SAKARYA UNIVERSITY JOURNAL OF COMPUTER AND INFORMATION SCIENCES
http://saucis.sakarya.edu.tr/
e-ISSN: 2636-8129
Publisher: Sakarya University
Vol. 7, No. 3, 2024, 510-520
DOI: 10.35377/saucis...1483985

RESEARCH ARTICLE

Optimal Allocation and Sizing of Multiple DGs with Reactive Power Capabilities in a Three-Phase Unbalanced Distribution System

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Article History:
Received: 14.05.2024
Accepted: 09.08.2024
Published Online: 31.12.2024

ABSTRACT
Nowadays, Distributed Generators (DGs) are widely adopted in distribution networks to deliver fast, reliable, and clean power to the consumer maximize environmental preservation, and mitigate the impact of energy production on the environment. However, recurring issues like poor voltage profiling/stability and power loss arising from improper allocation and unsuitable sizing of the DGs have made it necessary for methods and approaches to be sought in order to mitigate these issues. This study proposes a method that can be used in optimizing the allocation and sizes of the DGs. The study employs the IEEE 37 node test system in OpenDSS to carry out power flow. The DG size, node, and power factor are the coordinated control variables presented in this study to minimize the power loss. Genetic Algorithm, Pattern Search, Particle Swarm Optimization, and Grey Wolf Optimizer algorithms have been exploited in the IEEE 37 node test feeder to find the optimal location, sizes, and power factors of the DGs. Notable variations resulting from four different cases considering power loss as an objective function are also presented. Results indicate that optimally sized and placed DGs operated with optimal power factors have reduced power losses by enhancing the voltage profile. In addition, the effect of the reactive power capability of DGs on the distribution system has been shown.

Keywords: Unbalanced distributed network, IEEE 37 node test feeder, Distributed generation, Genetic algorithm, Power loss, Optimization

1. Introduction

Distributed Generation (DG) systems have a crucial role in the minimization of power losses, which occur during the transmission of electricity over long distances from power plants to end-users. Power losses are minimized when electricity travels vast distances from power plants to users using distributed generation (DG) systems. They accomplish this by generating power close to the site of consumption, hence lowering transmission losses and relieving system strain. Because DG systems are often more efficient than central power plants, they improve the overall system efficiency by lowering energy consumption and costs [1]. Distributed applications provide significant advantages, generate electricity for local injections, and interact with low-voltage transformers. Incorporating DG can reduce transmission line losses, increase grid resiliency, minimize additional generating costs, and reduce the need to invest in up-to-date utility generation capacity [2].

Electric utility systems seeking the development of energy by distributed PV allocation can reap a variety of advantages as well as offer backup in the worst-case scenario of disruption with correct calibration [2, 3]. The rising complexity of power distribution networks has fueled the demand for optimizing power systems through efficient and dependable solutions. Load flow studies must deal with a wide range of system configurations properly and rapidly, making them an essential analysis of power systems. The distribution systems are frequently unbalanced due to single-phase, two-phase, or three-phase loads while employing a radial system to generate power [4, 5].

The positioning and sizes of DGs have a significant impact on [6]: Voltage Regulation meaning at the point of use, DGs stabilize voltage, decreasing voltage variations' losses. Control of Reactive Power: DGs offer reactive power, which reduces how much electricity is needed for compensation equipment and power losses. Locating DGs in high-demand areas reduces transmission losses [7, 8]. Sizing DGs correctly enables effective functioning [9, 10, 11]. Various strategies, including heuristic algorithms, are used to solve the optimization challenge for DG systems [10]. MATLAB [12] is capable of running an optimization algorithm, which includes a Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), and Pattern Search (PS), to optimize the placement, sizing, and power factor of DG units in the system.

Cite as: Z. Aboumaria and S. Emiroğlu, "Optimal allocation and sizing of multiple DGs with reactive power capabilities in a three-phase unbalanced distribution System", *Sakarya University Journal of Computer and Information Sciences*, vol.7, no. 3, pp. 510-520, 2024. Doi: 10.35377/saucis…1483985

PSO Algorithms are a clever way to explore and improve optimization [13] within a search area. They are inspired by the social behavior found in regulated colonies. Using a group of people known as a "swarm," this program explores potentially interesting regions in the search space. We refer to these people as "particles" or "agents.". GWO algorithm optimizes solutions based on wolf pack behavior [14]. GAs are evolutionary algorithms that efficiently optimize DG systems, especially for difficult issues [15-17]. These algorithms have reduced losses by ensuring the voltage is within the defined limits. The results obtained from the algorithms are compared.

