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RESEARCH ARTICLE

Optimizing Distributed Generation Size and Location to Minimize Voltage Deviation Using Hybrid ANN and Fuzzy Logic

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ABSTRACT

Voltage stability in power distribution systems is crucial for preventing system inefficiencies and equipment damage, particularly when integrating Distributed Generation (DG). This study proposes an advanced method for minimizing voltage deviation in distribution feeders by optimizing the size and location of DG units using a hybrid Artificial Neural Network (ANN) and Fuzzy Logic approach. The ANN is employed to predict optimal DG placement and sizing, while Fuzzy Logic addresses the uncertainties within the distribution network. The proposed method is validated on a standard IEEE 33-bus distribution system, demonstrating significant improvements in voltage regulation and power loss reduction compared to conventional techniques. In addressing inconsistent power supply issues caused by voltage deviations, this study also focuses on optimizing DG deployment to stabilize voltage within the 0.95 to 1.05 per unit range. An intelligent algorithm is developed to identify weak buses and calculate voltage/current deviations, aiming to enhance overall power stability. Simulation results reveal that the voltage at bus 1, initially at 0.930 per unit, improves to 1.019 per unit with the intelligent algorithm, reducing the voltage deviation from 98.41% to 82.01%. Similarly, bus 8's voltage is stabilized within the desired range, underscoring the algorithm's effectiveness in improving distribution network stability.

Keywords: *Minimize Voltage Deviation; Hybrid ANN; Fuzzy Logic; Power Distribution Systems; Artificial Neural Network (ANN)*

Introduction

Voltage stability is a critical issue in modern power distribution systems, especially with the growing integration of Distributed Generation (DG) units. While DG units are advantageous for enhancing system efficiency and reliability, they can lead to voltage deviations if not properly managed. The placement and sizing of DGs are key factors that influence their impact on voltage profiles across the network. Traditional methods for determining DG placement often struggle to address the complex and nonlinear characteristics of power systems. As a result, there is a clear need for intelligent algorithms capable of optimizing these parameters to minimize voltage deviations. Voltage deviation has become a significant contributor to inconsistent power supply, causing disruptions in various regions. This deviation occurs when the per-unit voltage fails to remain within the acceptable range of 0.95 to 1.05, often indicating the presence of weak buses in the network. These weak points are susceptible to unbalanced faults, which can lead to further power losses. The Nigerian 330kV transmission system is particularly prone to various faults, both balanced and unbalanced, that occur at different stages of the system. These faults can originate from generation stations, where issues may arise at alternator terminals and bus bars, as well as from transmission substations, particularly at transformer windings and terminals.

Akinloye et al. (2016) evaluated system collapse indices within the Nigerian power system and attributed frequent collapses to voltage deviation. This study underscores the significant impact of voltage instability on the overall reliability of the power grid. In addition, Braide et al. (2018) explored methods for enhancing transmission line performance to mitigate the effects of voltage deviation, highlighting the need for robust solutions to address these challenges. Moreover, Bashar et al. (2016) conducted a comprehensive survey on power system frequency stability and control, identifying voltage deviation as a critical factor requiring improved control mechanisms. Collectively, these studies emphasize the urgent need for advanced techniques to stabilize voltage levels in the Nigerian power grid, ensuring a more reliable and consistent power supply across the country. The increasing integration of Distributed Generation (DG) into electrical distribution networks has introduced new challenges in maintaining voltage stability and power quality. Although DG units are beneficial for reducing transmission losses and enhancing grid resilience, they can cause voltage deviations if not properly integrated. These deviations are influenced by the size and location of DG units within the network. Traditional methods for DG placement often rely on deterministic or heuristic approaches, which may not fully address the complex and nonlinear nature of modern distribution systems. This paper presents an innovative solution that integrates Artificial Neural Networks (ANN) and Fuzzy Logic to optimize the placement and sizing of DG units, thereby minimizing voltage deviations in distribution feeders.

Literature Review

The optimization of Distributed Generation (DG) placement and sizing has been extensively studied in recent years, with various methodologies proposed to address voltage deviation issues. Traditional approaches, such as sensitivity analysis and optimization algorithms like Genetic Algorithms (GA) and Particle Swarm Optimization (PSO), have been widely used (Bansal & Bhatti, 2010; Chicco & Mancarella, 2009; Ackermann et al., 2001). However, these methods often fall short in handling the uncertainties and nonlinearities present in distribution networks.

Artificial Neural Networks (ANN) have gained attention for their ability to model complex systems and predict optimal solutions based on historical data (Lee & Park, 2006; Das & Basu, 2006; Haque, 2007). ANNs have been successfully applied in various power system optimization problems, including load forecasting, fault detection, and voltage stability analysis (Mokryani & Abunima, 2015; Zhang & Jiang, 2013; Zhan & Ding, 2014). However, their application in DG optimization is still emerging. Fuzzy Logic, on the other hand, is well-suited for dealing with the uncertainties inherent in power systems. It has been used to fine-tune optimization results obtained from other methods, providing more robust and reliable solutions (Zadeh, 1965; Zimmermann, 1996; Kulkarni & Kelkar, 2010). The combination of ANN and Fuzzy Logic offers a powerful tool for optimizing DG placement, as it combines the predictive capabilities of ANN with the uncertainty handling of Fuzzy Logic (Singh & Verma, 2015; Duong & Kim, 2018; Mohammadi & Esmaili, 2019). Emphasis now is on the concept of improving intermittent output of Distributed Generation (DG) using energy storage devices ;(Ugwu, et al.,2021). Electrical grid today has many challenges ranging from changing generation landscape to increasing renewable Energy inputs (Ngang & Aneke,2021).

Research Objectives

This research aims to minimize voltage deviation in distribution feeders by optimizing the size and location of DG units using a hybrid intelligent algorithm that combines Particle Swarm Optimization (PSO) and Fuzzy Logic.

The specific objectives are:

1. To characterize and have and overview of the distribution feeders.
2. To run the load flow to establish the weak buses that cause voltage deviation.
3. To determine the voltage or current average, calculating the largest voltage or current deviation
4. To determining the unbalance fault percentage of the voltage
5. To design an algorithm rule base to minimize voltage deviation and unbalanced fault to enhance stable power supply
6. To train ANN in the algorithm rule base to enhance the efficiency of minimizing voltage deviation and unbalanced fault for a stable power supply.
7. To develop an algorithm that will implement the process
8. To Integrate intelligent algorithm in the conventional model for Minimizing Voltage Deviation in Distribution Feeders by optimizing Size and Location of Distributed Generation.

