AIMS Energy, 10(6): 1216–1229.
DOI: 10.3934/energy.2022057
Received: 23 November 2022
Revised: 09 December 2022
Accepted: 15 December 2022
Published: 22 December 2022

http://www.aimspress.com/journal/energy

Research article

Placement analysis of combined renewable and conventional distributed energy resources within a radial distribution network

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Abstract: System islanding, relay tripping, and reverse power flow-like issues in the distribution network are all caused by randomly placed distributed energy resources. To minimize such problems, distributed energy resource (DER) optimal placement in the radial distribution network (RDN) is essential to reduce power loss and enhance the voltage profile. When placing DERs, consideration of constraints like size, location, number, type, and power factor (PF) should be considered. For optimal placement, renewable and nonrenewable DERs are considered. The effects of different types and PFs of DER placements have been tested on the IEEE 33 bus RDN to satisfy all limitations. Using various intelligent techniques, distributed energy resource units of optimal type, PF, size, quantity, and position were placed in the IEEE 33 bus RDN. These intelligent strategies for minimizing power loss, enhancing the voltage profile, and increasing the convergence rate are based on an adaptive neuro-fuzzy inference system, a genetic algorithm, and enhanced particle swarm optimization.

Keywords: distributed energy resources; ANFIS; EPSO; GA; radial distribution network

1. Introduction

Since the 1990s, generating plants near distribution networks (DNs) have been referred to as distributed energy resources (DERs). The random arrangement of energy resources creates various problems in the distribution network over time, such as system islanding, relay tripping, reverse power flow, etc. Many of these issues have recently begun to stifle DER implementation. Furthermore, it will raise investment and operating expenses while jeopardizing the electrical system's stability, safety and security. The benefits of optimal DER placement include reducing centralized generation capacity, improving network safety and security, and lowering total costs and CO_2 emissions [1].

The power transfer is bidirectional from unidirectional with the significant placement of a DER, and the DN becomes an active system from a passive system. The switch of power transfer due to a DER has caused substantial technological and economic implications for the power system. DNs were developed to deal with unidirectional power flows from the generator to the load [2]. Short-circuit currents in the network grow due to bidirectional power circulations, which impair relay operation. A DN with DER units is vulnerable to system islanding, which creates risks for the working staff and people traveling under the network and can result in overvoltage. Previously, most attention to DERs was focused on their location and operation in a DN, and most countries developed standards and strategies to address this. The approaches were generally used to preserve the supply voltage quality after the DER was installed, and the DER was regarded as a negative load. The method was to fit and forget the DER in the DN. DER changes the power transfer in the DN, which will alter system losses. If a little DER unit is positioned near a high load, it reduces power loss. Nevertheless, if large DER units are positioned away from the network load, it will increase power loss [3].

Today, DERs are generally not associated with the voltage control of the DN. Thus, a DER will usually select to perform at unity power factor (PF) to lower its power loss and stay free from any costs for reactive power use, whether the network requires it or not. In some nations, various techniques have been produced with dispersed consolidated heat and power plants performing at different PFs based upon various times of the day [4]. During optimal loads, reactive power is supplied to the system, while low system loads run at unity PF. Regardless of their benefits, DERs might bring about some obstacles, as explained below. The output power of a renewable DER unit (PV, wind, etc.) is not constant and thus cannot be transmitted from the network. Several DER units may result in voltage fluctuation. If DER units are not optimally sized and placed, they might result in overvoltages and too much power loss. The DER is the reason for the occurrence of harmonics in an electrical network. Incorrect sizing and placement of the DER unit might cause security concerns [5].