Many studies have applied optimization techniques like GA, PSO, PS, and GWO to solve power system problems. Typically, these studies focus on transmission systems or balanced distribution networks, and they often assume that distributed generators (DGs) operate at a unity power factor. However, real-world distribution systems exhibit imbalances due to uneven loading and line characteristics. In this research, we concentrated on the optimal DGs placement in unbalanced distribution systems, considering both unity power factor and optimal power factor scenarios. Our simulations revealed that optimizing the power factor of DGs can significantly lower system losses by leveraging their reactive power capabilities.

The paper is organized as follows Section 2, explains the objective function while satisfying all constraints, Section 3, describes the test system, and Section 4, there's explanation of the algorithms used in the study. Section 5 gives the simulation results, and the conclusion is given.

2. Problem Formulation

For the IEEE 37 node test system, the ideal amount and size of DG units to be deployed to cut down on system power loss and get the proper voltage profile are four. System power loss must therefore be expressed as a function of system bus voltages and DG capacity. The current load is steady, and the section load is evenly distributed [17].

Improving power system efficiency by reducing operating costs and eliminating energy losses is one benefit of optimizing power flow within power systems, among other benefits. Additionally, enhancing voltage stability strengthens the power system's dependability and stability [17-22]. Therefore, to employ an optimization algorithm, the optimization issue, including the objective function and constraints, must first be established [22].

2.1. Objective Function

Since power loss has directly affected system efficiency and economy, minimization of the power loss has been selected as an objective function. Minimizing the power losses enhances the power distribution system's performance and dependability, which lowers operating costs and improves energy efficiency [23].
The problem's goal function has been established as lowering the overall actual power loss. The objective function is:

$$min\, P_{loss} = \, min\left[\sum_{k=1}^{T} g_k\{V_i^2 + V_j^2 - 2V_iV_j\cos\left(\delta_i - \delta_j\right)\}\right] \tag{1}$$

where, g_k is the conductance at line k between i and j nodes, V_i, V_j and δ_i, δ_j are the voltage magnitudes of the node and angles of nodes i and j. T is the number of the line.

2.2. Constraint

The following are the constraints of the problem in the optimization process as given below.

2.2.1. Voltage Limitation

The following constraint is described to ensure that the voltage of any node remains within defined limits [22]:

$$V_{min,i} \ \leq V_i \ \leq V_{max,i}; \qquad i = 1, \dots, N_B \tag{2}$$

2.2.2. Power Flow Equation

The balance of active and reactive power must be defined as an equality constraint of the optimization problem [23]:

$$P_{ss} + \sum_{i=1}^{N_{DG}} P_{DG,i} = \sum_{j=1}^{N_B} P_{Dj} + \sum_{K=1}^{N_L} P_{L,K} \tag{3}$$

$$Q_{ss} + \sum_{i=1}^{N_{DG}} Q_{DG,i} = \sum_{j=1}^{N_B} Q_{Dj} + \sum_{K=1}^{N_L} Q_{L,K} \tag{4}$$

where, P_{ss}, $P_{DG,i}$, P_{Dj} and $P_{L,K}$ are the active power drawn from the substation, active power of the DGs, active power of load and active power loss, respectively. Also, Q_{ss}, $Q_{DG,i}$, $Q_{L,K}$ and Q_{Dj} are the reactive power drawn from the substation, reactive power of the DGs, reactive power loss and reactive power of the load, respectively.

2.2.3. The Total Active Power of DGs

The total active power output of multiple DGs installed in the test system should be less than or equal to the total real power of the loads.

$$\sum_{i=1}^{N_{DG}} P_{DG,i} \le \sum_{j=1}^{N_B} P_{Dj} \tag{5}$$

2.2.4. DG Capacity Limit

DG capacity limit is considered within the maximum and minimum power as: [24]

$$P_{DG\,min,i} \le P_{DG\,,i} \le P_{DG\,max,i}\ ;\ i = 1, \dots, N_{DG} \tag{6}$$

2.2.5. DG Power Factor Limit

The DG power factor is considered an inequality constraint for DGs operating under different power factors except 1.

$$Pf_{DG\,min,i} \le Pf_{DG\,,i} \le Pf_{DG\,max,i}\ ;\ i = 1, \dots, N_{DG} \tag{7}$$

