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ORIGINAL ARTICLE

Optimal Sizing of Distributed Generation for Reliability Improvement Using Monte Carlo Simulation and Load Flow in Active Distribution Networks

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Abstract

In recent decades, the optimal placement of energy storage systems and distributed generation (DG) has become one of the primary concerns for distribution network operators. Improper sizing and siting of these units can not only lead to system instability but also result in unnecessary costs. Therefore, developing an optimal planning model for the installation and sizing of energy storage systems and DG units is of great significance. In this paper, a model for the optimal placement of DG units is proposed to improve system reliability indices using Monte Carlo simulation. Moreover, load flow analysis in the distribution system is carried out using an enhanced forward–backward load flow method, which, unlike the traditional approach used in conventional distribution networks, takes into account the presence of DG units in active distribution networks. The objectives of this study include reducing losses, improving reliability, and enhancing the voltage profile in the distribution network. These goals are pursued using a genetic algorithm, and simulations are conducted on the IEEE 33-bus standard network.

Keywords: Genetic Algorithm, Enhanced Forward-Backward Load Flow, Active Distribution Network, Reliability.

1. Introduction

In recent decades, numerous studies have been conducted to integrate DG units into distribution networks and to optimally determine their placement in order to improve various network indices. For example, photovoltaic (PV) units, as renewable energy sources with reactive power control capabilities, have been considered in the optimization of energy storage systems and renewable resources (Li et al., 2023). In this paper, a novel voltage optimization model is proposed for distribution networks incorporating various PV inverter control technologies. The model includes both grid-following and grid-forming inverters with reactive power control capabilities and formulates detailed equality and inequality constraints. In (Shaghaghi et al., 2024), an economic objective function is proposed for the optimal expansion of DG units, focusing on their placement and sizing. A Genetic Algorithm is employed to minimize overall costs while enhancing power quality, reducing losses, and improving system reliability. Unlike previous works, the proposed model offers a clear economic perspective for DG development.

In (Ali et al., 2024), a multi-objective optimization model is proposed for the optimal allocation of Distributed Generation (DG), Battery Energy Storage Systems (BESS), and network reconfiguration (ONR). Using the I-BiCo algorithm, the optimal placement and sizing of these resources are determined. Simulation results demonstrate

that the coordinated integration of DG, BESS, and ONR reduces power losses, improves voltage profiles, and enhances overall system efficiency and sustainability.

In (Li et al., 2020), the optimal siting and sizing of Soft Opening Points (SOPs) in distribution networks are investigated to enhance system operation under the increasing integration of Distributed Generation (DG) and Electric Vehicles (EVs). The objectives are to minimize network losses and maximize EV charging satisfaction. The problem is formulated using continuous variables and transformed into a Second-Order Conic Programming (SOCP) model, which is solved using standard optimization tools. Simulation results confirm the effectiveness of the proposed approach.

In (Saboori & Hemmati, 2017), a coordinated planning model for energy storage systems and DG units is presented to integrate their planning processes. The proposed model simultaneously determines the optimal locations and capacities of both DG units and battery storage systems. It is applied to an active distribution system within a restructured electricity market, aiming to maximize the profit of distribution companies. The planning model is formulated as a nonlinear mixed-integer optimization problem and is solved using an advanced particle swarm optimization algorithm. It is worth noting that although, according to IEEE 1547, most DG units are designed to operate at a unity power factor (IEEE, 2024), reactive power exchange is permitted in many cases (Samadi et al., 2012).

In all of the aforementioned references and similar studies, it is evident that the integration of DG units significantly alters the behavior and characteristics of distribution networks. Their inclusion transforms a passive distribution system into an active one, impacting various network indices such as reliability, power losses, and voltage profile. Moreover, conventional analysis methods used for traditional distribution networks are no longer valid in the context of active distribution networks. This paper investigates the impact of DG units on network reliability using Monte Carlo simulation and genetic algorithms. Additionally, due to the active nature of the network, an enhanced forward-backward load flow method is employed instead of the traditional load flow approach. The following sections provide a detailed discussion of these topics.