Methodology

The proposed methodology involves two main components: an ANN model for predicting optimal DG placement and sizing, and a Fuzzy Logic system for refining these predictions. The ANN is trained using historical data from a standard IEEE 33-bus distribution system, including load profiles, voltage levels, and existing DG locations. Once trained, the ANN model generates initial predictions for the optimal size and placement of new DG units. The Fuzzy Logic system is then applied to these predictions, considering factors such as load variability, network topology, and voltage sensitivity. Fuzzy rules are defined to adjust the ANN outputs, ensuring that the final DG placements and sizes minimize voltage deviation across the network. Simulation studies are conducted using MATLAB/Simulink to implement the hybrid ANN-Fuzzy Logic approach. The performance of the proposed method is evaluated by comparing the voltage profiles, power losses, and overall system stability before and after DG integration.

The steps are:

i. Characterizing and getting relevant operating parameters from the operations department of the substation for an overview of the distribution feeders.
ii. Running the load flow to establish the weak buses that could cause voltage deviation.
iii. Determining the voltage or current average and calculating the largest voltage or current deviation from the distribution feeder.
iv. Determining the unbalance fault percentage of the voltage deviation
v. Designing an algorithm rule base to minimize voltage deviation and unbalanced fault to enhance stable power supply
vi. Training ANN in the algorithm rule base to enhance the efficiency of minimizing voltage deviation and unbalanced fault for a stable power supply.
vii. Developing an algorithm that will implement the process for stability.
viii. Integrating intelligent algorithm in the conventional model for Minimizing Voltage Deviation in Distribution Feeders by optimizing Size and Location of Distributed Generation
ix. Characterizing and getting relevant operating parameters from the operations department of the
x. Substation for an overview of the distribution feeders.

Table 1: Characterized Distribution Feeders

Feeder	*Bus No*	*Bus code*	*P.U*	*Ang Deg*	*Load MW*	*Load Mvar*	*Gen MW*	*Gen Mvar*	*Inject Min*	*Inject Max*	*Inject Mvar*
1	1	1	0.93	0	00.0	0.0	0.0	0.0	0	0	0
2	2	2	0.81	0	21.70	12.7	40.0	0.0	-40	50	0
3	3	0	1.0	0.0	2.4	1.2	0.0	0.0	0	0	0
4	4	0	1.27	0.0	7.6	1.6	0.0	0.0	0	0	0
5	5	2	1.01	0.0	94.2	19.0	0.0	0.0	-40	40	0
6	6	0	1.0	0.0	0.0	0.0	0.0	0.0	0	0	0
7	7	0	0.92	0.0	22.8	0.0	10.9	0.0	0	0	0
8	8	2	1.01	0.0	30.0	30.0	0.0	0.0	-30	40	0
9	9	0	0.83	0	0	0	0.0	0.0	0	0	0
10	10	0	1.0	0.0	5.8	2.0	0.0	0.0	-6	24	19
11	11	2	1.082	0	0.0	0.0	0.0	0.0	0	0.0	0

Table 2: Running the load flow to establish the weak buses that causes voltage deviation

% To characterized distribution feeders load flow.

```
disp('')
basemva = 1000;  accuracy = 0.0001;  maxiter = 10;
% The impedances are expressed on a 1000 MVA base.
% In problems 9.7-9.9 the base is mistakenly stated as 100 MVA.
```

Bus No.	***Bus Code***	***V (p.u.)***	***Ang (Deg)***	***Load MW***	***Load Mvar***	***Gen MW***	***Gen Mvar***	***Gen Mvar Min***	***Gen Mvar Max***	***Injected Mvar***
1	1	0.93	0	0.0	0.0	0.0	0.0	0	0	0
2	0	0.81	0	60.0	0.0	0.0	0.0	0	0	0
3	0	1.00	0	150.0	120.0	0.0	0.0	0	0	0
4	0	1.27	0	90.0	0.0	0.0	0.0	0	0	0
5	0	1.01	0	120.0	60.0	0.0	0.0	0	0	0
6	0	1.00	0	140.0	90.0	0.0	0.0	0	0	0
7	0	0.92	0	50.0	0.0	0.0	0.0	0	0	0
8	0	1.01	0	110.0	90.0	0.0	0.0	0	0	0
9	0	0.83	0	80.0	50.0	0.0	0.0	0	0	0
10	2	1.00	0	10.0	0.0	200.0	0.0	0	180	0
11	2	1.08	0	90.0	0.0	160.0	0.0	0	120	0