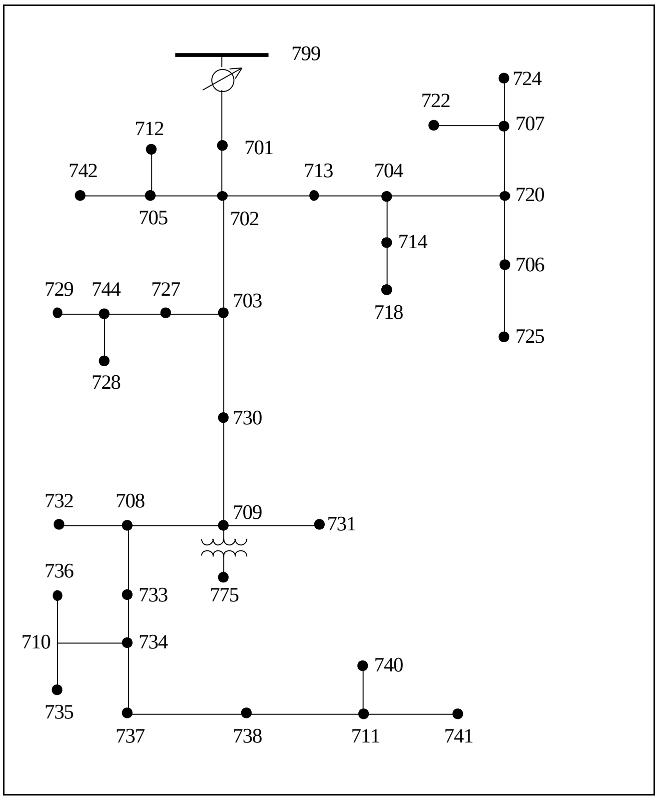

Figure 1. Single line diagram of IEEE 37 Test Feeder *[30]*

3. Unbalanced Radial Distribution System

The IEEE 37-node test system is a widely used distribution network for analyzing unbalanced radial distribution networks reflecting real-world complexities such as uneven loading and varied line characteristics [25, 26]. Our study used the IEEE 37 node distribution test system to model an unbalanced radial distribution network. This system allows us to rigorously assess how DGs can be optimally placed within an unbalanced distribution system [27, 28]. By examining both unit power factor and optimal power factor operated DGs, the simulations aimed to explore the potential for reducing system losses and enhancing overall performance.

This network is an unbalanced system with a medium voltage of 4.8kV, load size of 2547 KW and 1201 MVAr and consists of 37 nodes [29]. All data is given from [30, 31]. MATLAB [11] is employed to solve the optimization using GA, GWO, PS, and PSO to optimize the location, sizing, and power factor of DGs in the system. The IEEE 37 node unbalanced distribution system has adopted the concept. A comparison is made between the simulation results and those obtained using other methods. A single-line diagram of the IEEE 37-node test feeder has been displayed in Figure 1 [30]. Power flow simulations have been done using OpenDSS [32].

4. Optimization Algorithms

In our simulations, we employed several advanced optimization algorithms to enhance the distribution system's performance. GA, GWO, PS, and PSO have been used due to their proficiency in solving complicated problems to determine the place and size of DGs. [33, 34].

4.1. Genetic Algorithm

Evolutionary processes and natural selection mechanisms are the basis for Genetic Algorithms (GAs). They are used to look for almost-optimal answers to problems with search and optimization. The first step in the method is to create a population of candidate solutions represented as chromosomes at random. Then, a fitness function is used to evaluate these chromosomes to determine how well they address the given task. Based on these fitness evaluations, chromosomes are selected for reproduction, with the likelihood of selection proportional to their fitness scores. The selected chromosomes then undergo crossover, where segments of their genetic material are exchanged to produce new offspring. The mutation is applied to some offspring to introduce random variations and maintain genetic diversity. The newly created offspring and some of the best chromosomes from the current population form the next generation. This new population is then evaluated, and the selection cycle, crossover, and mutation go on until a termination criterion, such as the number of iterations or convergence tolerance, is met [35]. The process iterates to evolve and refine solutions to converge on the optimal or near-optimal answer [36]. The flowchart of the GA is shown in Fig. 2.

4.2. Particle Swarm Optimization

A computational technique called Particle Swarm Optimization (PSO) has been driven by the social interactions of fish and birds. Allowing a swarm of potential solutions, particles, to travel over the solution space can be utilized to find the best answers to issues [13].
Each particle of the swarm symbolizes a potential solution to the optimization problem. Firstly, the position and velocity of each particle are randomly initialized within the defined search space. The velocity of each particle has been used to update its position as in Eq. 8.

$$x_i^{new} = x_i^{old} + v_i \tag{8}$$

where v_i is the velocity of the i.th particle. Every particle's velocity is updated by its previous velocity, the distance to its personal best, and the global best.