Table1 Line data and reliability information of the IEEE 33-Bus Network

Line No.	From	To	R (ohm)	X (ohm)	Landa (f/year)	r (hours)	u (hours/year)
1	1	2	0.0922	0.047	649.35	70.92	46053.24
2	2	3	0.493	0.2512	1298.70	141.84	184212.95
3	3	4	0.3661	0.1864	1948.05	212.77	414479.14
4	4	5	0.3811	0.1941	2597.40	283.69	736851.80
5	5	6	0.819	0.707	3246.75	354.61	1151330.94
6	6	7	0.1872	0.6188	3896.10	425.53	1657916.55
7	7	8	0.7115	0.2351	4545.45	496.45	2256608.64
8	8	9	1.0299	0.74	5194.81	567.38	2947407.20
9	9	10	1.044	0.74	5844.16	638.30	3730312.24
10	10	11	0.1967	0.0651	6493.51	709.22	4605323.75
11	11	12	0.3744	0.1298	7142.86	780.14	5572441.74
12	12	13	1.468	1.1549	7792.21	851.06	6631666.21
13	13	14	0.5416	0.7129	8441.56	921.99	7782997.14
14	14	15	0.5909	0.526	9090.91	992.91	9026434.56
15	15	16	0.7462	0.5449	9740.26	1063.83	10361978.45
16	16	17	1.2889	1.721	10389.61	1134.75	11789628.81
17	17	18	0.732	0.5739	11038.96	1205.67	13309385.65
18	2	19	0.164	0.1564	1298.70	141.84	184212.95
19	19	20	1.5042	1.3555	12337.66	1347.52	16625218.75
20	20	21	0.4095	0.4784	12987.01	1418.44	18421295.02
21	21	22	0.7089	0.9373	13636.36	1489.36	20309477.76
22	3	23	0.4512	0.3084	1948.05	212.77	414479.14
23	23	24	0.898	0.7091	14935.06	1631.21	24362162.66
24	24	25	0.8959	0.7071	15584.42	1702.13	26526664.82
25	6	26	0.2031	0.1034	3896.10	425.53	1657916.55
26	26	27	0.2842	0.1447	16883.12	1843.97	31131988.58
27	27	28	1.0589	0.9338	17532.47	1914.89	33572810.17
28	28	29	0.8043	0.7006	18181.82	1985.82	36105738.23
29	29	30	0.5074	0.2585	18831.17	2056.74	38730772.77
30	30	31	0.9745	0.9629	19480.52	2127.66	41447913.79
31	31	32	0.3105	0.3619	20129.87	2198.58	44257161.28
32	32	33	0.3411	0.5302	20779.22	2269.50	47158515.24

2. Distributed generation placement

For simulation purposes, a sample network must first be selected to enable the evaluation and analysis of the obtained results. In this study, the IEEE 33-bus distribution system (Baran & Wu, 1989) is chosen, as it is commonly used for reliability analysis of distribution networks. Table I presents the line data and reliability information of the network, while Fig. 1 illustrates its single-line diagram.