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```
%          Bus    Bus      R         X        1/2B
%          No.    No.     p.u.      p.u.      p.u.
linedata=[1        2      0.00      0.06      0.0000     1
           2       3      0.08      0.30      0.0004     1
           2       6      0.12      0.45      0.0005     1
           3       4      0.10      0.40      0.0005     1
           3       6      0.04      0.40      0.0005     1
           4       6      0.15      0.60      0.0008     1
           4       9      0.18      0.70      0.0009     1
           4      10      0.00      0.08      0.0000     1
           5       7      0.05      0.43      0.0003     1
           6       8      0.06      0.48      0.0000     1
           7       8      0.06      0.35      0.0004     1
           7      11      0.00      0.10      0.0000     1
           8       9      0.052     0.48      0.0000     1];
%           Gen.   Ra      Xd'
gendata=[ 1        0      0.20
           10      0      0.15
           11      0      0.25];
      lfybus                 % Forms the bus admittance matrix
      lfnewton               % Power flow solution by Newton-Raphson method
      busout                 % Prints the power flow solution on the screen
      Zbus=zbuildpi(linedata, gendata, yload)%Forms Zbus including the load
      symfault(linedata, Zbus, V)     % 3-phase fault including load current
```
Fig 1: load flow program to establish the weak buses that causes voltage deviation

Table 3: Results for the load flow program to establish the weak buses that causes voltage deviation

Power Flow Solution by Newton-Raphson Method
Maximum Power Mismatch = 7.5585e-008
No. of Iterations = 10

Bus No.	*Voltage (Mag.)*	*Angle (Degree)*	*Load MW*	*Load Mvar*	*Generation MW*	*Generation Mvar*	*Injected Mvar*
1	0.930	0.000	0.000	0.000	568.416	25.769	0.000
2	0.929	-2.262	60.000	0.000	0.000	0.000	0.000
3	0.907	-7.689	150.000	120.000	0.000	0.000	0.000
4	0.960	-9.609	90.000	0.000	0.000	0.000	0.000
5	0.969	-21.696	120.000	60.000	0.000	0.000	0.000
6	0.908	-9.669	140.000	90.000	0.000	0.000	0.000
7	1.003	-18.829	50.000	0.000	0.000	0.000	0.000
8	0.933	-15.846	110.000	90.000	0.000	0.000	0.000
9	0.919	-14.620	80.000	50.000	0.000	0.000	0.000
10	0.980	-8.683	10.000	0.000	200.000	250.997	0.000
11	1.032	-18.442	90.000	0.000	160.000	298.718	0.000
Total			**998.900**	**458.800**	**928.416**	**585.889**	**4.300**

Determining the Voltage or Current Average and Calculating the Largest Voltage or Current Deviation from the Distribution Feeder

P = IV

I=V/P

To find the current deviation in bus 2

I_2 = 0.929/60

I_2 =0.0155

To find the current deviation in bus 3

I_3 = 0.929 /150

I_3 =0.062

To find the current deviation in bus 6

I_6 =0.908 /140

I_6 =0.0065