$$v_i^{new} = w \cdot v_i^{old} + c_1 \cdot r_1 \cdot \left(Pbest_i - x_i^{old}\right) + c_2 \cdot r_2 \cdot \left(Gbest - x_i^{old}\right) \tag{9}$$

w, c_1 and c_2 are the inertia weight, cognitive and social coefficients, respectively. Also, random numbers r_1 and r_2 are in [0,1].

$$Pbest_i^{new} = \begin{cases} x_i^{new} & if\ f\left(X_i^{k+1}\right) < f\left(Pbest_i^{old}\right) \\ Pbest_i^{old} & otherwise \end{cases} \tag{10}$$

The global best is updated if any particle's personal best has a better fitness value [37].

$$Gbest^{new} = \begin{cases} Pbest_i^{new} & if\ f(Pbest_i^{new}) < f(Gbest^{old}) \\ Gbest^{old} & otherwise \end{cases} \tag{11}$$

The algorithm goes through the flowchart until a termination criterion is met, as shown in the flowchart of PSO in Fig. 3.

4.3. Pattern Search

Pattern Search (PS) is an optimization algorithm that iteratively refines solutions by exploring a structured search pattern. The process starts with an initial solution x_0 and evaluates the objective function $f(x)$ at this point. The algorithm updates the solution in each iteration using the following equations [38].

$$\begin{aligned} x^u &= x + h_i \hat{e}_i \\ x^d &= x - h_i \hat{e}_i \end{aligned} \tag{12}$$

where $\hat{e}_i$ is a unit vector in position i and step size is initially $h=x_{max}-x_{min}$.

The search then updates x to be the best of the three alternatives (x, x_u, and x_d) finding the

$$x = \arg\min\left(f(x), f(x^u), f(x^d)\right) \tag{13}$$

If no improvement is found, the step size is decreased, and the search pattern is adjusted. The flowchart starts with initializing the solution and step size, proceeds to evaluate the objective function, updates the solution, checks for improvement, adjusts the search pattern or step size, and iterates until a termination criterion is met as shown in Fig. 4. Fig. 4 shows the flowchart of the PS. This iterative refinement approaches the near-optimal or optimal solution by systematically exploring the search space [39].

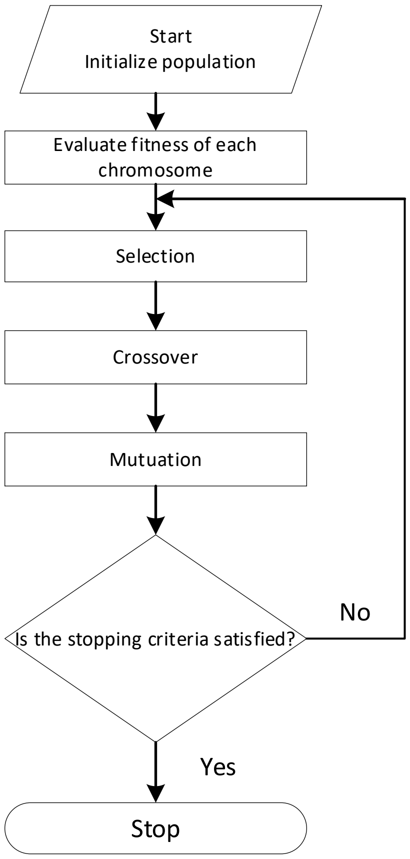

Figure 2. Flowchart of GA

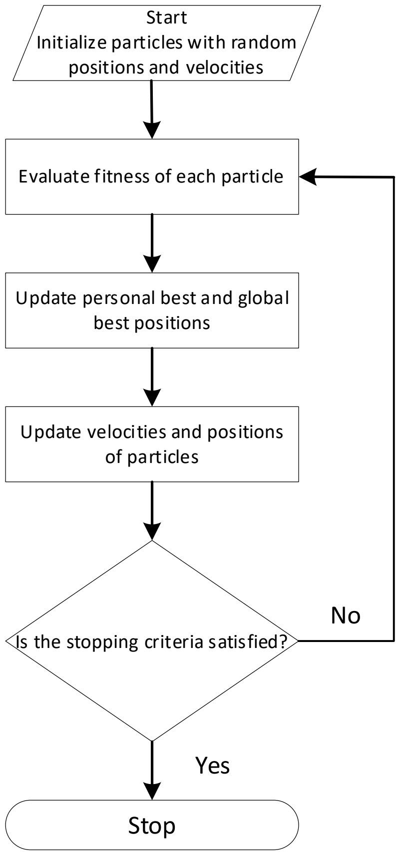

Figure 3. Flowchart of PSO

4.4. Grey Wolf Optimization

The Grey Wolf Optimization (GWO) algorithm is a nature-inspired optimization technique that simulates the hierarchical hunting mechanism of grey wolves [40]. The algorithm involves a population of candidate solutions, each represented as a grey wolf categorized into four groups: delta, beta, and alpha wolves, according to their fitness value. The position update of each wolf is guided by the positions of the delta, beta, and alpha wolves [40]. The GWO algorithm's flowchart is depicted in Fig. 5. The mathematical update rules are given by [40]:

$$\vec{D} = \left|\vec{C}.\overrightarrow{X_p}(t) - \vec{X}(t)\right| \tag{14}$$
$$\vec{X}(t+1) = \overrightarrow{X_p}(t) - \vec{A}.\vec{D}$$

where
$$\vec{A} = 2\vec{a}.\overrightarrow{r_1} - \vec{a}$$
$$\vec{C} = 2.\overrightarrow{r_2}$$

where t is the iteration number, $\vec{X}$ and $\overrightarrow{X_p}$ position and hunting position vector of wolves. A and C are coefficient vectors. $\vec{a}$ varies from 2 to 0, the random vectors $\overrightarrow{r_1}$ and $\overrightarrow{r_2}$ are in [0, 1] [41].

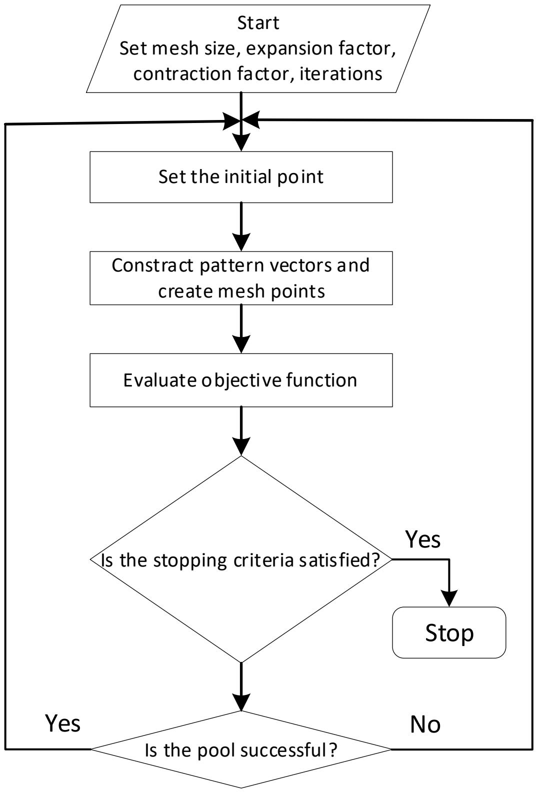

Figure 4. Flowchart of PS

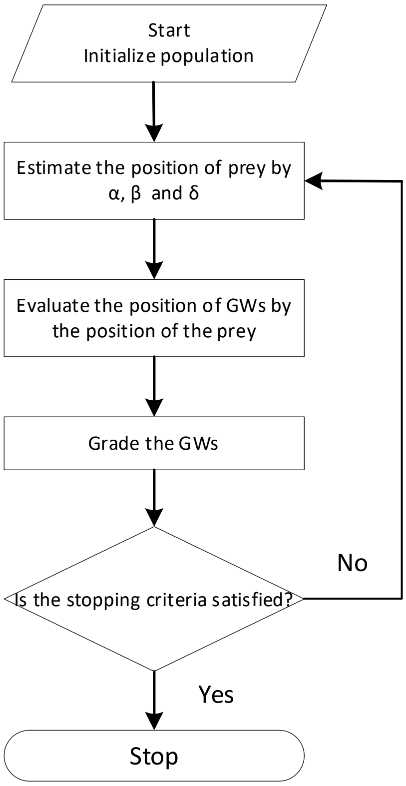

Figure 5. Flowchart of GWO

The position of optimal wolves can be calculated as follows [42].

$$\overrightarrow{D_\alpha} = \left|\overrightarrow{C_1}.\overrightarrow{X_\alpha} - \vec{X}\right|, \overrightarrow{D_\beta} = \left|\overrightarrow{C_2}.\overrightarrow{X_\beta} - \vec{X}\right|, \overrightarrow{D_\delta} = \left|\overrightarrow{C_3}.\overrightarrow{X_\delta} - \vec{X}\right| \tag{15}$$
$$\overrightarrow{X_1} = \overrightarrow{X_\alpha} - \overrightarrow{A_1}.\overrightarrow{D_\alpha}, \overrightarrow{X_2} = \overrightarrow{X_\beta} - \overrightarrow{A_1}.\overrightarrow{D_\beta}, \overrightarrow{X_3} = \overrightarrow{X_\delta} - \overrightarrow{A_1}.\overrightarrow{D_\delta}$$
$$\vec{X}(t+1) = \frac{\overrightarrow{X_1} + \overrightarrow{X_2} + \overrightarrow{X_3}}{3}$$