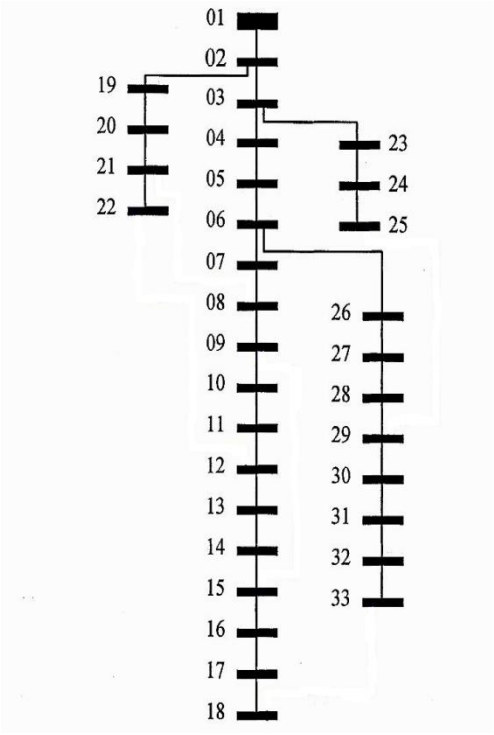

Fig.1. Single-line diagram of the distribution network

3. Load flow of the distribution network

Load flow methods commonly used for transmission networks, such as Gauss-Seidel and Newton-Raphson, face convergence difficulties and are inefficient in distribution networks due to the high resistance-to-reactance (r/x) ratio (Vempalle & Dhal, 2022). Consequently, specialized studies have been conducted on load flow analysis in distribution networks, leading to the development of various tailored methods. One of the most widely used approaches is the Backward-Forward Load Flow method, particularly suitable for radial networks (Fakir et al., 2024; Fang et al., 2025; Padole & Moharil, 2022; Murari et al., 2023). In this method, the main bus is considered a slack bus with known voltage magnitude and angle. Initially, the voltages of all other buses are assumed to be equal to that of the slack bus. A four-step iterative algorithm is then applied repeatedly until convergence is achieved.

A. Node power calculation:

If the power absorbed by the loads changes—such as in the case of constant current or constant impedance loads—or if capacitors are present (whose reactive power changes due to voltage variations during the algorithm's iterations), the power at each bus must be recalculated in each iteration. However, the power absorbed by constant power loads (similar to PQ buses) remains unchanged in consecutive iterations.

B. Backward sweep

At this stage, the branch powers are aggregated. Starting from the end buses and moving toward the slack bus, the branch powers are calculated as follows:

$$S_n = S_i + \sum_{m \in M} S_m + Loss_n \quad (1)$$

In the above equation, S_n represents the power of branch n, i is the end node of branch nnn, and S_i is the power injected into the load connected to node i. M is the set of branches connected to branch n at node i, S_m denotes the power of branch m, and $Loss_n$ is the loss of branch n, which is assumed to be zero in the first iteration

C. Forward sweep

In this stage, the node voltages are updated. Starting from the branches connected to the slack bus and moving towards the end branches, the currents in the sending bus of branch n (i.e., j) and the voltages in the receiving bus of branch n (i.e., i) are calculated using equations (2) to (4):

$$J_n = \left(S_n / V^j\right)^* \quad (2)$$

$$V^i = V^j - Z_n . J_n \quad (3)$$

$$Loss_n = (V^i - V^j) I_n^* \quad (4)$$

D. Voltage mismatch calculation

After completing the above steps in each iteration, the voltage mismatch for the buses is calculated using equation (5) (where k is the iteration counter). If the mismatch (ΔV^i) exceeds the convergence criterion, the steps are repeated until convergence is achieved.

$$\Delta V^{i^{(k)}} = \left|V^{i^{(k)}}\right| - \left|V^{i^{(k-1)}}\right| \quad (5)$$

4. Inclusion of distributed generation in load flow

Distributed generation (DG) units with PQ control are modeled as negative loads in the system. However, when incorporating DG units controlled as PV buses, the load flow algorithm needs to be modified. The compensation method is employed to control the voltage at PV nodes. The core idea behind this method is that, to determine the voltage at a PV node, the amount of reactive current injected by the unit must first be calculated. In PV nodes, the generator constants, such as real power output (P) and voltage magnitude (V), are specified. The node is then treated as

a PQ bus. After the load flow algorithm converges, the following three steps must be performed:

1. The voltage mismatch at the PV bus is calculated using equation (6):

$$\Delta V^i = \left|V_{sp}^i\right| - \left|V_{cal}^i\right| \le \varepsilon, \qquad i = 1 : n_{PV} \tag{6}$$

Where ΔV^i is the voltage mismatch at node i, n_{PV} is the number of PV nodes, V_{sp}^i is the set voltage magnitude at bus i, and V_{cal}^i is the calculated voltage magnitude at bus i.