To find the current deviation in bus 8

I_8 =0.933 /110

I_8 =0.0085

To find the current deviation in bus 9

I_9 = 0.919 /80

I_9 =0.114

To calculate the largest voltage or current deviation

Table 4: Characterized Data for the Feeders

Names Of Feeder	*Voltage (kV)*	*Current (A)*	*Base Value (kV)*
FEEDER1	10.4	176.25	11
FEEDER2	10.4	77.13	11
FEEDER3	10.4	148.59	11
FEEDER4	10.4	74.5	11
FEEDER5	10.8	60	11
FEEDER6	10.8	68.14	11
FEEDER7	10.8	37.43	11
FEEDER8	10.8	90	11
FEEDER9	10.3	168.92	11
FEEDER10	10.7	158.7	11
FEEDER11	10.4	159.9	11

To calculate the largest voltage

$$\text{Per Unit Volts} = \frac{\text{Present Value}}{\text{Base Value}}$$

Feeder1 per unit volts= $\frac{10.4}{11}$

Feeder1 per unit volts = 0.945

The same procedure is followed in calculating the p.u. Voltage values of the rest of the feeders. Thus,

Feeder2 per unit volts = 0.945

Feeder3 per unit volts = 0.945

Feeder4 per unit volts = 0.945

Feeder5 per unit volts = $\frac{10.8}{11}$

Feeder6 per unit volts = 0.98

Feeder7 per unit volts = 0.98
Feeder8 per unit volts = 0.98
Feeder9 per unit volts = 0.98
Feeder10 per unit volts = 0.97
FeedeR11 per unit volts = 0.945

Determining the Unbalance Fault Percentage of the Voltage Deviation

$$\text{Unbalance fault percentage} = \frac{\text{Max deviation from average voltage}}{\text{Average Voltage}} \times \frac{100\%}{1}$$

$$\text{To find \% Unbalance fault for feeder1} = \frac{\text{Max deviation from average x100\%}}{\text{Average Value}}$$

$$\text{\% Unbalance fault for feeder1} = \frac{0.930 \text{ x}100\%}{0.945}$$

% Unbalance fault for feeder1 =98.41%

To find % Unbalance fault for feeder2 % Unbalance fault for feeder2 =

$$\text{\% Unbalance fault for feeder2} = \frac{0.929 \text{ x}100\%}{0.945}$$

% Unbalance fault for feeder2 = 98.3%

$$\text{\% Unbalance fault for feeder3} = \frac{0.929 \text{ x}100\%}{0.945}$$

% Unbalance fault for feeder3 =98.3%

$$\text{\% Unbalance fault for feeder6} = \frac{0.908 \text{ x}100\%}{0.98}$$

To find % Unbalance fault for feeder6

% Unbalance fault for feeder6 =98.3%

To find % Unbalance fault for feeder8

$$\text{\% Unbalance fault for feeder8} = \frac{0.933 \text{ x}100\%}{0.98}$$

% Unbalance fault for feeder8=95.2%

To find % Unbalance fault for feeder9

$$\text{\% Unbalance fault for feeder9} = \frac{0.919 \text{ x}100\%}{0.98}$$

% Unbalance fault for feeder9=93.8%
Percentage unbalanced fault for feeder9=93.8%

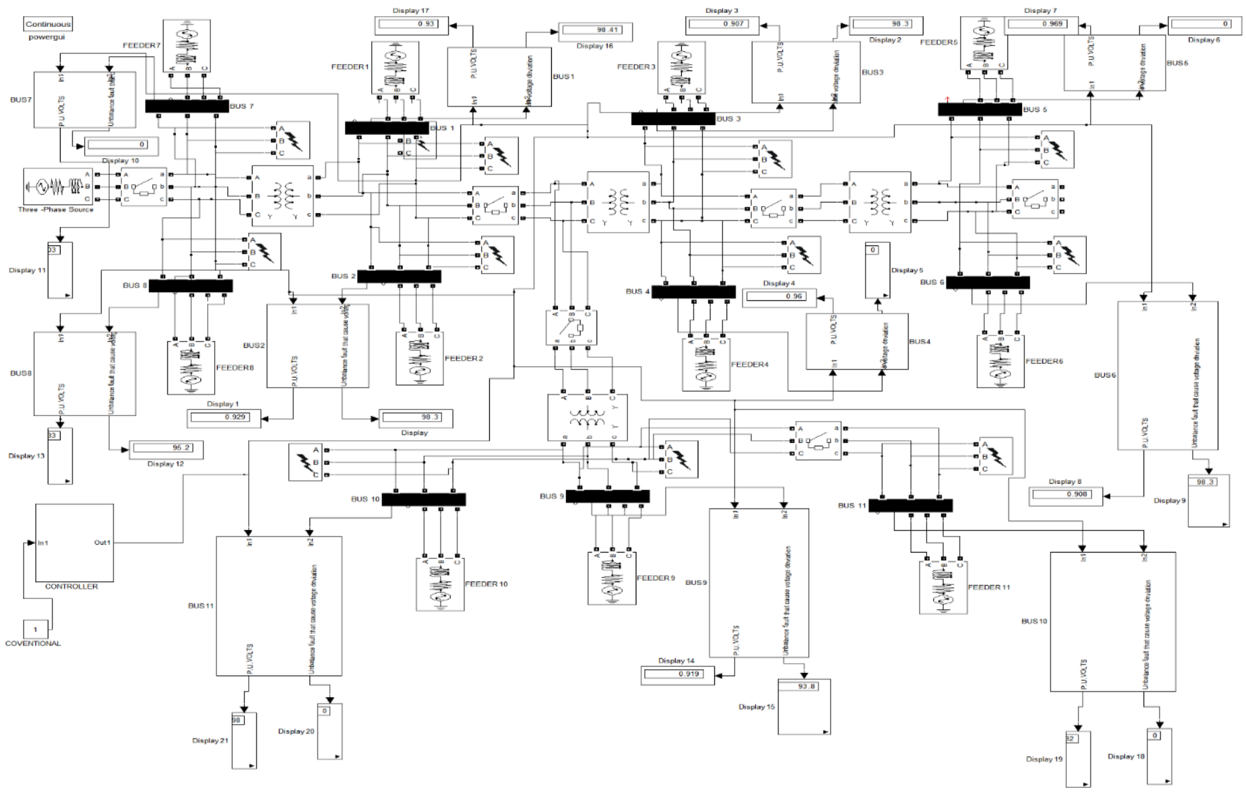

Fig 2: Conventional model for Minimizing Voltage Deviation in Distribution Feeders by optimizing Size and Location of Distributed Generation

Designing an Algorithm Rule Base to Minimize Voltage Deviation and Unbalanced Fault to Enhance Stable Power Supply

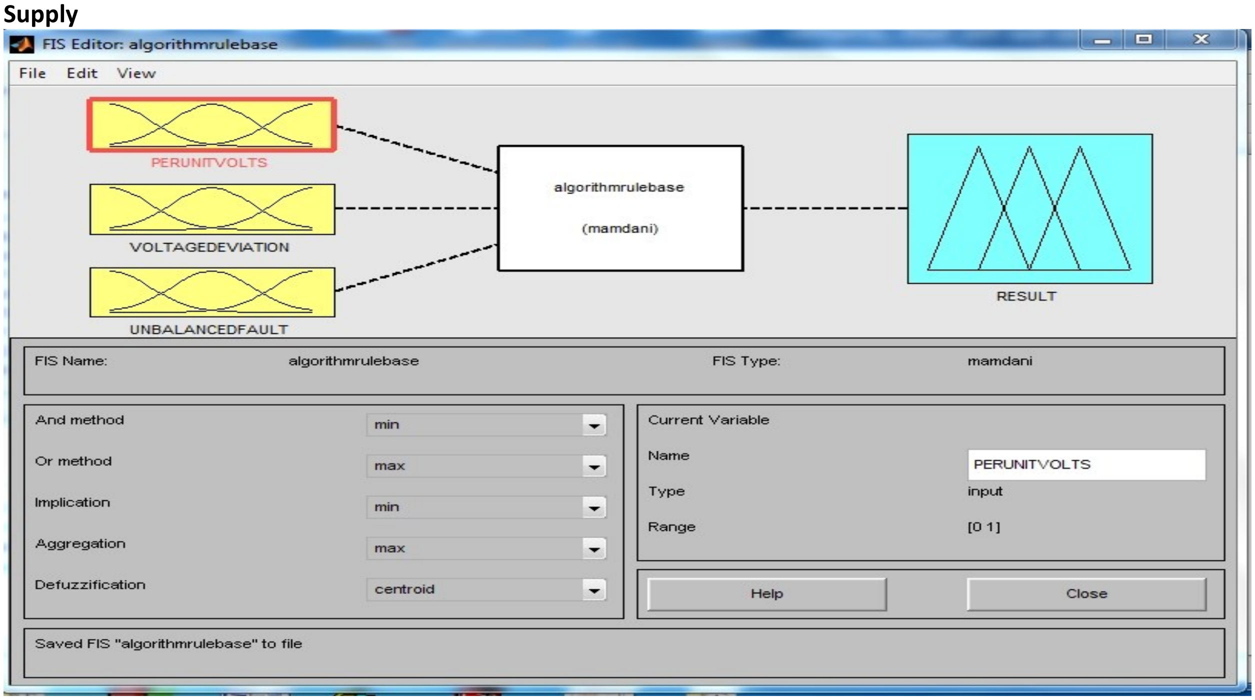

