1 \tag{5}$$

where P_i is a binary variable that indicates whether a PMU is placed at bus *i* (1 if placed, 0 otherwise), and c_i represents the cost associated with placing a PMU at bus *i*. The constraint ensures that each bus is observed by at least one PMU, either directly or indirectly.

2.2. Objective function-2: SMRI optimization

In this scenario, the SMRI is maximized to enhance system observability. *SMRI* is defined as the number of times each bus is observed, either directly or indirectly, through the placement of PMUs. It is mathematically represented as: [33,34]

$$SMRI_{max} = \frac{1}{n} \sum_{j=1}^{N} R_j^k \tag{6}$$

where n is the number of buses in the system, and O_j represents the number of times bus *j* is observed by the installed PMUs. The goal is to maximize the *SMRI* while minimizing the number of PMUs used.

3. Optimal PMU locations for distribution system state estimation

3.1. Why optimization

The placement of PMUs in the distribution system is a complex, non-linear problem[35]. A major factor in placing PMUs in optimal locations. Several algorithms have been proposed to address this challenge in the literature which have low time response, as an attempt we utilize BOA [36] which emergingas a highly effective method for determining optimal PMU locations. The BOA mimics the natural foraging behaviour of butterflies, using both global and local search strategies to find the best locations for PMU installation.

The BOA's strengths lie in its adaptability to various optimization problems, ease of implementation, and scalability. These attributes make it well-suited for the task of optimizing PMU placement, ensuring that the system remains fully observable under different operating conditions.

3.2. Implementation of BOA for PMU locations

The BOA is based on the natural movements of butterflies, which rely on sensory receptors to detect food sources. The global search process involves butterflies moving towards the best-known location, while the local search process involves movement based on the fragrances released by nearby butterflies.

3.3. Optimal PMU locations using BOA

In the context of PMU placement, the global search process represents the exploration of potential PMU locations across the entire system, while the local search focuses on refining the placement of PMUs in specific regions.

The BOA's optimization process includes the following steps:

STEP 1: Initialization of the algorithm and problem parameters.

STEP 2: Initialization of the population of butterflies (PMU placements).

STEP 3: Calculation of fitness values (system observability).

STEP 4: Updating the population based on global and local search strategies.

STEP 5: Checking for convergence and terminating the process when the optimal solution is found.

All of the above-mentioned steps are mentioned in the below Flowchart of **Figure 3**.

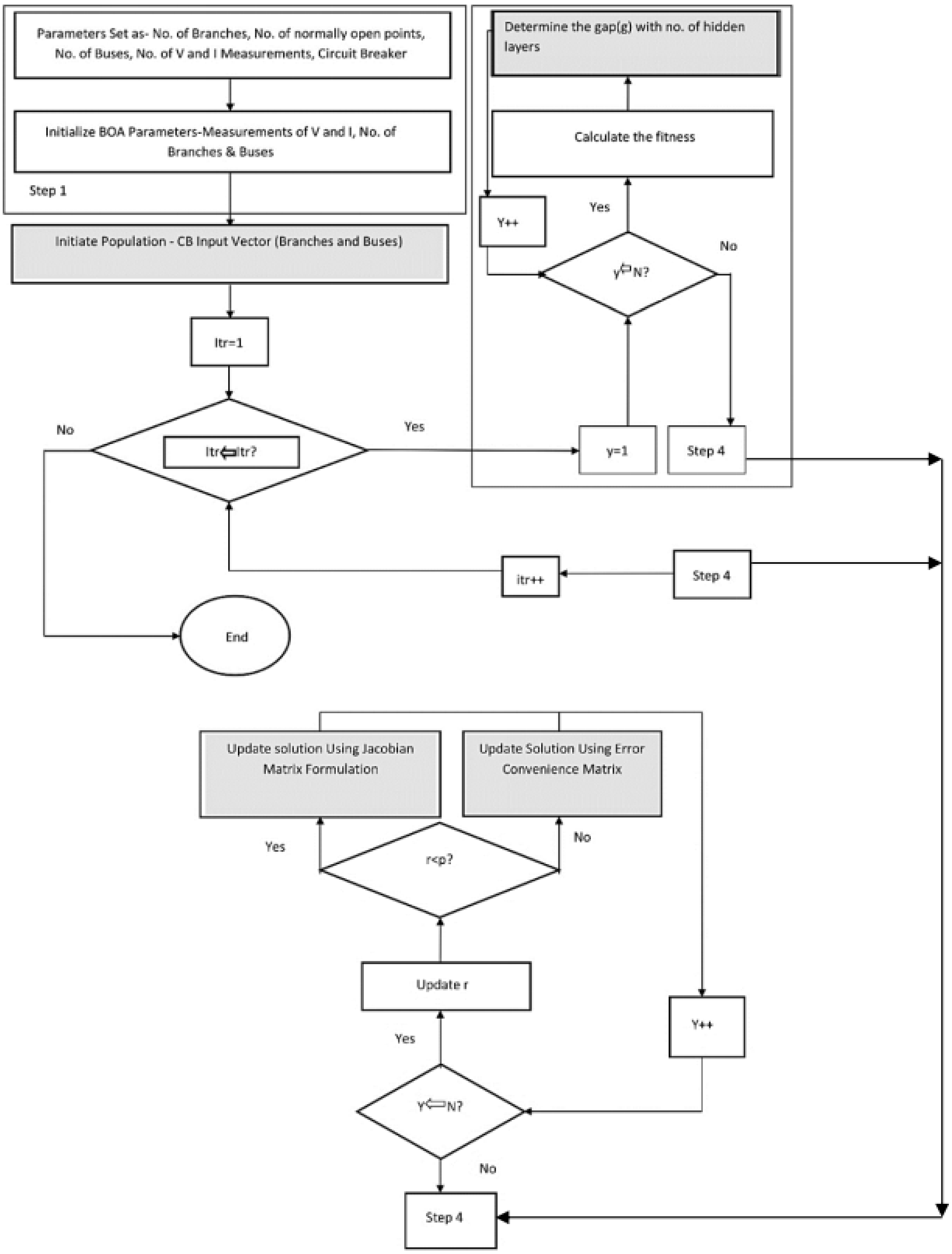

Figure 3. Flowchart of the general BOA steps.