2. If the voltage mismatch is within the defined range, the voltage at the PV node has converged. However, if the voltage mismatch at a PV node exceeds the allowable value, the voltage is maintained at the set value by compensating the reactive power generated by the generator at the bus. Ignoring voltage changes due to active power, the required reactive power (Q) for compensation is calculated using equation (7):

$$X.\Delta Q = \Delta V \tag{7}$$

In the above equation, X is the square matrix representing the sensitivity of the reactance of the PV nodes, with dimensions of $n_{PV-unconverged}$, where $n_{PV-unconverged}$ is the number of PV nodes whose voltages have not yet converged to the specified value. ΔQ and ΔV are the vectors of the reactive power injection and voltage mismatch of the PV nodes, both having dimensions of $n_{PV-unconverged} \times 1$. If $\Delta V > 0$, the generator must produce more reactive power, and if $\Delta V < 0$, the generator must produce less reactive power. In other words:

$$Q_{new}^i = Q_{old}^i \pm \Delta Q^i \tag{8}$$

3. After calculating ΔQ, the reactive power generation limit of the DG is controlled by equation (9):

$$Q_{G,\min}^i \le Q_{new}^i \le Q_{G,\max}^i \tag{9}$$

In this equation, $Q_{G,\min}^i$ and $Q_{G,\max}^i$ are the lower and upper limits of the reactive power for bus i. If equation (9) is not satisfied, the amount of reactive power generated by the generator that violates it is selected; otherwise, Q_{new}^i is adjusted.

The backward-forward sweep load flow is then repeated, and the steps are iterated until the voltage of all PV nodes converges. The flowchart of the load flow algorithm considering PV buses is shown in Fig. 2.

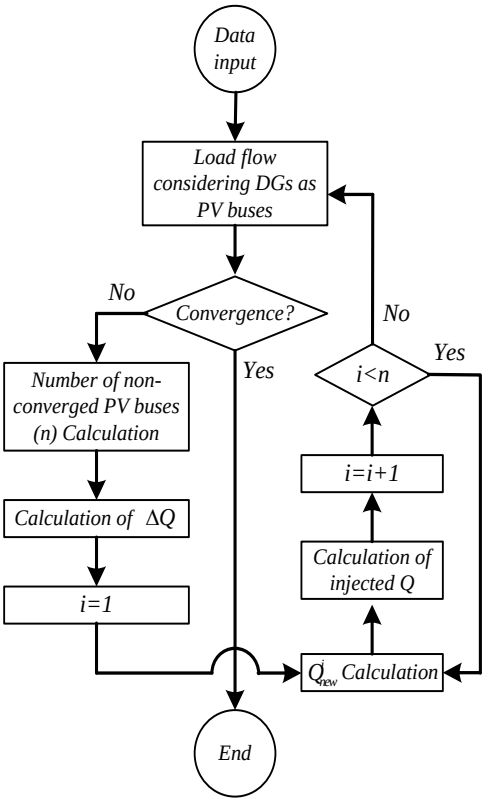

Fig.2. Load flow flowchart in active distribution network

5. Objective function for placement

In this paper, different objective functions are used for the placement of distributed generation units. One of these objective functions is the reduction of system losses, which is calculated as the sum of the square of the current passing through the lines multiplied by their ohmic resistance, as shown in equations (10) and (11):

$$loss_i = r_i \left|I_i\right|^2, \quad i = 1, 2, ..., line\ numbers \tag{10}$$

$$F_{Loss} = \sum_{i=1}^{N_l} loss_i \tag{11}$$

Another objective function used in this project is the improvement of the voltage profile, meaning the bus voltages are closer to 1 p.u. Equation (12) shows how it is calculated:

$$F_{Dev} = \sqrt{\sum_{i=1}^{N_B} (1 - V_i)^2} \tag{12}$$

Monte Carlo simulation is used to improve the third objective function, which is reliability. The Monte Carlo method is used for analyzing stochastic processes. In this method, by simulating the random operation of the model through repeated experiments, the real behavior of the original model is estimated in such a way that:

1. The more experiments conducted, the more accurate the results will be.
2. The simulation results fluctuate but tend to converge to a final value.
3. The average of the results is not an exact representation of the final result, and the final value may be higher or lower than the average.
4. If the experiment is repeated, the process and the obtained results may differ, which confirms the randomness of the process.