The placement of a DER creates different running restrictions for the DN. All of these constraints are considered during problem formulation for optimal DER placement. For optimal placement of a DER, size, location, number, kind, and PF are all constraints to be considered. Using diverse methodologies, the majority of research [6–8] has yielded promising results in overcoming numerous challenges in the radial distribution network (RDN) related to the DER location, voltage profile, power loss, and so on. Ahmadi et al. [9] have provided an optimum option consisting of roof photovoltaics (PV) as a dispersed generation to a 162-bus DN in Kabul. A genetic algorithm (GA) has been applied for power loss reduction and is advanced for sizing and positioning of the PV at practical offered places. This method tends to lower the dependence on conventional power plants and enhances the efficiency of the existing network, reducing the overall power loss and voltage discrepancy. Optimum multi-configuration and allotment of capacitors and batteries, in addition to the wind power generation incorporated into the DN, have been examined by Ahmadi et al. [10], who utilized a Pareto-based epsilon multi-objective GA. This approach was applied to a 162-bus DN to find the most effective setup to meet the optimization requirements, with the features being power loss, voltage inconsistency, etc.

However, there are certain limits regarding computational time and system efficacy, the effects of different types and PFs of DERs, and the solution's convergence rate. This research selects the DER type, PF, and size of DER units for optimal placement in the RDN at suitable locations. Energy storage-based renewable DERs and non-renewable DERs are considered for optimal placement. Then, three intelligent techniques are applied to constrain these issues discussed above. These intelligent techniques are based on adaptive neuro-fuzzy inference system (ANFIS), GA, and enhanced particle swarm optimization (EPSO) methodologies. These intelligent techniques are modeled, taking care of the constraints related to the DER placement to minimize the power loss and enhance the voltage profile and best convergence rate.

2. Objective problem formulation

Power loss and voltage for all branches of an RDN are determined via backward and forward load flow analysis.

2.1. Power Loss Index (PLI)

The PLI is the division of the total power loss of an RDN with DER placement to the total power loss of an RDN without a DER, and it can be used to calculate the real power loss minimization with DER placement.

$$PLI = \left(\frac{P_{DER,Tl}}{P_{Tl}}\right) \tag{1}$$

The PLI can be reduced with the optimal placement of DERs to reduce overall power loss [11].

2.2. Voltage Inconsistency Index (VII)

Optimal placement of a DER in the RDN improves the network voltage profile.

$$VII = max\left(\frac{|V_1|-|V_j|}{|V_1|}\right) where j = 1,2\ldots,n \tag{2}$$

where V_1 is the nominal voltage, i.e., 1 per unit (p.u), and V_j is the voltage at any node *j* of the RDN. The suggested solution reduces the VII to near zero by optimally placing a DER in the RDN [12].

2.3. Problem formulation

This problem is formulated to minimize real power loss and voltage inconsistency, thus enhancing the network voltage profile that is offered as follows:

$$min(P_T) = min(\beta_1 PLI + \beta_2 VII) \tag{3}$$

where β_1 and β_2 are the weighting variables [13].

2.4. Voltage Sensitivity Constraint (VSC)

A DER (at 30% load) was positioned at each load node one by one to determine the VSC of the RDN. For a DER unit placed at node j, the VSC for node j is as follows:

$$VSC_j = \sqrt{\frac{\sum_{j=1}^{n} \left(1-V_j\right)^2}{n}} \tag{4}$$

The voltage at node j is V_j, and the total nodes in RDN are n. The optimal location for DER placement will be the node with the lowest VSC [14].

2.5. Optimal sizing for DERs

Place the DER at the node with the lowest VSC to determine the optimal DER size. At a constant PF, gradually increase the size of the DER from the smallest to the largest range equivalent to the branch load capacity until minimal power loss is achieved. For a DER, this is the optimal size [15].

Only the resultant service is approved if all constraints are met; else, it should be denied. The best type of DER will be selected for the multiple combinations of renewable and nonrenewable DERs based on the DER PF and the type's effect on the voltage profile and power loss of the RDN.

3. Intelligent techniques for the optimal placement of DERs

The intelligent techniques based on ANFIS, EPSO and GA methodologies have been applied to the selected multiple combinations of renewable and nonrenewable DER to determine the optimal position and sizes for DER placement in an IEEE 33 bus RDN. Finally, a comparison will be made between the intelligent techniques' voltage profiles, power losses and convergence rates.