4. Fault identification and classification

The BOA has proven to be an efficient tool for optimizing PMU placement, yielding a high SMRI in various test scenarios, including the IEEE 33-bus system.

However, to maximize the benefits of optimal PMU placement, it is essential to employ a reliable learning algorithm for fault identification, as grid conditions are constantly evolving. ML algorithms, particularly Artificial Neural Networks (ANN), offer the flexibility and adaptability necessary for efficient fault detection.

4.1. Learning algorithm

In this work, the fault identification process is enhanced using machine learning algorithms, which operate through iterative trial-and-error approaches to achieve high efficiency. Given that the system is constantly subject to changes and fault conditions, the adaptability of machine learning makes it a suitable choice for improving fault detection accuracy.

The training process for machine learning models is crucial. In our case, repeated training with variations in the dataset allows the model to generalize better, reaching an accuracy of around 85%. Without an adaptable algorithm, the improvements made during the OPP process would not be fully utilized. As system faults vary over time, it is essential to have a machine learning algorithm capable of adapting to these dynamic changes, ensuring both accuracy and speed in fault detection.

4.2. Implementation

The implementation of the learning algorithm for fault location is closely tied to the quality and size of the dataset, as well as the choice of neural network architecture. The steps involved in implementing the machine learning approach include:

Data Collection and Preparation: Data is collected from transmission lines, including fault locations and relevant features such as voltage, current, and power measurements. The dataset is labelled, and data is divided into training, validation, and test sets.

Data Pre-processing: Input and output data are normalized to bring them to a similar scale. Fault location labels are encoded, and the data is prepared for the neural network model.

Neural Network Architecture: The chosen architecture is a feed-forward neural network, which connects input features to output classifications through hidden layers. The number of hidden layers and neurons in each layer is determined based on the complexity of the problem.

Training: The neural network is trained using the Bayesian regularization algorithm, implemented via the Levenberg-Marquardt optimization method. This method adjusts the weights and biases of the network to minimize error. Training is terminated once the maximum number of epochs is reached or the desired level of performance is achieved. **Figure 4** mentioned the machine learning flowchart.