5. Simulation Results

The optimization algorithms have been evaluated and simulated on a computational system running Windows 11 with a processor of Intel Core i7 3770, 16 GB of RAM, and NVIDIA GeForce GT 640 Graphics. Also, the parameters of the algorithm used in the simulations are given in Table 1.

Table 1. The Control Parameters Used in the Simulation of Optimization Algorithms

Algorithm	**Parameter**	**Value**
GA	Population size, Elite count, Crossover, Scaling factor,	50, 0.05, 0.8, 0.4
PSO	Swarm size, Inertia Coefficient (w), Cognitive Coefficient (c_1), social Coefficient (c_2), Inertia Damping Weight	50, 1, 2, 2, 0.99
PS	Mesh Contraction, Mesh expansion	0.5, 2
GWO	Search agent	50

For the first case, all DGs are operated to unit power factor, four DGs produce only real power to the system, there is no reactive power generated by DGs, the four methods are applied such as GA, PSO, PS and GWO. The performance of GA for obtaining the optimal DG placement and the size are better than other algorithms in Table 2 in terms of power loss. In this case, two control variables are used for each DG for the optimization algorithm, so in total, we have 8 control variables for four DGs, which are the bus number and size of DGs. The maximum iteration was selected as 100 before the population number was 50. The maximum active power limit for DGs is 2547 kW. The total DG size is equal to or smaller than the total real load value because this is the optimization constraint it means to be satisfied for all algorithms. Before DG installation, In the base scenario, the lowest and highest voltages are 0.9664 pu and 1.0607 pu, respectively. For ideally sized and arranged DGs, the least and most voltages for the GA outcomes are 0.9915 pu and 1.0477 pu, respectively. Table 2 displays the node voltages that have remained within the defined limits for all algorithms while the voltages are not within the limit before optimization. Also, the power losses are decreased after the optimization for all algorithms, as shown in Table 2.

The four DGs are installed as follows, for GA at nodes 737,703, 701, and 707, for PSO at nodes 736, 744, 727, and 718, for PS 734, 701,713 and 722, and finally at 737, 730, 701, 722 for GWO method as given in Table 2. In this case, the GA gives better results because the minimum loss value is 19.302 kW with a maximum loss reduction value of 73.85%. Table 3 shows the second case's most appropriate location, size, and power factor. In this case, DGs are operating with a lagging power factor to use their reactive power capabilities. Then, three control variables are used for each DG for the optimization algorithm, so in total, we have 12 control variables for four DGs, which are the bus number, size, and power factor of DGs.

Table 2. Various Approaches to Optimal DG Size and Position for an IEEE 37-node System Operating at a Unity Power Factor

Case	**Method**	**Installed DG**					**Total DG Power**	**Ploss (kW)**	**Loss Reduction (%)**	**Vmin**	**Vmax**
Base Case	-	Without DG	Total Real Load(kW)= 2457				-	73.81	-	0.9664	1.0607
			DG 1	**DG 2**	**DG 3**	**DG 4**					
4 DGs	**GA**	**Node**	737	703	701	707	2426.6	19.302	73.85%	0.9915	1.0477
		Size (kW)	637.94	853.35	584.06	351.24					
	PSO	**Node**	736	744	727	718	2354.4	19.693	73.32%	0.9916	1.0475
		Size (kW)	747.3	303.75	1012.7	290.64					
	PS	**Node**	734	701	713	722	2457	19.94	72.98%	0.9915	1.0478
		Size (kW)	863.78	659.63	663.71	269.88					
	GWO	**Node**	737	730	701	722	2455.8	19.354	73.78%	0.9903	1.0478
		Size (kW)	610.71	508.18	1052	284.91					

Table 3. Optimal DG Size and Location with Different Methods for IEEE 37 Node System at Optimal Power Factor