3.1. ANFIS

An ANFIS is a neuro-fuzzy approach that combines a neural network (NN) and a fuzzy system. In an ANFIS, the criteria can be approximated as if the ANFIS style stands for both the Sugeno as well as Tsukamoto fuzzy versions. With minor restrictions, the ANFIS design resembles the radial basis feature network. The fuzzy reasoning considers the system's inaccuracy and unpredictability to be designed, while the NN provides a feeling of adaptability. First, the fuzzy design and its input variables are obtained with the help of the rule set drawn out from the input-output details of the system being designed. Second, the NN is used to tune the rule set of the first fuzzy design to create the last ANFIS design of the system. The ANFIS includes five layers. The first layer is composed of membership features as computation layers. The subscription can be any membership feature. The 2nd layer is utilized to locate minimally or multiply the inputs from the regulation base. The 3rd layer is utilized to stabilize the weights for the ANFIS structure. The 4th layer output is the direct feature of the 3rd layer's outcome and produces the regulation outcome. In the 5th layer, each regulation outcome is summarized [16].

Layer 1: Each node n is adaptive with a node feature.

$$L_n^1 = \sigma_{a_n}(X) \tag{5}$$

where the input to node n is X, a_n is the etymological variable connected with this node feature and σ_{a_n} is the membership function of a_n. Typically, $\sigma_{a_n}(X)$ is selected as

$$\sigma_{a_n}(X) = \frac{1}{1+\left[\left(\frac{X-c_n}{a_n}\right)^2\right]b_n} \tag{6}$$

or

$$\sigma_{a_n}(X) = exp\left\{-\left(\frac{X-c_n}{a_n}\right)^2\right\} \tag{7}$$

The property specification set is (a_n, b_n, c_n), and X is the input.

Layer 2: All nodes are set nodes that determine the firing stamina W_n of a regulation. The outcome of each node is the item of all inbound signals to it, and it is also provided by

$$L_n^2 = \sigma_{a_n}(X)X\sigma_{b_n}(Y), n = 1,2 \tag{8}$$

Layer 3: All nodes are set nodes here. Each n^{th} node computes the n^{th} regulation's ratio's as the sum of all regulations' firing stamina. The normalized firing stamina is supplied by the n^{th} node's result.

$$L_n^3 = \overline{W_n} = \frac{W_n}{W_1+W_2}, n = 1,2 \tag{9}$$

Layer 4: All nodes are adaptive nodes here with a node feature given by

$$L_n^4 = \overline{W_n}F_n = \overline{W_n}(P_nX_n + Q_nY_n + R_n), n = 1,2 \tag{10}$$

$\overline{W_n}$ is the output of Layer 3 and (P_n, Q_n, R_n) is the subsequent parameter set.

Layer 5: There is only one set node in this layer, and it computes the overall result as the total of all inbound signals [17]:

$$L_n^5 = OverallOutcome = \sum_n \overline{W_n}F_n = \frac{\sum_n W_nF_n}{\sum_n W_n} \tag{11}$$

3.2. EPSO

The idea behind making up the particle swarm optimization (PSO) algorithm is to imitate the search process of particles for food far from their location. The positioning of each particle z means the optimal solution of the analysis, like the DER's optimal placement in the network. The initial particle are generated randomly, comparable to different other transforming algorithms. Practically, each particle must move to update its positioning. To update the movement of each particle, three keynotes are utilized: the inertia (i), the overall positioning (O_k) and the particle optimal positioning (p_{kj}) [18].

The speed of every particle remains in between a specifically stated range of $s_{k,\min} \leq s_k \leq s_{k,\max}$. A high speed for $s_{k,\max}$ can mislead the particles to increase past the optimal solution, whereas a minimized value of $s_{k,\max}$ can minimize the ability of the PSO algorithm to escape localized optimal positioning [19].