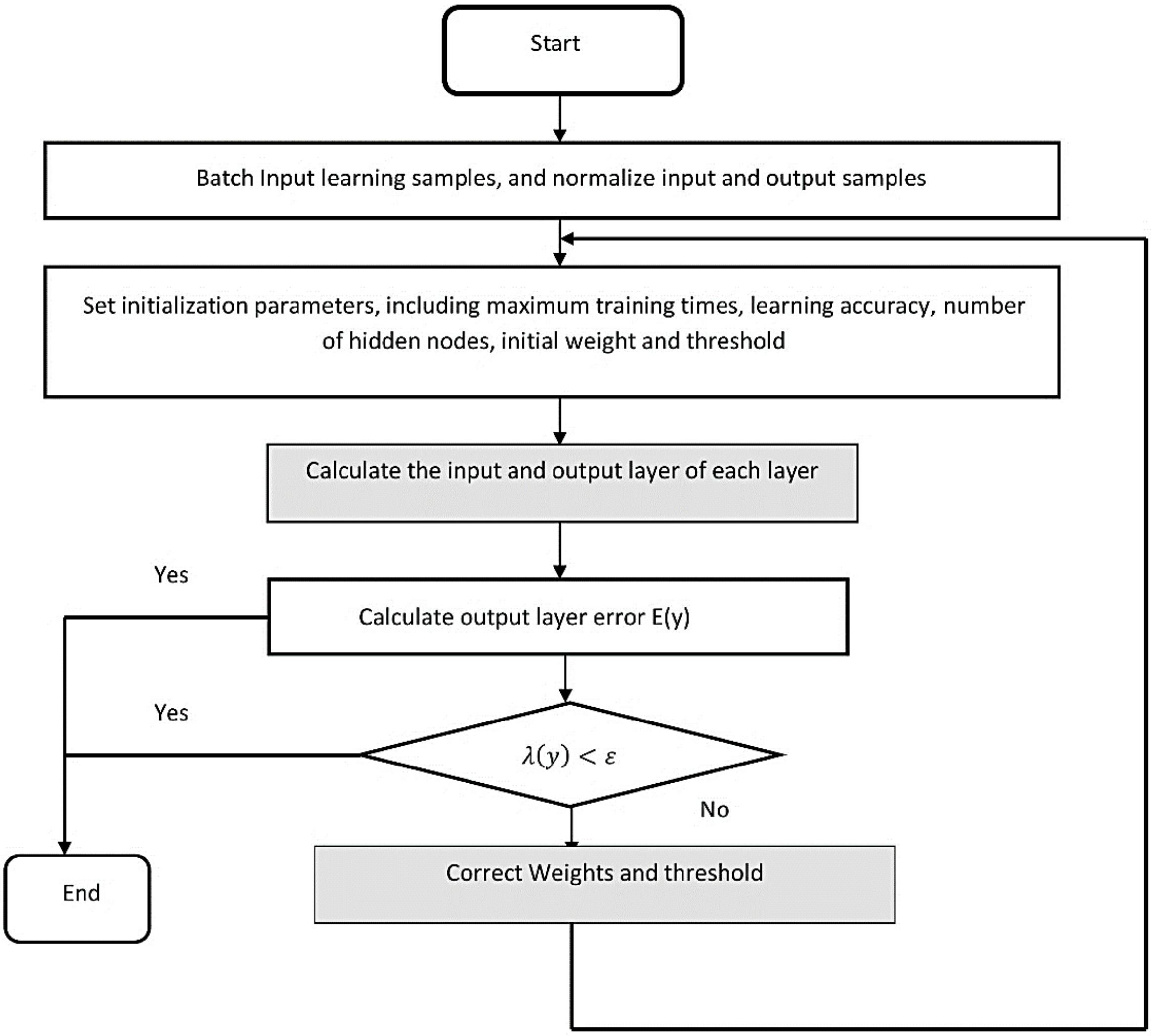

Figure 4. Machine learning flowchart.

4.3. Levenberg-Marquardt algorithm

The Levenberg-Marquardt algorithm is designed to minimize the sum of squared residuals in nonlinear least-squares problems. The objective function is formulated as:

$$\text{Minimize} \sum [f(x; p) - y]^{\wedge}2$$

where

- $f(x; p)$ represents the model function with parameters p and input x, and
- y represents the observed data.

The Algorithm 1 combines aspects of gradient descent and the Gauss-Newton method, adjusting parameters iteratively to reach the optimal solution.

In our system, the algorithm modifies the weights and biases of the neural network based on the following update rule:

Algorithm 1 Levenberg-Marquardt algorithm

1: jj = jX * jX
2: je = jX * E
3: dX = −(jj + I*mu)\je

where J is the Jacobian matrix, I is the identity matrix, and e is the error vector. The adaptive variable μ ensures stability and prevents the algorithm from getting stuck in local minima. Training is completed when one of the following conditions is met:

- Maximum training time is reached.
- The desired performance level is achieved.
- The performance gradient becomes too small.

4.4. ML utilization over the OPP

Figure 5 Illustrates the single-line circuit diagram of the IEEE 33-bus system, which includes bus classification into three zones and the corresponding locations of PMU placement. The system data are taken from the paper [37]

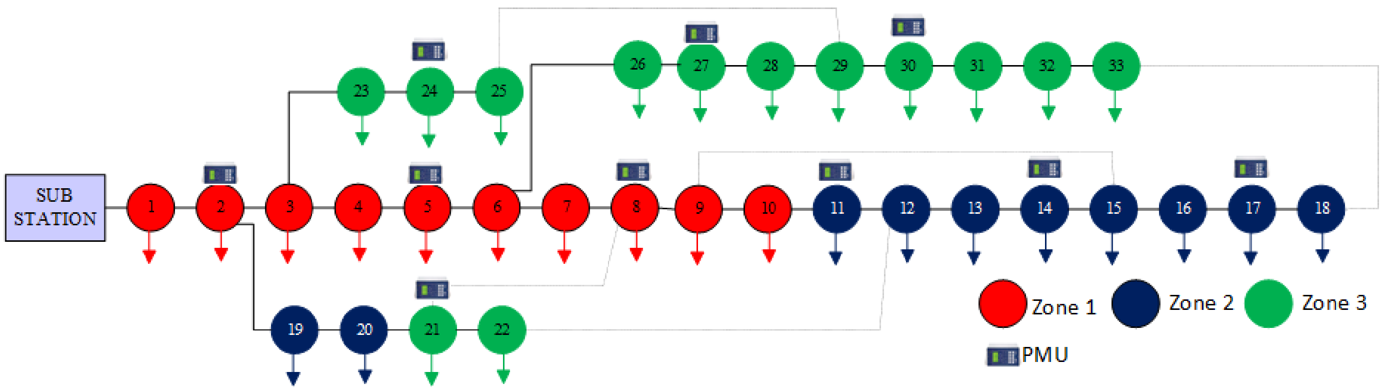

Figure 5. Bus classification scheme.

Selected PMU measurements for fault identification include voltage, current, angle, and power information. These variables are stored in a matrix structure to mitigate storage and memory issues associated with ANN.

The PMU reading selection is as follows.

- Zone 1 controller ANN1 - (PMUmat1 PMU2 PMU 3 ...... PMU10) -
- Zone 2 controller ANN2 - (PMUmat1 PMU2 PMU 3 ...... PMU10) –
- Zone 3 Controller ANN3- (PMU 3 ...... PMU10)

Figure 6 shows the implementation of PMU in Matlab. Short circuit faults are a primary cause of power outages in electrical networks, typically classified into four main types: LG, LL, LLG, and LLL, primarily analyzed at the transmission level. However, at the distribution level, these fault types result in ten different phase combinations due to their imbalance and asymmetry. In the proposed system, LG and LLG faults are analyzed, following the same procedure for other types of faults. Consequently, the case studies do not include faults other than LG and LLG. Faults are generated at each bus and a MATLAB model is employed to compute the voltage and magnitude for each bus. The data collected from all buses is then used as the ANN input.

The **Figure 7** illustrates a simulation of a fault occurring at bus 1. This means that in the depicted visual diagram, a fault scenario, such as a short circuit or another type of electrical fault, is simulated at the specific location denoted as "bus 1." The purpose of the simulation is to analyze the impact of the fault on the electrical system and its components at this particular bus within the more extensive power network.

The ANN is trained using input data collected from the PMUs after the fault analysis. When a fault occurs in the system, the ANN promptly compares the received input data from the PMUs with the trained data. This comparison allows the ANN to accurately identify the fault type in the system and pinpoint the fault's location. This process involves the ANN recognizing deviations in the measurement's indicative of a fault. By analysing these deviations, the ANN can classify the fault type (e.g., LG, LLG) and determine the specific location within the system where the fault has occurred.