Case	Method	Installed DG					Total DG Power kW	Ploss (kW)	Loss Reduction (%)	Vmin	Vmax
Base Case	-	Without DG	Total Real Load(kW)= 2457				-	73.81	-	0.9664	1.0607
			DG 1	DG 2	DG 3	DG 4					
4 DGs	GA	Node	737	703	701	722	2447.3	7.0936	90.39%	0.9986	1.0363
		Size (kW)	656.27	743.66	791.74	255.6					
		Power factor	0.90521	0.906	0.85332	0.77254					
	PSO	Node	737	709	701	720	2455.1	7.148	90.32%	0.9968	1.0353
		Size (kW)	518.16	559.14	896.94	480.83					
		Power factor	0.9013	0.90984	0.88098	0.88838					
	PS	Node	738	733	701	704	2456.4	8.3903	88.63%	0.9968	1.0353
		Size (kW)	341.44	631.19	772.38	711.38					
		Power factor	0.6875	1	0.75	0.9375					
	GWO	Node	738	733	702	722	2383.52	7.3664	90.02%	0.9992	1.036
		Size (kW)	435.93	432.84	1267	247.75					
		Power factor	0.92891	0.87854	0.91204	0.8546					

The power losses also decreased with the optimization of all algorithms, as given in Table 3. The four DGs are installed as follows, for GA at nodes 737,703, 701, and 722, for PSO at nodes 737, 709, 701, and 720, for PS 738, 733,701 and 704, and finally at 738, 733, 702, 722 for GWO method as given in Table 3. In this case, the GA gives better results with a minimum loss value of 7.0936 kW and a maximum loss reduction value of 90.39%.

When comparing the results obtained with GA for two scenarios representing DG operating at unity power factor and different power factors, the power loss reduction in the first scenario was 73.85%, while in the second scenario, it was 90.39%. This indicates that DGs with reactive power capability significantly reduced power losses more in the second scenario. Thus, utilizing DGs with reactive power capabilities led to a decrease in total power losses.

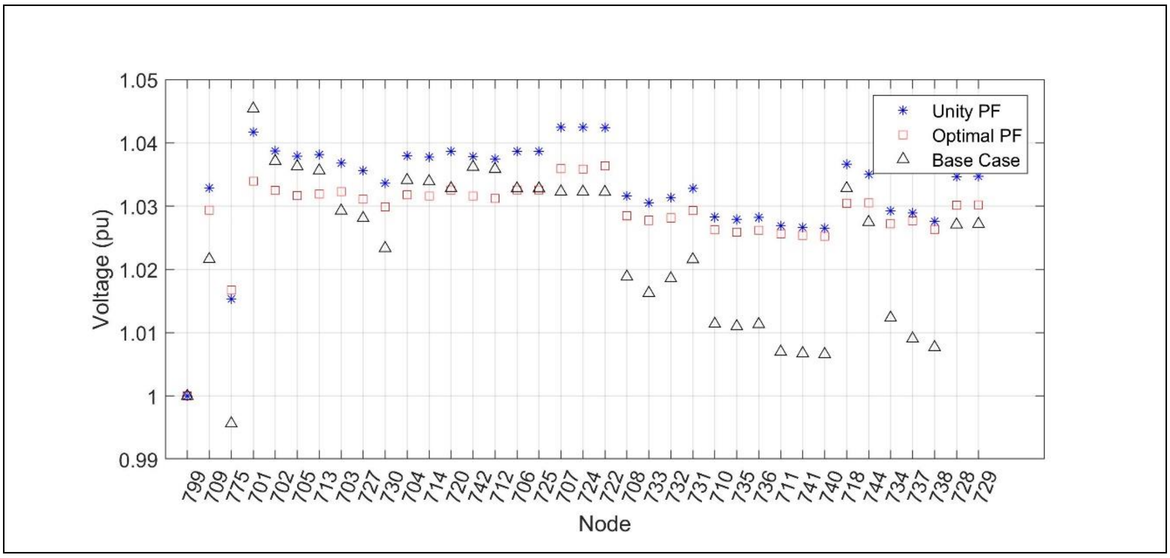

Figure 6. Voltage Profile of Phase for the Base Case, the Cases DGs Operated at Unity and Optimal Power Factor

The voltage profile was boosted and real power loss was significantly reduced following the insertion of DG units in the system as shown in Figures 6, 7 and 8. The constraints are satisfied as given; the GA gives the finding as improving power loss diminution outcomes in this scenario, with a 90.39% power loss reduction and the lowest voltage value of 0.99 pu and the highest voltage value of 1.03pu, respectively.

