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Optimal Integration of Distributed Energy Resources in Distribution Network Using Nature Inspired Artificial Intelligence Techniques

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Abstract— *This research proposes a unique technique to optimize the integration of distributed energy resources (DERs) inside distribution networks, with the goal of improving system performance and meeting ancillary service requirements. This study employs Metaheuristic Optimization Techniques, especially a hybrid ABC-WOA algorithm, to determine the ideal position and size of DERs. The proposed model's effectiveness is assessed using detailed simulations of benchmark distribution systems, including the IEEE 33-bus and 69-bus test networks. Using MATLAB 2021a and the MATPOWER 7.1 toolbox, the optimization procedure exhibits remarkable convergence behavior, as shown in convergence graphs for both systems. The findings show considerable improvements in voltage profile and a decrease in active power losses after the installation of DGs, demonstrating the efficacy of the suggested strategy. Detailed analyses, including voltage magnitudes, active power losses, and comparison tables displaying the locations and capacities of the DGs, demonstrate the ABC-WOA-based optimization model's practical feasibility and benefits in improving the integration of DERs into distribution networks.*

Key Words: Distributed energy resources (DERs), Distribution network, Metaheuristic optimization techniques, ABC-WOA algorithm, System performance, Optimization, Voltage profile.

1. INTRODUCTION

In recent years, there have been several improvements in the electric power industry. Customers are becoming pickier about dependability and power quality, while distribution network operators (DNOs) are being forced to increase energy efficiency to save costs as a result of the current trend toward deregulation in the power industry. Shunt capacitors (SCs) and distributed generators (DGs) are two examples of distributed energy resources (DERs) that are crucial for obtaining increased energy efficiency in distribution system functioning. To meet smart grid efficiency objectives of loss reduction and high-quality electricity provided to the end user, integrated solutions to well-formulated challenges that reflect the reality on the ground where all such devices coexist are needed[1]. While improper DER placement may raise system losses as well as network capital and operating costs, optimal DER placement can enhance network performance in terms of better node voltage profiles, decreased power flows, reduced feeder losses, improved power quality, and reliability of electric supply. Regardless of the specific motivation for a DNO, such as permitting the connection of more DG capacity, decreasing energy losses, or enhancing network dependability, the DG planning tools need to include fundamental network limitations like voltage and heat thresholds[2].

In recent times, there have been several efficacious endeavors to address the issue of the ideal distribution of either SCs or DGs independently[3]. Nevertheless, the deployment strategy of DERs in tandem is more feasible and can independently configure and manage the flow of both reactive and actual power in a distribution network (DN) [4]. Using analytical or heuristic techniques, this simultaneous allocation method and have shown the mutual influence of these devices on the distribution network's performance. An analytical method for the simultaneous installation of SCs and DGs to minimize investment costs. By using an analytical technique to identify voltage support zones, they narrowed the search area, and then used a hybrid ABC-WOA to address the issue.

ABC-WOA technique was used to ascertain the ideal position and amount of distributed generation (DG) power factor in order to reduce power losses under different circumstances[5].It has been shown that the results have significantly improved in terms of loss reduction and voltage profile improvement. A heuristic method in which the best candidate sites are found by a node sensitivity analysis, and the capacity of the SCs/DGs is then found through the recommendation of a heuristic curve fitting procedure. To address this multi-objective optimization issue, a combined imperialist competitive algorithm (ICA)–genetic algorithm (GA) approach. Using this strategy, dispersed resource placement and size are initially determined by the ICA, and these solutions are then further refined by the GA operators[6].

To reduce power losses, several DG types are used for actual and reactive power injections. ABC-WOA together with an analytical method is used to address the issue. The authors concluded that bigger systems are better suited for the heuristic method. Nevertheless, the issue goals in these efforts have mainly been loss reduction and node voltage improvement; peak power losses, feeder current profiles, and substation capacity release for DER allocation have not been considered.

Another operational technique that has been widely employed to accomplish several performance goals, including power loss reduction, voltage profile improvement, and congestion control, is distribution network reconfiguration, or DNR. As a result, a coordinated strategy for DER allocation in conjunction with DNR may more successfully accomplish goals like improved substation capacity release, reduced peak power losses, and greater energy efficiency. The electricity distribution company typically installs SCs, although private investors own DGs. In order to assign DGs and SCs concurrently, the electric utility should provide the DG investor a coordinated solution for the location and scale of DERs. As a matter of fact, a concerted effort of this kind may provide the greatest possible advantages for the network operator and/or users, as well as assess the viability of DER investment in comparison to other conventional planning choices[7].

appropriate placement of DERs in DN requires determining the appropriate quantity, size, and location. It is a nonlinear, complicated combinatorial optimization problem. Swarm and evolutionary optimization approaches, such as GA and PSO, have been shown to achieve global or near-global optima. When applying these approaches to large-scale applications[8], it's important to prevent premature or sluggish convergence due to the vast search area available.

Only a few of the highest-priority nodes on this list are chosen for DER allocation. However, these methodologies are not infallible and only give general recommendations on the importance of prospective nodes. The node sensitivities are determined assuming no such devices are installed. Selecting just the top few nodes as sensitive components did not provide an accurate representation of the distribution network[9].