5. Simulation findings, analysis, and discussion

To validate the proposed model, a variety of systems, including conventional IEEE test cases, were analyzed. All simulations were performed using MATLAB, and fault identification was tested across multiple test systems, including the IEEE 33-bus system.

Test Case 1: IEEE RBTS -2;
Test Case 2: IEEE 15 Bus system;
Test Case 3: IEEE 33 Bus system;
Test Case 4: IEEE 69 Bus system;
Test Case 5: IEEE 85 Bus system.

5.1. Sensor (PMU) location strategy for distributed state estimation

The BOA successfully identified the optimal PMU locations for several IEEE test systems, ensuring maximum system observability. The results, summarized in **Table 2**, show the efficiency of the BOA in minimizing the number of PMUs required for complete system monitoring. For example, nine PMUs were sufficient to monitor the entire IEEE RBTS-2 Test System, with optimal placement at buses 1, 4, 7, 10, 13, 16, 19, 21, and 23. The below **Table 3** shows the comparison PMU spots and Redundancy Evaluation.

Table 2. Optimal PMU spots ensuring maximum system observability through BOA algorithm.

Test System	No. of PMUs	PMU Location	SMRI	Latency in Sec
IEEE 15	5	2, 4, 9, 11, 13	20	0.023
IEEE RBTS -2	9	1, 4, 7, 10, 13, 16, 19, 21, 23	24	0.050
IEEE 33	10	2, 5, 8, 11, 14, 17, 21, 24, 27, 30	34	0.071
IEEE 69	23	1, 3, 5, 8, 12, 15, 18, 21, 24, 27, 30, 33, 38, 41, 44, 48, 50, 52, 55, 58, 61, 64, 69	81	0.144
IEEE 85	32	2, 4, 6, 8, 10, 12, 13, 15, 17, 19, 22, 24, 26, 27, 29, 32, 35, 37, 41, 45, 47, 50, 53, 55, 58, 62, 64, 67, 70, 73, 81, 84	102	0.196

Table 3. Comparison of optimal PMU spots and redundancy evaluation.

Methods	IEEE 15 Bus		IEEE 33 Bus		IEEE 69 Bus		IEEE 85 Bus	
	No. of PMU	**SMRI**	**No. of PMU**	**SMRI**	**No. of PMU**	**SMRI**	**No. of PMU**	**SMRI**
Proposed Method	5	20	10	34	23	81	32	102
AGA [23]	-	-	11	33	26	84	-	-
Greedy Algorithm [24]	7	22	14	38	27	85	-	-
CES [25]	-	-	11	33	25	82	-	-
NSGA [26]	5	19	11	32	23	80	-	-
MST [10]	5	19	11	32	23	80	-	-
ACO [2]	6	21	12	36	24	82	-	-

5.2. Fault detection using machine learning in distributed state estimation

The machine learning model was trained using the MATLAB Simulink toolbox to detect faults using input data from PMUs. The model was tested on the IEEE 33-bus system, where short-circuit faults, including LG and LLG faults, were simulated. The ANN was able to accurately classify and locate faults in the system by analysing deviations in voltage and current measurements from the PMUs.

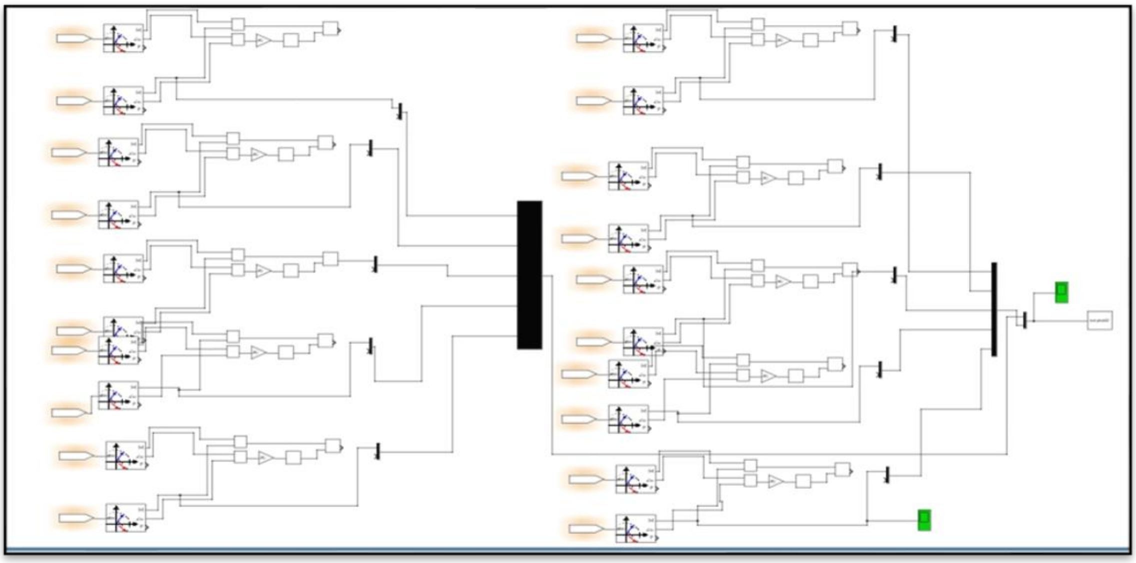

Figure 6. Implementation of PMU unit in MATLAB.