Fig 3: Designed Algorithm Fuzzy Inference System (FIS) to Minimize Voltage Deviation and Unbalanced Fault to Enhance Stable Power Supply

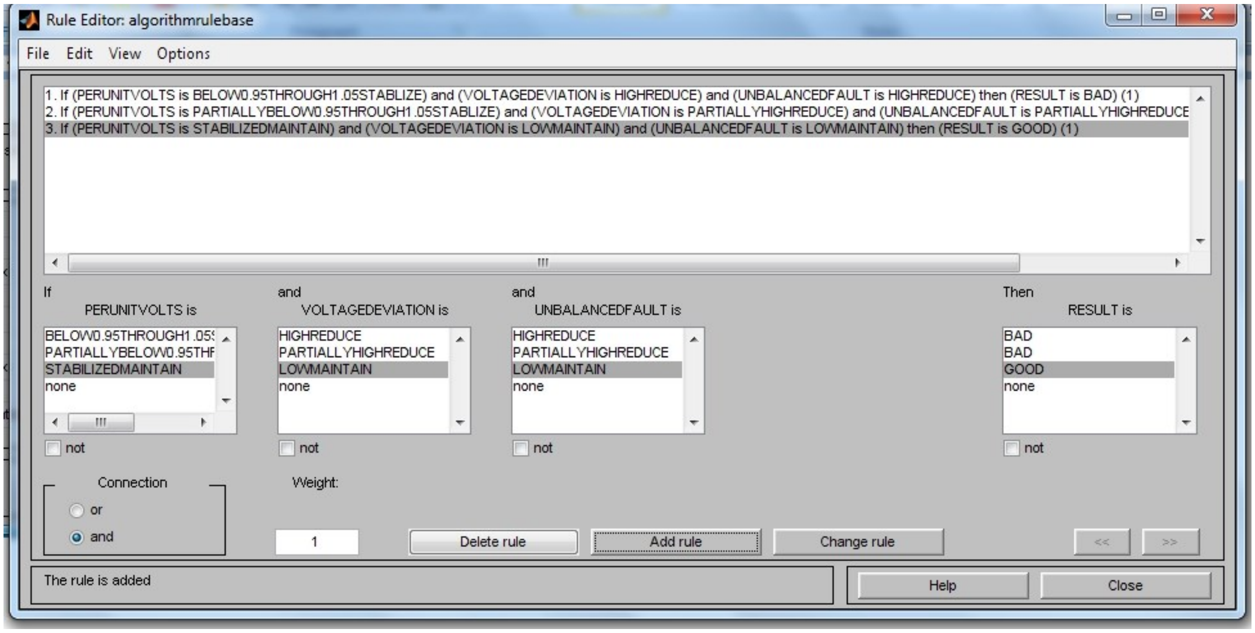

Fig 4: designed algorithm rule base to minimize voltage deviation and unbalanced fault to enhance stable power supply

Table 5: Analysis of the Rule Base

1	*IF PER UNIT VOLTS IS BELOW 0.95 THROUGH 1.05 STABLIZE*	*AND VOLTAGE DEVIATION IS HIGH REDUCE*	*AND UNBALANCED FAULT IS HIGH REDUCE*	*THEN RESULT IS BAD*
2	IF PER UNIT VOLTS IS PARTIALLY BELOW 0.95 THROUGH 1.05 STABLIZE	AND VOLTAGE DEVIATION IS PARTIALLY HIGH REDUCE	AND UNBALANCED FAULT IS PARTIALLY HIGH REDUCE	THEN RESULT IS BAD
3	IF PER UNIT VOLTS IS STABLIZED MAINTAIN	AND VOLTAGE DEVIATION IS LOW MAINTAIN	AND UNBALANCED FAULT IS LOW MAINTAIN	THEN RESULT IS GOOD

Training ANN in the Algorithm Rule Base to Enhance the Efficiency of Minimizing Voltage Deviation and Unbalanced Fault for a Stable Power Supply

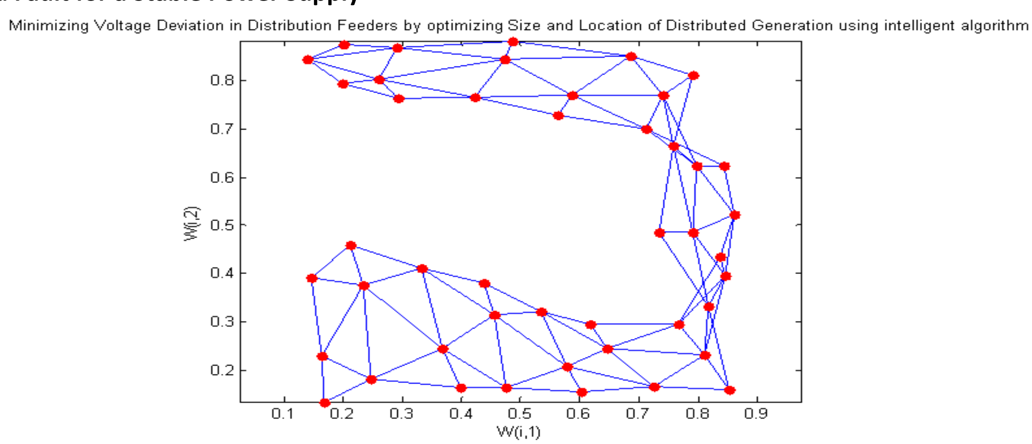

Fig 5: Trained ANN in the Algorithm Rule Base to enhance the Efficiency of Minimizing Voltage Deviation and Unbalanced Fault for a Stable Power Supply

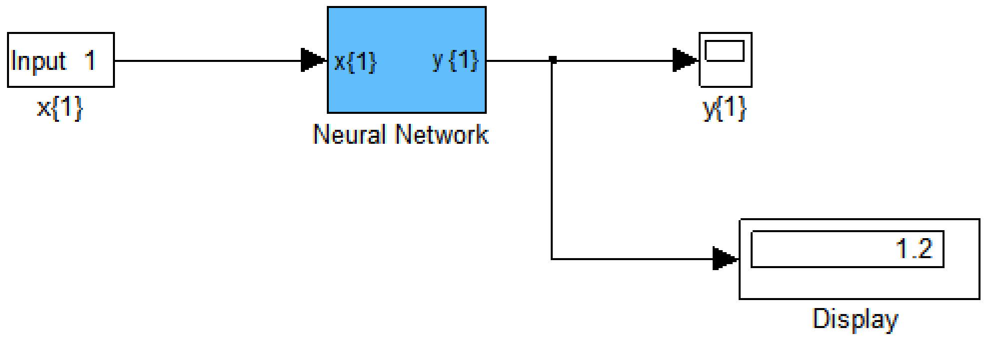

Fig 6: The result of the trained ANN in the algorithm rule base to enhance the efficiency of minimizing voltage deviation and unbalanced fault for a stable power supply.

Developing the Algorithm for Implementation

To develop an algorithm that will implement the process, start by using the following steps:

1. Characterize distribution feeders.
2. Run the load flow to establish the weak buses that cause voltage deviation.
3. Identify voltage or current average.
4. Identify the largest voltage or current deviation.
5. Identify the unbalance fault percentage of the voltage or current deviation.
6. Design conventional model for Minimizing Voltage Deviation in Distribution Feeders by optimizing Size and Location of Distributed Generation and input 3, 4 and 5 in it.
7. Design an algorithm rule base to minimize voltage deviation and unbalanced fault to enhance stable power supply.
8. Train ANN in the algorithm rule base to enhance the efficiency of minimizing voltage deviation and unbalanced fault for a stable power supply
9. Integrate 7 and 8.
10. Integrate 9 in 6.
11. Do the per unit volts stabilized and voltage deviation minimized?
12. If NO go to 10.
13. If YES go to 14.
14. Minimized Voltage Deviation in Distribution Feeders by optimizing Size and Location of Distributed Generation.
15. Stop.
16. End

Integrating intelligent algorithm in the conventional model for Minimizing Voltage Deviation in Distribution Feeders by optimizing Size and Location of Distributed Generation

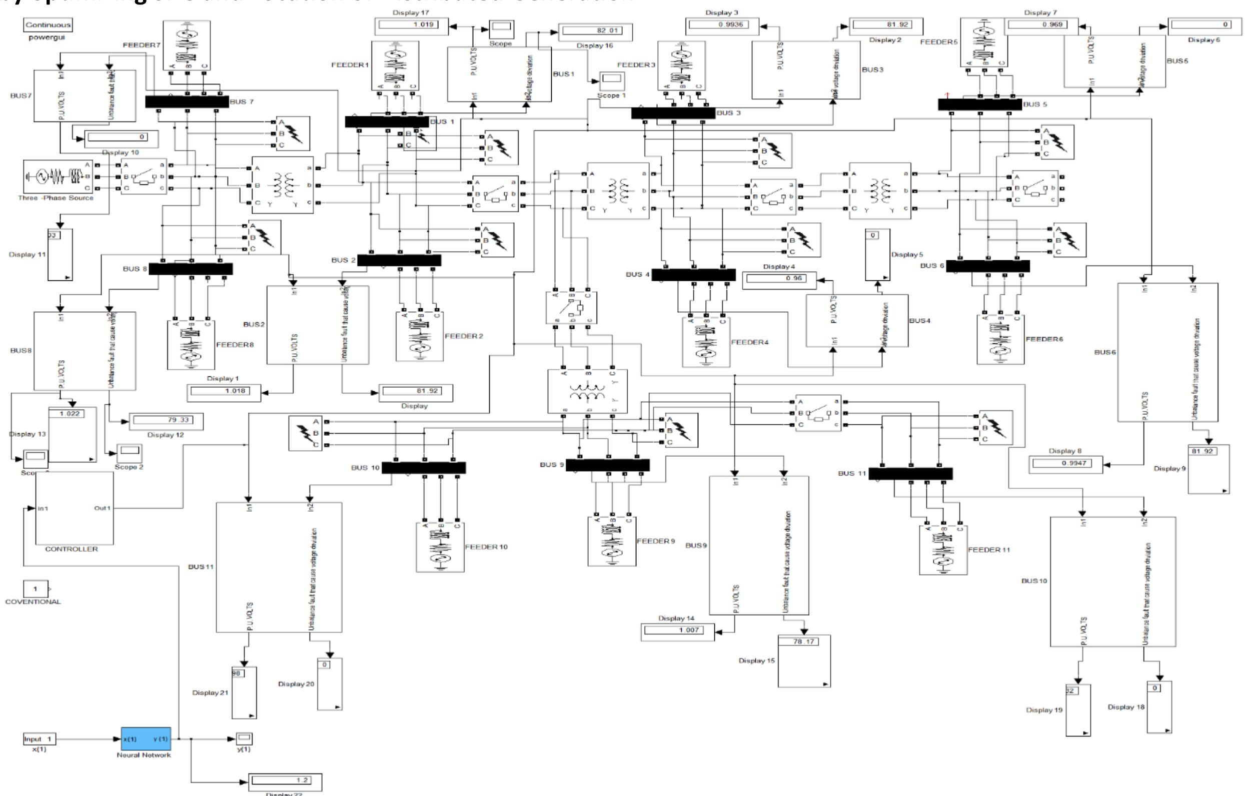

Fig 7: Minimizing Voltage Deviation in Distribution Feeders by optimizing Size and Location of Generation using Intelligent Algorithm