To estimate generation, a model is used in which each unit has a normal probability distribution A_i where g_i is the production level. For each distributed generation unit, the available capacity $\tilde{g}_i$ random variable that can take values (0 to 100%) with a probability A_i according to equation (13):

$$\tilde{g}_i(g_i, p_i) = g_i \quad , A_i \tag{13}$$

In this case, the total capacity of distributed generation is:

$$\tilde{G}_A = \sum_{i=1}^{N} \tilde{g}_i \tag{14}$$

Where $\tilde{G}_A$ is a random variable. The steps for applying Monte Carlo simulation are as follows:

1. Obtain the cumulative distribution function of the variable being evaluated.
2. Generate uniform random numbers between 0 and 1.
3. Determine the value of the variable using the random number and the probability distribution function.
4. Repeat the simulation steps to improve the accuracy of the results.

For the network under consideration, calculations are first performed without considering the distributed generation units. The calculated values are then used to initialize the optimization algorithm. Additionally, to evaluate reliability, the Average Energy Not Supplied (AENS) is used, as shown in equations (15) and (16):

$$AENS = \sum L_{a_i} U_i \Big/ \sum N_i \tag{15}$$

$$F_{Rel} = AENS / AENS_B \tag{16}$$

The overall objective function is formed by the weighted aggregation of the individual objective functions, as shown in equation (17):

$$F_{Total} = w_{Loss} F_{Loss} + w_{Dev} F_{Dev} + w_{Rel} F_{Rel} \tag{17}$$

6. Simulation results

To optimize the objective function, the Genetic Algorithm toolbox in MATLAB was used. Figure 3 illustrates the convergence process of the algorithm in placing a distributed generation unit to reduce losses, improve the voltage profile, and enhance the network's reliability.

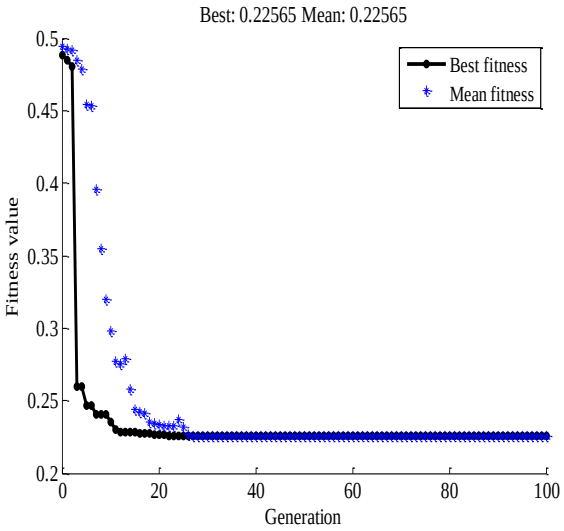

Fig.3. Convergence of the objective function for the placement of a distributed generation unit

According to the conducted simulations, a distributed generation unit with a capacity of 400 kVA is placed at bus number 25. The installation of this unit at the specified bus improves the network's reliability. Table 2 presents the results of this placement.

Table2 Changes in reliability indices with the introduction of distributed generation

Index	SAIDI	SAIFI	CAIDI	AENS	Loss
Without DG	*12.42*	*7.35*	*1.69*	*62.1*	*0.164*
With DG	*11.46*	*6.8*	*1.68*	*57.3*	*0.0412*

Fig. 4, Fig. 5, and Table 3 present the results obtained from the integration of 2 and 3 distributed generation units in the target distribution network. The results indicate that, when considering all three indices simultaneously, the use of two distributed generation units proves to be more effective than using three or one unit. The primary reason for this is the excessive deviation of the voltage profile from the standard value with a higher number of distributed generation units.