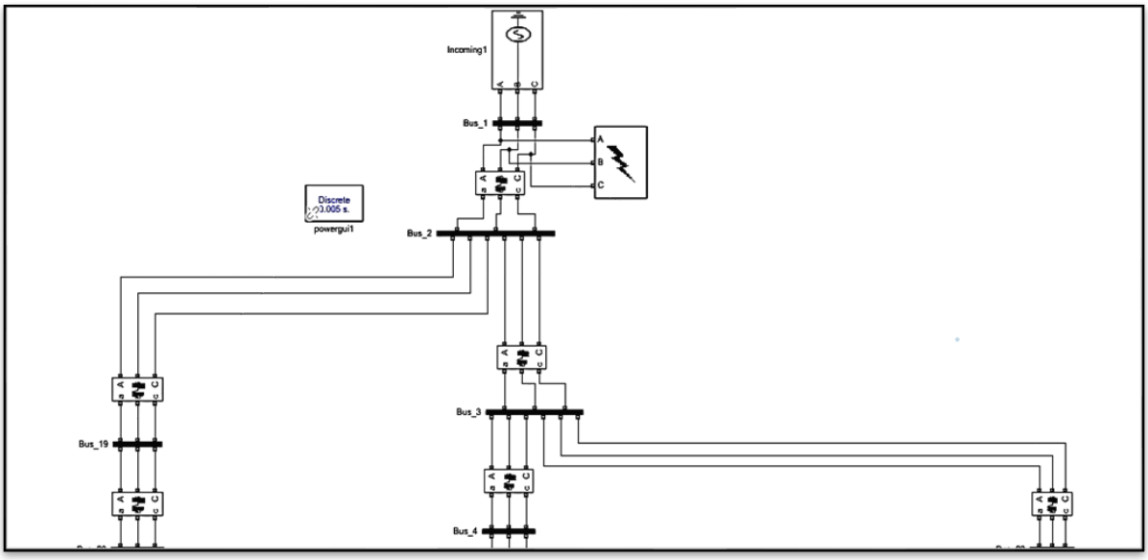

Figure 7. MATLAB model for fault simulation in BUS 1.

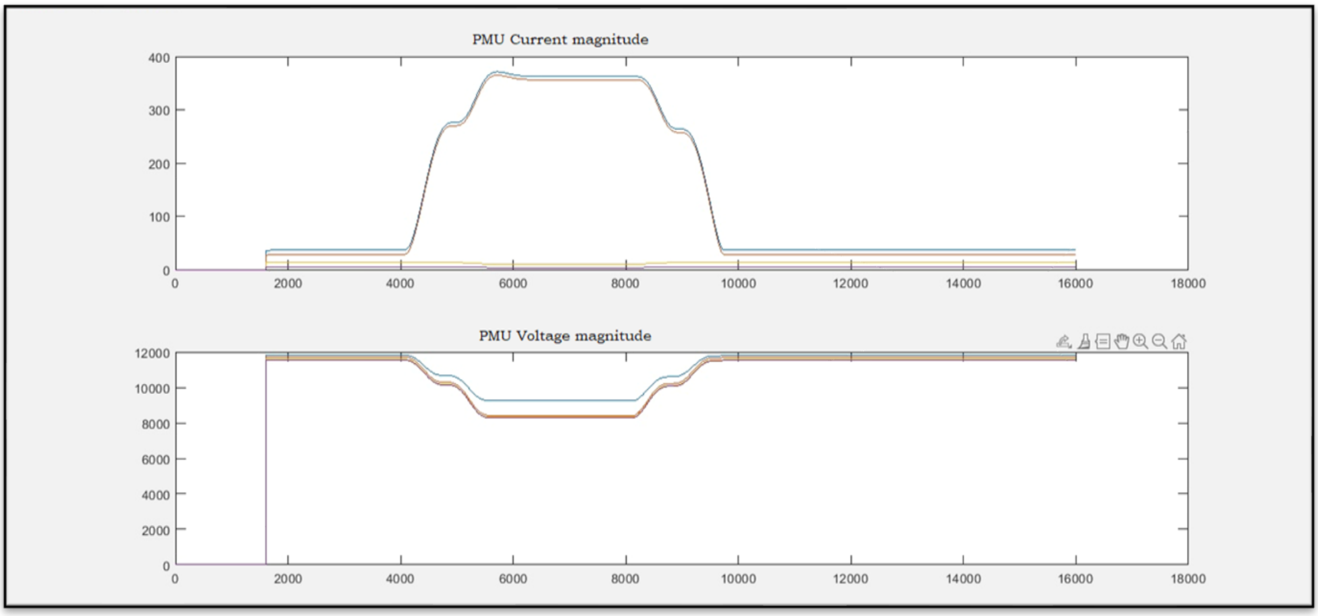

Figure 8. PMU voltage and current for LG fault.