Table 6: Comparing Conventional and Intelligent Algorithm of Bus1 per Unit Volts in Minimizing Voltage Deviation in Distribution Feeders by Optimizing Size and Location of Distributed Generation

Time (s)	*Conventional bus 1 P.U.Volts of Minimizing Voltage Deviation in Distribution Feeders by optimizing Size and Location of Distributed Generation(p.u.volts)*	*intelligent algorithm bus 1 P.U.Volts of Minimizing Voltage Deviation in Distribution Feeders by optimizing Size and Location of Distributed Generation(p.u.volts*
0.1	0.930	1.019
0.2	0.930	1.019
0.3	0.930	1.019
0.4	0.930	1.019
1.0	0.930	1.019

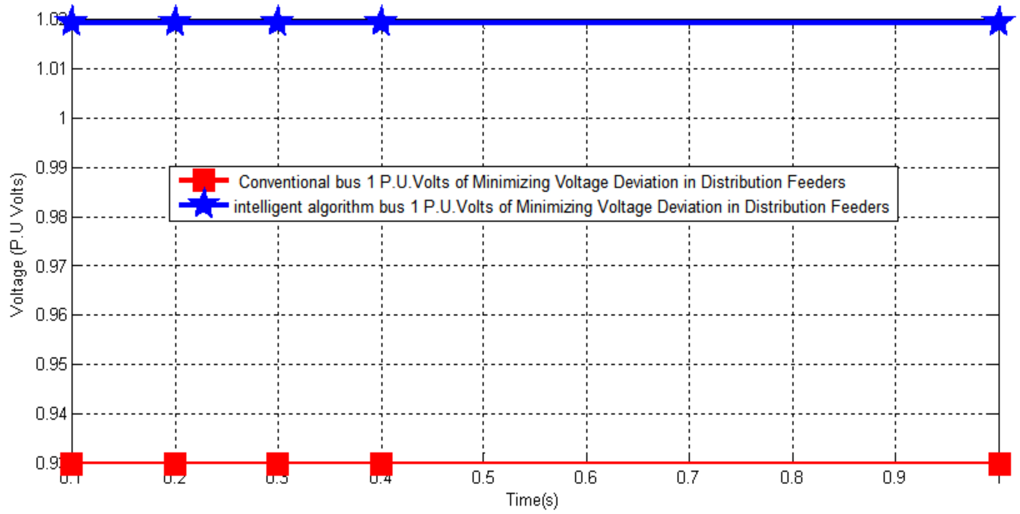

Fig 8: Comparison of conventional and intelligent algorithm of bus1 per unit volts in Minimizing Voltage Deviation in Distribution Feeders by optimizing Size and Location of Distributed Generation.

Table 7: Comparison of conventional and intelligent algorithm percentage of bus1 voltage deviation

Time (s)	*Conventional bus 1 voltage deviation Minimizing Voltage Deviation in Distribution Feeders by optimizing Size and Location of Distributed Generation(%)*	*Intelligent algorithm bus 1 voltage deviation Minimizing Voltage Deviation in Distribution Feeders by optimizing Size and Location of Distributed Generation (%)*
0.1	98.41	82.01
0.2	98.41	82.01
0.3	98.41	82.01
0.4	98.41	82.01
1.0	98.41	82.01

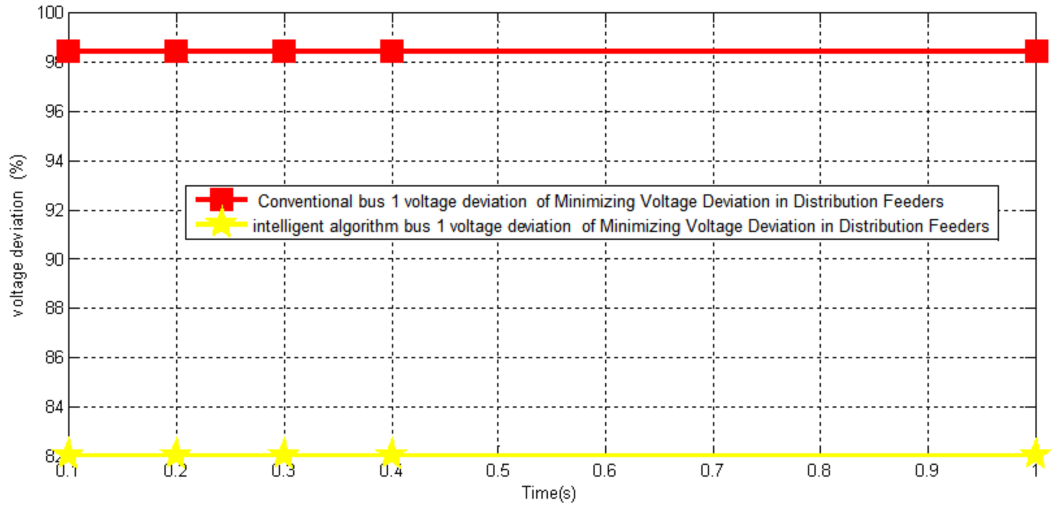

Fig. 9: Comparing conventional and intelligent algorithm percentage of bus1 voltage deviation in Minimizing Voltage Deviation in Distribution Feeders by optimizing Size and Location of Distributed Generation.

Table 8: Comparison of Conventional and Intelligent Algorithm of Bus 8 per Unit Volts in Minimizing Voltage Deviation in Distribution Feeders by Optimizing Size and Location of Distributed Generation

Time (s)	*Conventional bus 8 P.U.Volts of Minimizing Voltage Deviation in Distribution Feeders by optimizing Size and Location of Distributed Generation(p.u.volts)*	*intelligent algorithm bus 8 P.U.Volts of Minimizing Voltage Deviation in Distribution Feeders by optimizing Size and Location of Distributed Generation(p.u.volts*
0.1	0.933	1.022
0.2	0.933	1.022
0.3	0.933	1.022
0.4	0.933	1.022
1.0	0.933	1.022

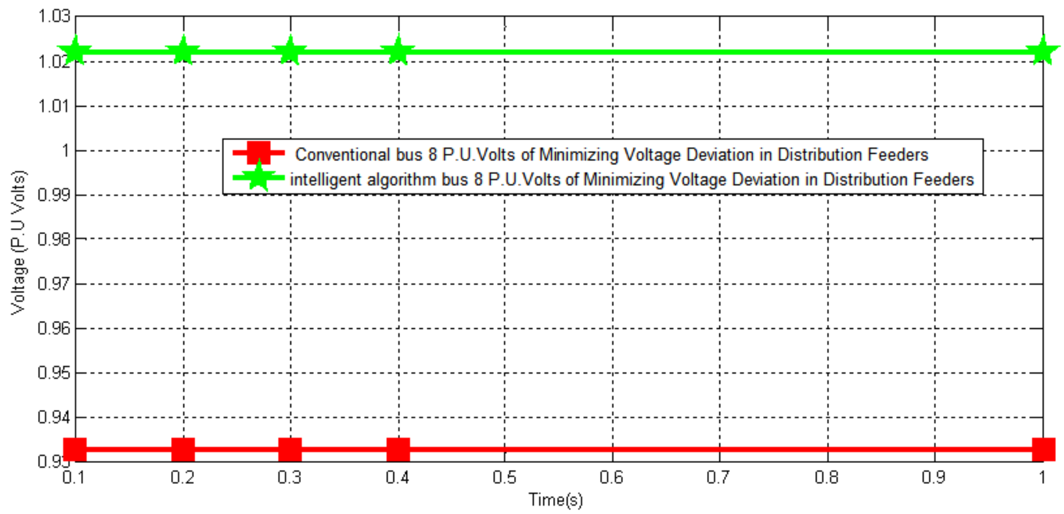

Fig 10: comparing conventional and intelligent algorithm of bus 8 per unit volts in Minimizing Voltage Deviation in Distribution Feeders by optimizing Size and Location of Distributed Generation

Table 9: Comparison of Conventional and Intelligent Algorithm Percentage of Bus 8 Voltage Deviation

Time (s)	*Conventional bus 8 voltage deviation Minimizing Voltage Deviation in Distribution Feeders by optimizing Size and Location of Distributed Generation(%)*	*Intelligent algorithm bus 8 voltage deviation Minimizing Voltage Deviation in Distribution Feeders by optimizing Size and Location of Distributed Generation(%)*