The process has been updated for performance improvement of PSO in terms of overall and localized search techniques, i.e., EPSO. EPSO reduces the probability of being captured in localized optimal positioning and being reliant on the EPSO's initial specifications. The improved process efficiency enhances the PSO's ability by enhancing its searchability. This recommended two-stage improved approach is reviewed as abiding by the idea of the flying journey to be used as an added efficient localized browsing, and it is applied in the preliminary phase. In the next phase, the particles are approached as one of the most efficient existing particles in every iteration. Initially, the average of the particles is identified (a_P); afterward, the range between the most efficient particle and a_P is determined and added to the whole population.

The movement reviewed above will force the whole particles to promptly change its positioning toward one of the most efficient solutions. Lastly, the selection of the particles can be increased efficiently. Utilizing these two fundamental changed processes improves the PSO's searchability and convergence rate [20].

3.3. GA

The GA has been used to appoint an optimization algorithm that implements an approximately global search. The search relies on the information obtained by evaluating various elements in the search location. Each existing element is called an individual, and the collection of existing elements is called the people. The GA keeps this collection of existing elements instead of a singular existing element, as in many optimization solutions. The people are expected to secure near the optimum with successive applications at every iteration of the GA.

The main activities constitute the basic variant of GA programs. The people attach a high-level affirmation of the difficulty of the GA programs by implementing detailed distinctive main actions. The main activities are the specifications offered as input to the GA programs. The GA that creates outstanding results for various valuable problems comprises the following:

- Individuals are randomly organized collection-wise, their location integrated as if each previous collection of individuals creates a new collection in the crossover.
- Some individuals are randomly tailored to reach numerous other elements of the searching location in mutation.
- In choice, the individuals are assessed after a crossover along with a mutation. They are chosen or otherwise for being positioned in the new people with a possible standard that gives a more excellent option to the much better individuals [21].

GA advantages are that they require no proficiency information about the response location. They are immune to being embedded in a localized optimal location and can be utilized to fix numerous optimization issues. Rather than evaluating a solitary feasible solution, its search analyzes a team simultaneously. This technique enables an extra detailed expedition of the remedy area while looking for the global optimum. It likewise minimizes the possibility of being entrapped in a localized optimum. The design of a fitness function suitable for the issue identifies the success of the optimum strategy. The people's fitness leads the growth process in a given populace. These features make it possible for a GA to use complex or alternating elements best while keeping the existing results. A GA does not need this kind of information. Hence, it is appropriate to optimize the procedure.

A transformative technique must be accepted to create individuals for the following action.

Individuals are established by their fitness and, simply, one of the most efficient individuals takes the following action. With this, exceptional individuals are not dropped out of the race. Numerous children stem from crossover, along with mutation [22].

4. Results and discussion

The effects of different DER types and their PFs on the voltage profile and real power loss associated with an IEEE 33 node RDN have been quantified. The ANFIS, EPSO and GA techniques deal with the optimal location and size of selected DER units from the previous section results placed in the IEEE 33 node RDN, and their effects on the voltage profile, power loss and convergence rate are shown. All of the techniques' results were compared to the RDN without any DER.

4.1. Effects of Different DER Types and Their PFs on the RDN

An IEEE 33 bus RDN of 12.66 kV and base power of 100 MVA was utilized to test the effects of different types of DERs placement. The total real and reactive power load demand of this RDN was 2.795 MW and 1.360 MVAR, respectively.

The modeling of the IEEE 33 node RDN and load flow analysis requires some assumptions, which are as follows:

- For DER placement, the nodes connected with the loads must be considered, and one must ignore the nodes connected with the sources.
- The voltage considered at the preliminary node is 1.0 p.u.
- The range considered for the upper and lower values of node voltages is in between ± 0.05 p.u.
- Not more than one DER should be positioned at each node.
- The loads employed in RDN models should be consistent with continuous power.

Five types of DERs are mainly based on their power supplying capacity and PF.

- DER at the lagging PF: A DER unit that supplies both real and reactive power, such as synchronous generators.
- DER at the leading PF: A DER unit that produces actual power while consuming reactive power, such as induction generators for wind farms.
- DER at unity PF: A DER unit that supplies real power, such as a PV cell or a fuel cell.
- DER at zero PF: A DER unit that exclusively absorbs reactive power, such as a synchronous compensator.
- DER at zero PF: A DER unit that only produces reactive power to improve the voltage profile, such as kVAR compensators, capacitor banks, and synchronous condensers [23].