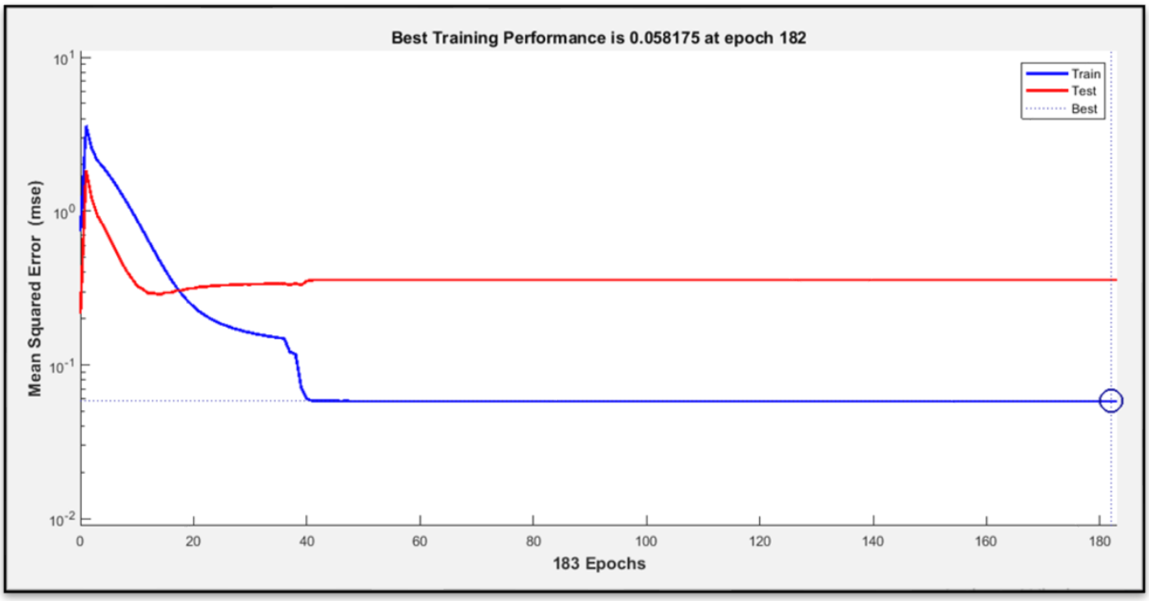

Figure 9. Machine learning model's training performance.

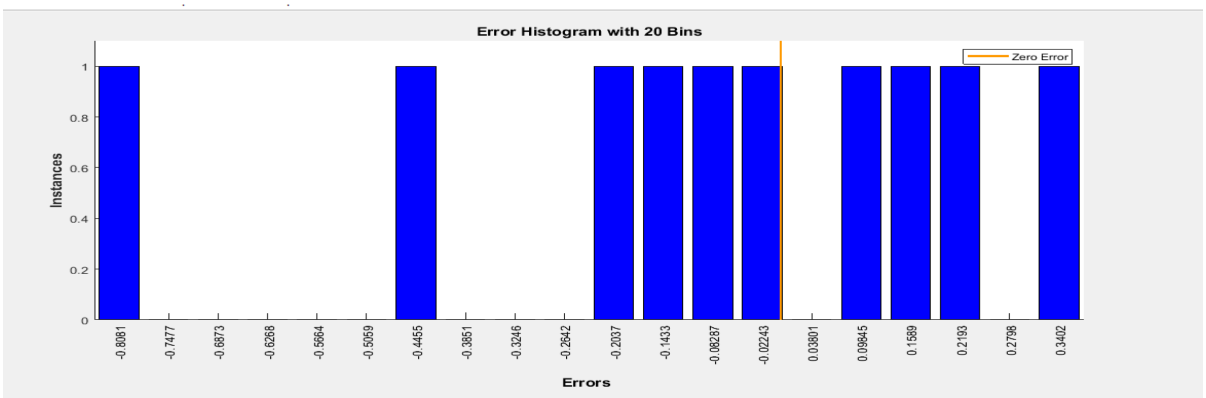

Figure 10. Error histogram with 20 bins.

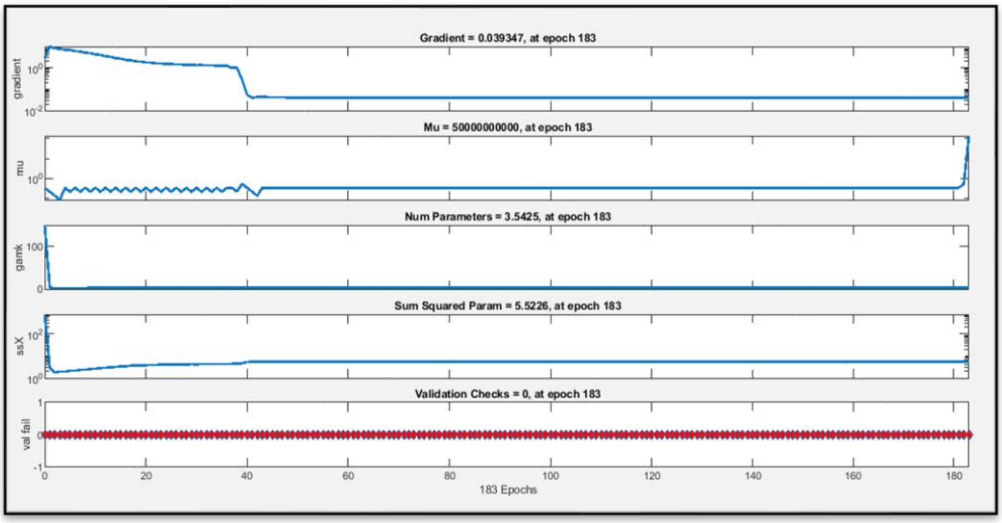

Figure 11. Machine learning model's performance on a validation dataset.

For instance, **Figure 8** illustrates the PMU voltage and current measurements during an LG fault. The machine learning model demonstrated a high level of accuracy in identifying faults, with training performance reaching a peak accuracy of 99.8% after 182 epochs, as shown in **Figure 9**. Furthermore**, Figure 10**'s error histogram confirms that most predictions had errors close to zero, indicating strong model performance.

5.3. Certain observations

The following key observations can be drawn from the simulation results:

- The use of the BOA significantly improved efficiency over other optimization methods. This resulted in better placement of PMUs for dynamic state estimation modules.
- The SMRI calculated for the IEEE 33-bus system showed higher efficiency compared to other methods, primarily due to the superior optimization capabilities of BOA.
- Repeated training of the ML model, based on dynamic situations, improved fault detection accuracy. This adaptability allowed the system to respond to a variety of real-world fault conditions more effectively than single, simulated processes.
- Machine learning models, particularly neural networks, proved to be an open-source and flexible solution that can be continually refined and adapted over time for better performance.
- The graphical results shown in **Figure 11** demonstrated that the training and performance of the machine learning model remained consistent, even in dynamic estimation systems. This reliability makes it applicable to real-world grid management scenarios.
- From a practical standpoint, this research offers a solution that can be directly implemented in distribution systems. The proposed method, with its integrated use of BOA for PMU placement and machine learning for fault detection, helps enhance grid stability by predicting and preventing faults.