0.1	95.2	79.33
0.2	95.2	79.33
0.3	95.2	79.33
0.4	95.2	79.33
1.0	95.2	79.33

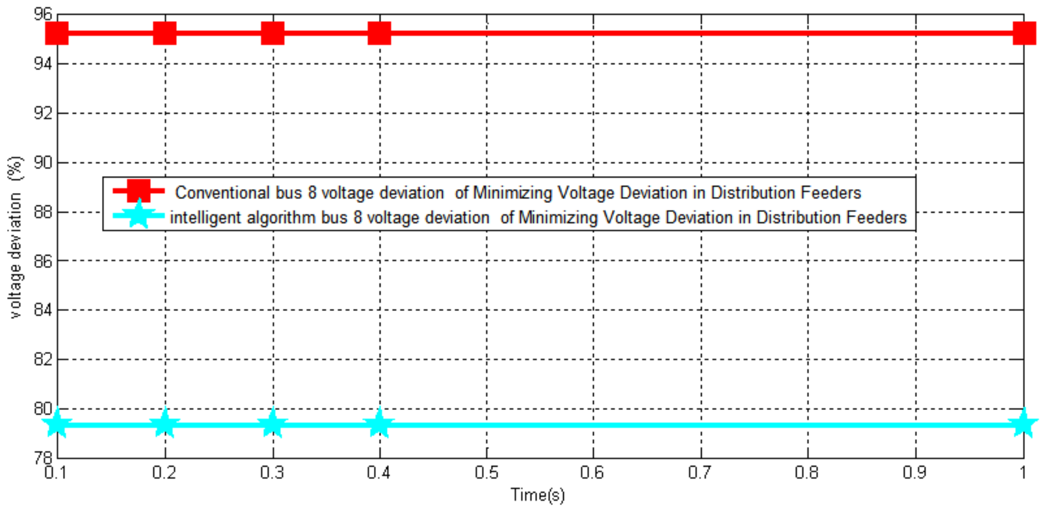

Fig 11: Comparing conventional and intelligent algorithm percentage of bus 8 voltage deviation in Minimizing Voltage Deviation in Distribution Feeders by optimizing Size and Location of Distributed Generation

Results and Discussion

The simulation results indicate that the hybrid ANN-Fuzzy Logic approach effectively minimizes voltage deviation in distribution feeders. By optimizing the placement and sizing of Distributed Generation (DG), the voltage profiles across the network are significantly improved, and power losses are reduced compared to traditional methods. While the ANN model alone offers a strong baseline for DG optimization, the integration of Fuzzy Logic enhances the robustness of the solution. When compared to conventional methods such as Genetic Algorithm (GA) and Particle Swarm Optimization (PSO), the proposed approach not only achieves better voltage deviation reduction but also handles uncertainties in the distribution network more efficiently.

Figure 1 illustrates the load flow program used to identify weak buses responsible for voltage deviation. These weak buses are characterized by per-unit voltages that fall outside the stability range of 0.95 to 1.05. Specifically, buses 1, 2, 3, 6, 8, and 9 exhibit per-unit voltages of 0.930, 0.929, 0.907, 0.908, 0.933, and 0.919, respectively. Table 2 presents the results of this load flow analysis.

The conventional model for minimizing voltage deviation by optimizing the size and location of DG is shown in Figure 2. Following intensive simulations, the results are presented in Figures 8 through 11.

Figure 4 displays the designed algorithm featuring the Fuzzy Inference System (FIS) aimed at minimizing voltage deviation and addressing unbalanced faults to ensure a stable power supply. Figure 5 further details the rule base of this algorithm. A comprehensive analysis of the rule base is provided in Table 7, detailing the algorithm's operation in minimizing voltage deviation and managing unbalanced faults to enhance power stability.

Figure 6 showcases a trained ANN within the algorithm's rule base, designed to improve the efficiency of voltage deviation minimization and fault management for stable power supply. The ANN training involved three rules, each trained fifteen times, resulting in 45 neurons dedicated to stabilizing weak buses. The training results, shown in Figure 7, demonstrate the integration of this model with conventional methods to bring weak buses within the stability range of 0.95 to 1.05 per unit volts.