The results obtained from placing different DER types were compared to the RDN with no DER. This comparison is for the effects of voltage profile and real power loss of the RDN, as shown in Table 1. DER_a (0 PF) had a lower voltage profile than the RDN with no DER. Hence, DER (0.9 PF lag), DER (Unity PF), DER (0.9 PF lead), and DER_s (0 PF) are beneficial for enhancing the voltage profile of the RDN. Figure 1 displays the voltage profile comparisons of different types of DER units.

Table 1. Comparison of different types of DERs at different PFs.

DER type	Voltage profile (p.u)	Real power loss reduction (kW)
With no DER	0.9293	0
DER (0.9 PF lag)	0.9458	8.89
DER (0.9 PF lead)	0.9371	−1.7
DER (Unity PF)	0.9412	7.9
DER_a (0 PF)	0.9270	−1.85
DER_s (0 PF)	0.9307	7.13

Real power losses in the DER (0.9 PF lead) and DER_a (0 PF) are even more than that of the RDN with no DER. The DER (0.9 PF lag), DER (Unity PF) and DER_s (0 PF) have lowered the power losses relative to the other types and the RDN with no DER. Figure 2 shows the reductions in the real power loss for different types of DER units. In conclusion, placement of the DER (0.9 PF lag) and DER (Unity PF) units are well matched for voltage profile enhancement and real power loss minimization in the RDN.

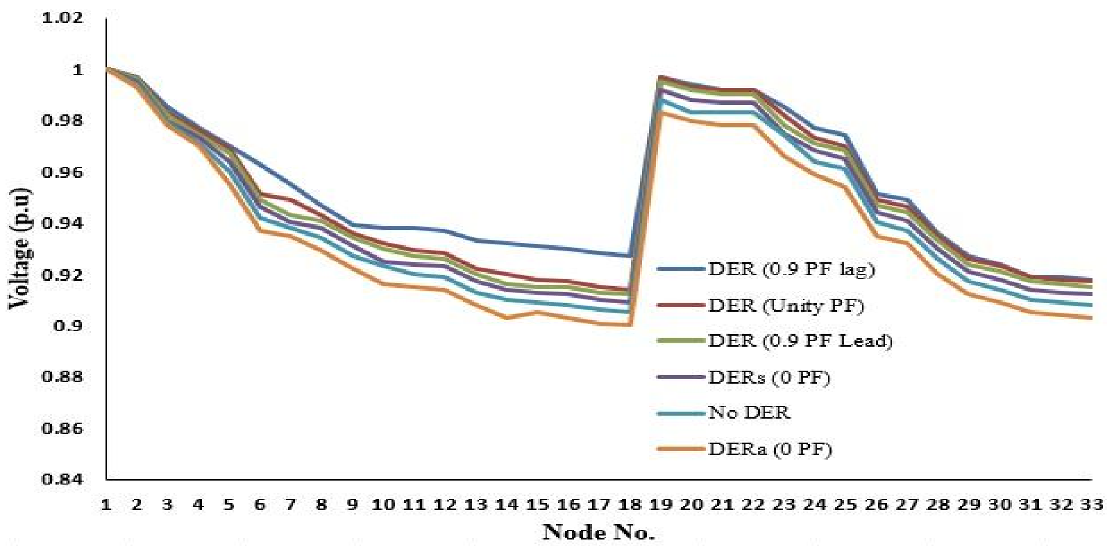

Figure 1. Voltage profile comparison.