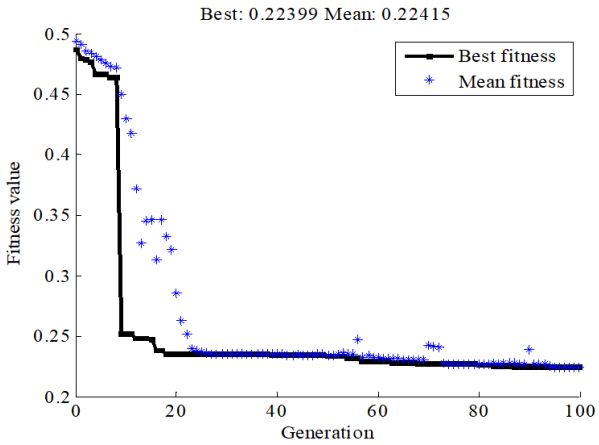

Fig.4. Convergence of the objective function for the placement of two distributed generation units

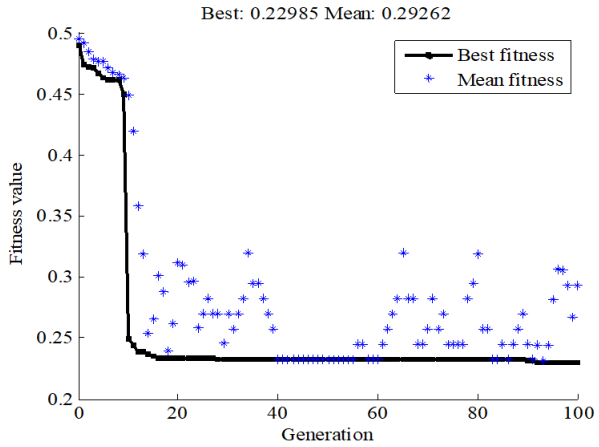

Fig.5. Convergence of the objective function for the placement of three distributed generation units

Table3 Distributed generation units placement results

No. of DG(s)	Fitness	Mean	Size(kVA)	Bus Place
1	0.22565	0.22565	400	25
2	0.22399	0.22415	151	18
			280	25
3	0.22985	0.29262	282	9
			156	13
			121	25

As the results demonstrate, the use of distributed generation units offers several advantages, including improved reliability, reduced power losses, and enhanced voltage profiles. These units can help reduce load shedding by enabling islanding and freeing up feeder capacity, which ultimately contributes to greater network reliability. The capacity of these units plays a crucial role in enhancing reliability. A higher capacity allows the units to inject more power into loads during island mode. Additionally, the larger the capacity of the distributed generation units, the more feeder capacity is freed, resulting in reduced overload on the feeder where the unit is installed. The placement of the distributed generation unit is also critical. These units should be strategically located where loads have low reliability to maximize their positive impact on network reliability.

Another advantage of distributed generation units is the improvement of voltage profiles. These units increase the voltage at the connection points and significantly help to smooth the voltage profile across the network. Furthermore, by reducing the current flowing through the lines, they contribute to a reduction in losses. However, it is important to note that the presence of high-capacity distributed generation units may lead to certain challenges. For instance, they can increase short-circuit levels in the network and, in some cases, may even result in higher losses.

7. Conclusion

As previously mentioned, improper placement of distributed generation units can lead to a decline in network performance from various perspectives, such as voltage profiles, reliability, and losses. On the other hand, optimal placement can enhance these indices, benefiting the system operator. This paper addresses the placement of distributed generation units while simultaneously considering all three of these critical indices. The simulations were conducted using the Genetic Algorithm toolbox in MATLAB, applied to the IEEE 33-bus network. To account for the inherent uncertainty in distributed generation, Monte Carlo simulation was employed. Additionally, due to the active nature of the distribution network, an enhanced forward-backward load flow model was used. The results from these simulations demonstrate that the proposed method offers a set of optimal solutions, improving the three indices by determining the optimal location and capacity of distributed generation resources within the distribution network.

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