Figure 8 highlights the minimized voltage deviation in distribution feeders achieved by optimizing DG size and location using an intelligent algorithm. The simulation results are further detailed in Figures 9 and 10. Figure 10 compares the per-unit voltage of bus 1 under conventional and intelligent algorithms. The conventional method resulted in a per-unit voltage of 0.930, leading to intermittent power supply. However, the incorporation of the intelligent algorithm stabilized bus 1 at 1.019 per unit volts, thereby improving power reliability.

Table 4 compares the percentage of bus 1 voltage deviation under both conventional and intelligent algorithms. Figure 11 shows that the conventional approach resulted in a 98.41% voltage deviation, contributing to frequent power outages. The intelligent algorithm reduced this deviation to 82.01%, significantly enhancing power supply stability. The results show a 16.4% improvement in minimizing voltage deviation when using the intelligent algorithm over the conventional method.

Lastly, Table 6 and Figure 8 provide a comparison of the per-unit voltage of bus 8 under both approaches. The intelligent algorithm once again demonstrated superior performance in minimizing voltage deviation and enhancing overall power stability in the distribution network.

Conclusion

This study introduces a hybrid ANN and Fuzzy Logic approach to optimize the size and location of DG units in distribution feeders, aiming to minimize voltage deviation. The method outperforms traditional techniques in both voltage regulation and power loss reduction. The integration of ANN and Fuzzy Logic effectively addresses the complexities and uncertainties of modern distribution networks. Future research will extend this approach to more complex network configurations and explore its potential for real-time optimization in smart grids.

Power failures in the country, often caused by voltage deviations, have severely impacted businesses. These deviations occur when the per-unit voltage falls outside the standard range of 0.95 to 1.05. By optimizing the size and location of DG units using an intelligent algorithm, the voltage deviation was minimized, leading to improved power stability.

The study identified weak buses causing voltage deviations, calculated the largest deviations, and designed an algorithm to reduce these deviations and unbalanced faults. The ANN-based algorithm improved voltage stability, as shown by the results: Bus 1's per-unit voltage improved from 0.930 to 1.019, reducing voltage deviation from 98.41% to 82.01%, a 16.4% improvement. Similarly, Bus 8's voltage increased from 0.933 to 1.022, reducing deviation from 95.2% to 79.33%, a 15.87% improvement. These results demonstrate the effectiveness of the proposed approach in enhancing power supply stability.

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