6. Conclusions

The integration of deep learning techniques for fault detection and PMU placement optimization in radial power distribution networks significantly enhances system resilience. In this study, we leveraged advanced artificial intelligence methods to improve two critical aspects of power system management: fault detection and real-time monitoring.

Through the use of the BOA, we were able to determine optimal PMU placements, maximizing system observability while minimizing the number of required units. At the same time, the machine learning models, particularly neural networks, demonstrated high efficiency in detecting and classifying faults with an accuracy rate of around 85%. The use of MATLAB-based simulations for fault conditions, such as LG and LLG faults, provided a robust validation framework for the proposed approach.

By implementing these techniques, power systems can detect and locate faults more accurately and in real-time. This significantly reduces system downtime and enhances the overall resilience of the grid, ensuring that it can quickly recover from disturbances while maintaining continuous operation.

6.1. Core takeaways

Optimized PMU Placement: The use of BOA enables the strategic placement of PMUs, minimizing cost and maximizing system observability.Enhanced Fault Detection: Deep learning models, such as neural networks, can identify and classify faults with high accuracy, improving fault management in radial power networks.System Resilience: The proposed framework enhances the power system's ability to withstand and recover from faults, reducing disruptions to end-users and increasing grid stability.

Contributions and societal implications

The research findings contribute directly to the practical implementation of fault detection and monitoring systems within distribution grids. The improvements in system observability and fault detection efficiency pave the way for more reliable electricity networks, which is crucial in reducing energy poverty and ensuring sustainable energy supplies. The application of green energy, supported by real-time monitoring with PMUs, also has the potential to significantly reduce emissions and promote the use of renewable resources.

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References

1. Adhikari PM, Vanfretti L, Chang H, et al. Real-Time Control of a Battery Energy Storage System Using a Reconfigurable Synchrophasor-Based Control System. Energies. 2023; 16(19): 6909. doi: 10.3390/en16196909
2. Arefin AA. Application of the phasor measurement unit for protecting unintentional islanding of the distribution system. Power System Protection in Future Smart Grids. 2024: 109-132. doi: 10.1016/b978-0-323-91780-3.00005-2
3. Andic C, Ozturk A, Turkay B. A robust crow search algorithm based power system state estimation. Energy Reports. 2023; 9: 490-501. doi: 10.1016/j.egyr.2023.09.075
4. da Silva Pessoa AL, Oleskovicz M. Fault location algorithm for distribution systems with distributed generation based on impedance and metaheuristic methods. Electric Power Systems Research. 2023; 225: 109871. doi: 10.1016/j.epsr.2023.109871