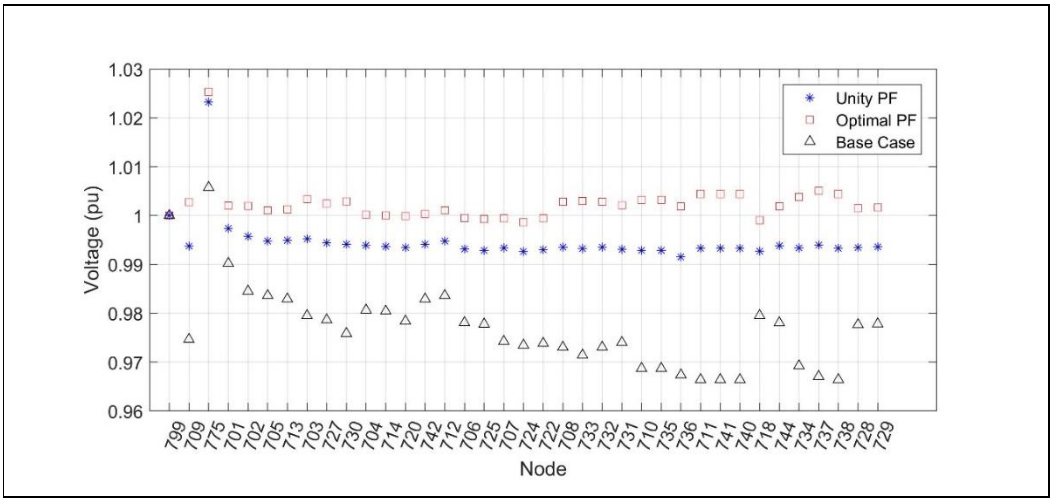

Figure 7. Voltage Profile of Phase b for the Base Case, the Cases DGs Operated at Unity and Optimal Power Factor

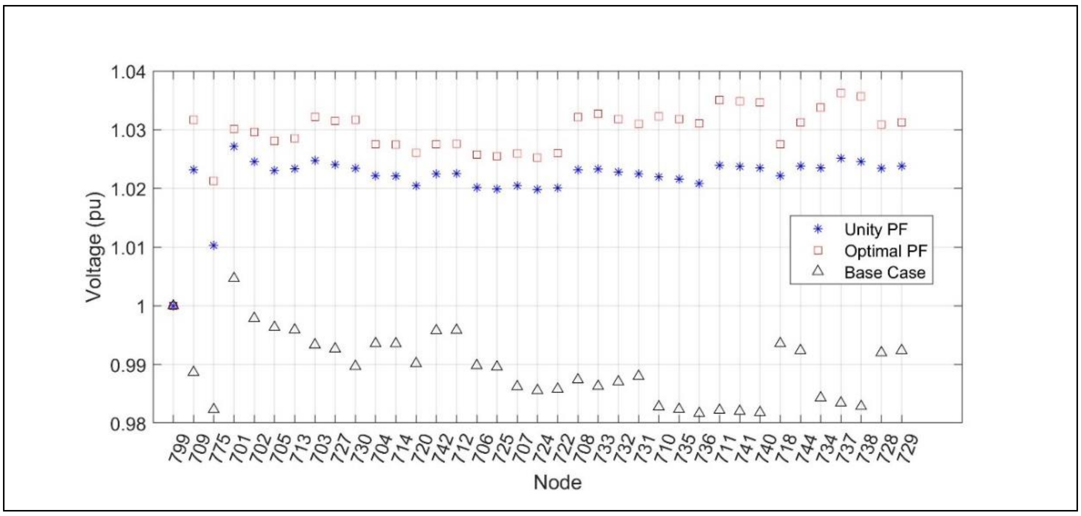

Figure 8. Voltage Profile of Phase c for the Base Case, the Cases DGs Operated at Unity and Optimal Power Factor

6. Conclusion

This paper shows that DG unit integration in the distribution test system aims to minimize power loss by improving the voltage profile. In this study, several heuristic optimization algorithms have been utilized to resolve the DGs unit allocation and sizing problem. Compared to other optimization algorithms used in the study, GA yields better results for optimal locations and sizes in reducing power losses. The approaches drop the active power losses by ensuring the voltages are within the defined limits. By improving the voltage profile of the whole network, power losses have been minimized through the use of optimally located and sized distributed generations, which in turn supports reducing network load. The utilization of DGs' reactive power capabilities demonstrates that when they perform at the ideal power factor, the power losses more than DGs operated under the unity power factor due to the lack of reactive power capability.

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Article Information Form

Acknowledgments
We express our gratitude to the referees for their insightful comments that enhanced the paper's presentation.

Authors' Contributions
The two authors worked together to complete this project. The final manuscript was read and approved by all the authors.

Conflict of Interest
There is no conflict of interest declared by the writers.

Funding
Funding has not been revealed by the writers.

Plagiarism Statement
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