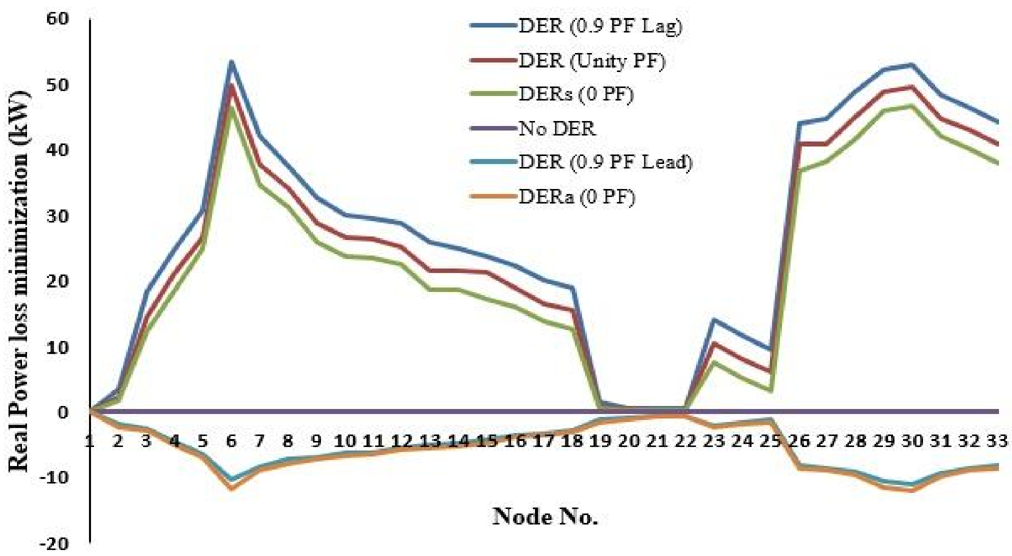

Figure 2. Real power loss reduction comparison.

4.2. Multiple DER placement in the RDN with various techniques

Two non-renewable-type DERs (0.9 PF lag) and PV-type renewable DERs (Unity PF) were considered for placement in the IEEE 33 node RDN based on the previous section results. The real power loss for the RDN without DER placement was 227.75 kW, and the minimum bus voltage was 0.9273 p.u. The acquired results for the IEEE 33 node RDN were compared by using the ANFIS, EPSO and GA techniques, as shown in Table 2. The ANFIS technique reduced real power loss by 24.08%, compared to 13.26% for the EPSO technique and 10.56% for the GA technique. The voltage profile comparison and real power loss comparison results are shown in Figures 3 and 4, respectively. For the RDN without a DER based on the ANFIS method, the bus voltage increased from 0.9273 p.u to 0.9813 p.u.