5. Babu R, Gupta VK. Analysis of Bus Vulnerability Conducted Using a Synchronized Phasor Measurement Unit in Order to Achieve the Maximum Observability. Transactions on Energy Systems and Engineering Applications. 2023; 4(2): 1-23. doi: 10.32397/tesea.vol4.n2.523
6. Biswas S, Follum J, Etingov P, et al. An Open-Source Library of Phasor Measurement Unit Data Capturing Real Bulk Power Systems Behavior. IEEE Access. 2023; 11: 108852-108863. doi: 10.1109/access.2023.3321317
7. Zhou C, Zou G, Zheng M, et al. Reference Phasor-Based Data Self-Synchronization Scheme for Line Current Differential Protection in Active Distribution Networks. IEEE Transactions on Smart Grid. 2024; 15(2): 1466-1480. doi: 10.1109/tsg.2023.3313188
8. Chavez JJ, Kumar NV, Azizi S, et al. PMU-voltage drop based fault locator for transmission backup protection. Electric Power Systems Research. 2021; 196: 107188. doi: 10.1016/j.epsr.2021.107188
9. Ciancetta F, Fioravanti A, Luiso M, et al. Performance of PMU in an electric distribution grid during transients. International Journal of Emerging Electric Power Systems. 2023; 25(5):709-721. doi: 10.1109/PQ.2019.8818247
10. Meenakshi Devi M, Geethanjali M. Hybrid of Genetic Algorithm and Minimum Spanning Tree method for optimal PMU placements. Measurement. 2020; 154: 107476. doi: 10.1016/j.measurement.2020.107476
11. Ahmad F, Rasool A, Ozsoy E, et al. Distribution system state estimation-A step towards smart grid. Renewable and Sustainable Energy Reviews. 2018; 81: 2659-2671. doi: 10.1016/j.rser.2017.06.071
12. Duque FG, de Oliveira LW, de Oliveira EJ, et al. A cost-benefit multiobjective approach for placement of meters in electrical distribution systems. Electric Power Systems Research. 2021; 191: 106897. doi: 10.1016/j.epsr.2020.106897
13. Dua GS, Tyagi B, Kumar V. Fault Detection Technique for Distribution Networks and Microgrids Using Synchrophasor Data. IEEE Transactions on Industry Applications. 2023; 59(6): 7368-7381. doi: 10.1109/tia.2023.3305362
14. Hassini K, Fakhfakh A, Derbel F. Optimal Placement of μPMUs in Distribution Networks with Adaptive Topology Changes. Energies. 2023; 16(20): 7047. doi: 10.3390/en16207047
15. Im J, Ban J, Kim YJ, et al. PMU-Based Distributed State Estimation to Enhance the Numerical Stability Using Equality Constraints. IEEE Transactions on Power Systems. 2024; 39(2): 4409-4421. doi: 10.1109/tpwrs.2023.3303230
16. Lee KY, Park JS, Kim YS. Optimal Placement of PMU to Enhance Supervised Learning-Based Pseudo-Measurement Modelling Accuracy in Distribution Network. Energies. 2021; 14(22): 7767. doi: 10.3390/en14227767
17. Lin W, Wang Q, Long J, et al. Optimization method of PMU placements base on costs and risk assessments of state estimation. Energy Reports. 2023; 9: 348-355. doi: 10.1016/j.egyr.2023.09.106
18. Mukherjee M, Roy BKS. Optimal ${\rm{\mu }}$PMU, PDC, and Communication Link Placement in Distribution Network Using Binary Carnivorous Plant Algorithm. IEEE Transactions on Industry Applications. 2023; 59(6): 7701-7715. doi: 10.1109/tia.2023.3304616
19. Rahman NHA, Zobaa AF. Optimal PMU placement using topology transformation method in power systems. Journal of Advanced Research. 2016; 7(5): 625-634. doi: 10.1016/j.jare.2016.06.003
20. Theodorakatos NP, Moschoudis AP, Lytras MD, et al. Research on optimization procedure of PMU positioning problem achieving maximum observability based on heuristic algorithms. 11Th international conference on mathematical modeling in physical sciences. 2023; 2872: 120032. doi: 10.1063/5.0162934
21. Theodorakatos NP, Lytras MD, Kantoutsis KT, et al. Optimization-based optimal PMU placement for power state estimation and fault observability. 11Th international conference on mathematical modeling in physical sciences. 2023; 2872: 120033. doi: 10.1063/5.0162941
22. Pattanaik V, Malika BK, Rout PK, et al. Contingency-resilient PMU placement using Fuzzy Logic and Discrete Artificial Bee Colony algorithm for comprehensive network observability. e-Prime - Advances in Electrical Engineering, Electronics and Energy. 2023; 5: 100275. doi: 10.1016/j.prime.2023.100275
23. Peng J, Sun Y, Wang HF. Optimal PMU placement for full network observability using Tabu search algorithm. International Journal of Electrical Power & Energy Systems. 2006; 28(4): 223-231. doi: 10.1016/j.ijepes.2005.05.005
24. Ngo QH, Nguyen BLH, Vu TV, et al. State Estimation for Power Distribution System Using Graph Neural Networks. 2023 IEEE Electric Ship Technologies Symposium (ESTS). Published online August 1, 2023. doi: 10.1109/ests56571.2023.10220523
25. Andreoni R, Macii D, Brunelli M, et al. Tri-Objective Optimal PMU Placement Including Accurate State Estimation: The Case of Distribution Systems. IEEE Access. 2021; 9: 62102-62117. doi: 10.1109/access.2021.3074579

26. Rashidi F, Abiri E, Niknam T, et al. Optimal placement of PMUs with limited number of channels for complete topological observability of power systems under various contingencies. International Journal of Electrical Power & Energy Systems. 2015; 67: 125-137. doi: 10.1016/j.ijepes.2014.11.015
27. Rezapour H, Jamali S, Bahmanyar A. Review on Artificial Intelligence-Based Fault Location Methods in Power Distribution Networks. Energies. 2023; 16(12): 4636. doi: 10.3390/en16124636
28. Sonal, Ghosh D. Novel trends in resilience assessment of a distribution system using synchrophasor application: A literature review. International Transactions on Electrical Energy Systems. 2021; 31(8). doi: 10.1002/2050-7038.12934
29. Todescato M, Carli R, Schenato L, et al. Smart Grid State Estimation with PMUs Time Synchronization Errors. Energies. 2020; 13(19): 5148. doi: 10.3390/en13195148
30. Tshenyego O, Samikannu R, Mtengi B, et al. A Graph-Theoretic Approach for Optimal Phasor Measurement Units Placement Using Binary Firefly Algorithm. Energies. 2023; 16(18): 6550. doi: 10.3390/en16186550
31. Basetti V, Chandel AK. Optimal PMU placement for power system observability using Taguchi binary bat algorithm. Measurement. 2017; 95: 8-20. doi: 10.1016/j.measurement.2016.09.031
32. Kong X, Wang Y, Yuan X, et al. Multi Objective for PMU Placement in Compressed Distribution Network Considering Cost and Accuracy of State Estimation. Applied Sciences. 2019; 9(7): 1515. doi: 10.3390/app9071515
33. Naveenkumar K, Kannan R, Ganesan S, et al. Distribution system state estimation with stability assessment using bio-inspired computing. IET Sci Meas Techol 2021; 14(10): 1003–1013. https://doi.org/10.1049/iet-smt.2020.0049
34. Raghuvamsi Y, Teeparthi K. A review on distribution system state estimation uncertainty issues using deep learning approaches. Renewable and Sustainable Energy Reviews. 2023; 187: 113752. doi: 10.1016/j.rser.2023.113752
35. Ngo QH, Nguyen BLH, Vu TV, et al. Physics-informed graphical neural network for power system state estimation. Applied Energy. 2024; 358: 122602. doi: 10.1016/j.apenergy.2023.122602
36. Makhadmeh SN, Al-Betar MA, Abasi AK, et al. Recent Advances in Butterfly Optimization Algorithm, Its Versions and Applications. Archives of Computational Methods in Engineering. 2022; 30(2): 1399-1420. doi: 10.1007/s11831-022-09843-3
37. IEEE PES AMPS DSAS Test Feeder Working Group. Available Online: http://sites.ieee.org/pes-testfeeders/ (accessed on 2 September 2023).