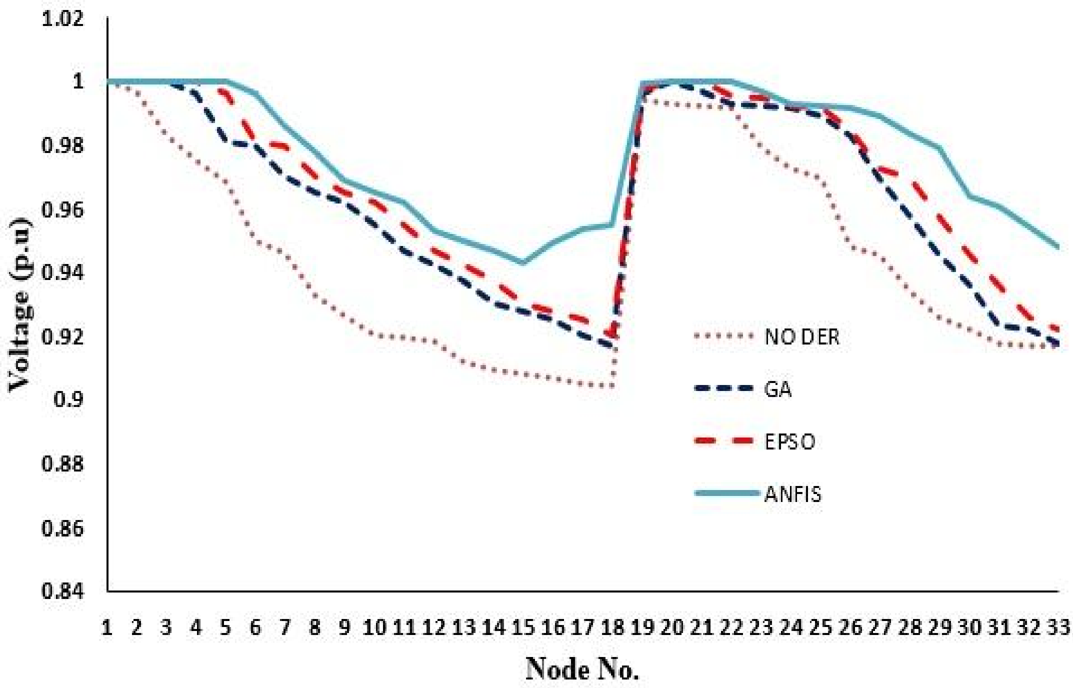

Figure 3. Voltage profile comparison analysis.

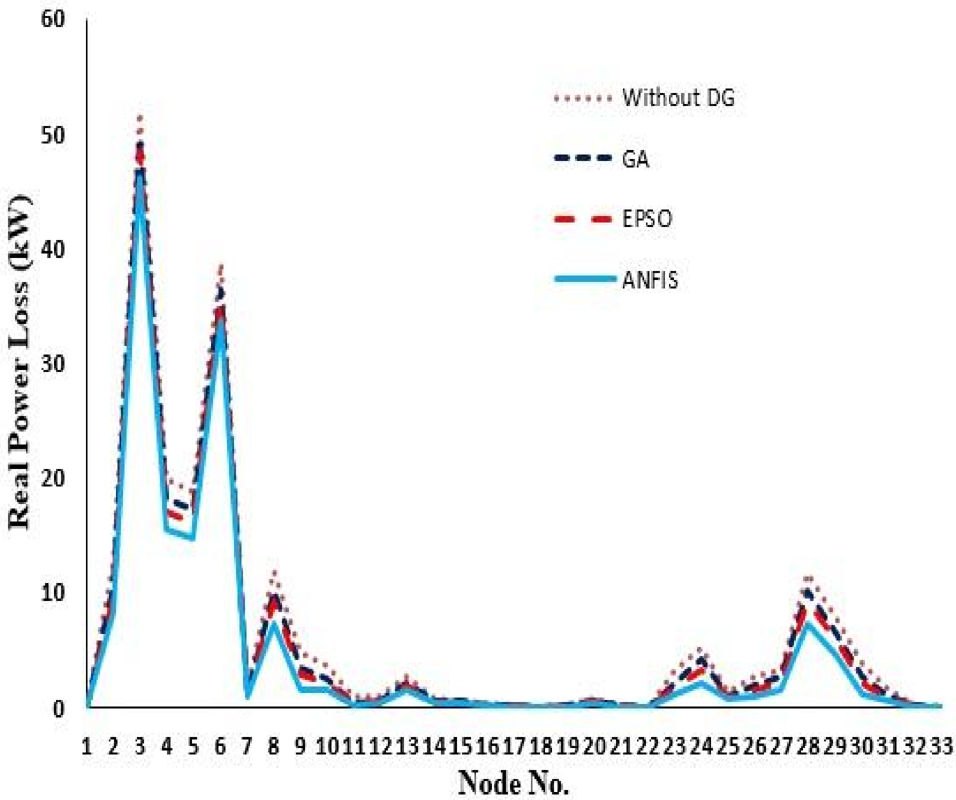

Figure 4. Analysis of real power loss.

Table 2. Comparison of power loss and voltage profiles of intelligent techniques.

Intelligent techniques applied on IEEE 33 node RDN	Real Power Losses P_{loss} (kW)	P_{loss} minimization (kW)	P_{loss} minimization (%)	Voltage Profile (p.u)
With no DER	227.75	-	-	0.9273
GA	203.68	24.07	10.56	0.9597
EPSO	198.07	29.86	13.26	0.9693
ANFIS	172.89	54.86	24.08	0.9813

The ANFIS based adaptive scheme has generated promising results for optimal sizing and placement of multiple DERs in an RDN at the optimal location, as shown in Table 3. It has resulted in a maximum reduction of power loss and an enhancement of the voltage profile.

Table 3. Comparison of DER size and location of adaptive schemes.

Techniques applied on IEEE 33 node RDN	DER Size (MVA)			DER Node Location		
	DER (0.9 PF lag)	DER (0.9 PF lag)	DER (Unity PF)	DER (0.9 PF lag)	DER (0.9 PF lag)	DER (Unity PF)
GA	3.21	3.43	3.54	18	20	23
EPSO	2.88	2.97	3.13	20	22	25
ANFIS	2.53	2.65	2.82	19	21	24

As shown in Figure 5, The GA's fitness/convergence rate was around 87 iterations and the EPSO's was around 75, while the ANFIS only needed 53 iterations to achieve the ideal results. The ANFIS technique outperformed the other methods used in this research in terms of solution quality.

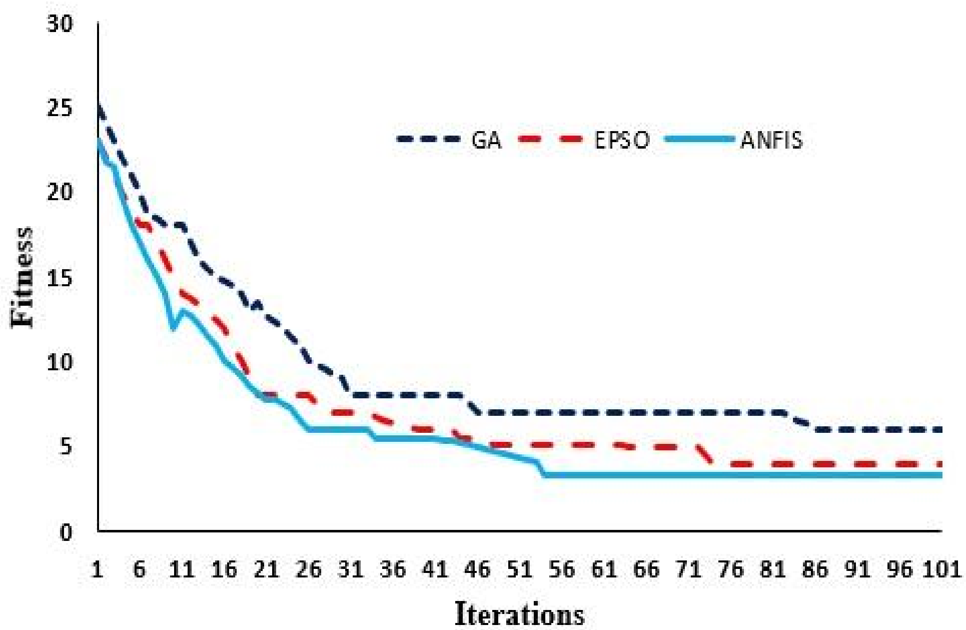

Figure 5. Fitness/convergence rate comparison of intelligent techniques.

5. Conclusions

The effects of different types of DERs have been checked by analyzing the IEEE 33 node RDN's voltage profile and real power loss minimization. Two non-renewable-type DERs (0.9 PF lag) and PV-type renewable DERs (Unity PF) were considered for placement in an IEEE 33 bus RDN. These three multiple DERs are well suited for an RDN in terms of reducing power loss and improving the voltage profile when using ANFIS, EPSO, and GA techniques. These three optimally sized multiple DER units were positioned at the optimal positions in the IEEE 33 node RDN for power loss minimization, voltage profile enhancement, and the best convergence rate. Constraints, including the size, location, number, kind, and PF, were examined and satisfied for optimal DER placement. Compared to the EPSO, GA, and no-DER models in terms of optimal DER placement in the RDN, the ANFIS technique maintained a better voltage profile, power loss minimization and the best convergence rate.

Conflict of interest

There are no conflicts of interest to declare.

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