2. BACKGROUND

2.1 Artificial Bee Colony (ABC) Optimization

ABC's mechanical bee hive contains three distinct species: resorted to the use of bees, which are tasked with finding specific food sources; observer bees, scout bees, who hunt for food sources at random, and worker bees, who watch the utilized bees dance around the hive to choose a food source, are examples of the former. Observers and observers are commonly referred to as jobless beekeepers since they are unemployed. Initially, it is up to the scout bees to locate all sources of food.

Here is how the ABC algorithm often works[10] :

Initialization phase-

The scout bees set the control parameters and initiate the population of food source vectors (m=1....SN, SN:). Each nutrient source, denoted by, represents a vector solution to an optimization problem where the objective function is minimized by optimizing a set of n independent variables, denoted by [11], It's possible to use the following definition while setting things up:

$$y_{mx} = l_x + rand(0,1)*(u_x - l_x) \qquad (1)$$

Employees Bees Phase-

Utilized bees will seek out new food sources close to those they've previously visited and remembered providing a higher concentration of nectar. They look around the area for food sources and assess their viability (fitness). [12] They may, for instance, use the formula that is included inside the equation in order to discover a food source that is situated in the immediate area:

$$\upsilon_{mx} = y_{mx} + f_{mx}(y_{mx} - y_{kx}) \qquad (2)$$

where is a randomly chosen food source, is a parameter index determined at random, and is a randomly chosen integer between and [-a, a]. After establishing fitness, a greedy selection is made between it and existing food source. The formula below may be used to calculate the fitness value of the solution for minimization problems.

$$fit_m(\vec{y}_m) = \begin{cases} \dfrac{1}{1+f_m(\vec{y}_m)} & \text{if } f_m(\vec{y}_m)^3 0 \\ 1+abs(f_m(\vec{y}_m)) & \text{if } f_m(\vec{y}_m)<0 \end{cases} \qquad (3)$$

Onlooker Bees phase-

There are two categories of bees who are unable to find work: onlooker bees and scout bees. Using the term presented in equation, you can compute the probability value with which an observer bee chooses.

$$p_m = \frac{fit_m(\vec{y}_m)}{\sum_{m=1}^{SN} fit_m(\vec{y}_m)} \qquad (4)$$

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An observer bee picks a food source at random, and then uses the equation to find a nearby source and assess its fitness. Between and, Like the utilizing bee's phase, self-absorbed selection is utilized during this phase.

2.1 WOA Algorithm

The Whale Optimization programme (WOA) is an optimization programme that is built on how humpback whales interact with each other and how they hunt. The WOA programme tries to find food in the water like humpback whales do. In the WOA algorithm, a point vector in the search space is used to show each possible answer. The algorithm starts with a group of possible answers that are generated at random from the search field. A possible solution's quality is judged by how well it answers the optimization problem[13]. This is done with a fitness function. The algorithm works by going through several steps called iterations. Each iteration has three main steps: Search, surround, and bubble are all options. During the search stage, the position of each feasible solution is modified such that it is closer to the best answer identified so far. [14]. This step is a simulation of how humpback whales look for food. They do this by following the best available signs.

The WOA algorithm has been shown to be effective at solving a wide range of optimization problems, such as those in engineering design, data mining, and machine learning. The method is easy to use and only has a few settings that need to be tweaked. But, like other optimization algorithms, the WOA algorithm's success depends on the problem being solved and how the algorithm settings are set [15]. So, to get the best results for a given problem, it is important to carefully tune the algorithm's settings[16].

Table 1 Whale Optimization Algorithm

Algorithm 1 The Standard Whale Optimization Algorithm

Initialize a population of random whales
$W^* =$ the best search agent
$t = O$
While $(t <$ iterations)
  for each whale
    Update WOA parameters
    and p)
    if $(p < 0.5)$
      if $(|B| < L)$
        $W^{t+1} = W^* - B.Dis$
      else if $(|B| \geq L)$
        $W^{t+1} = W_{rand} - B.Dis$
      end if
    else if $(p \geq 0.5)$
      $W^{t+1} = Dis^{'}.e^{x.r}.\cos(2\pi r) + W^*$
    end if
  end for
  Evaluate the whale W^{t+1}
  Update W^* if W^{t+1} if better
  $t = t + 1$
end while
return W^*

2.2 Objective Function:

$$f(x) = \sum_{i=1}^{N} \left[Metric(x_i) - Metric(x_{i-1}) \right]$$

Where,

x_i denotes the set of hyper parameters at that iteration.

N is the overall number of iterations.

$Metric(x_i) - Metric(x_{i-1})$ indicates the improvement in the segmentation measure gained by adjusting the hyper parameters from iteration $i-1$ to i iteration.

The objective function $f(x)$ computes the total improvement in the segmentation metric during the duration of the optimization procedure. The hybrid ABC-WOA algorithm attempts to maximize this objective function by repeatedly modifying the hyper parameters to improve segmentation performance.

This study utilized a hybrid ABC-WOA optimization method to specifically select relevant features associated with soil moisture and temperature data from the provided dataset. Through this approach, we effectively isolated critical information, essential for subsequent analysis and modelling. This feature selection process aimed to enhance the accuracy and efficacy of our study's predictive models in the context of smart irrigation systems.

Table 2 Proposed Algorithm

Algorithm 1 Hybrid ABC-WOA Algorithm for Hyper parameter Tuning

1: Initialize parameters, hyper parameters, population for ABC and WOA
2: **while** not convergence criteria met **do**
3: **for** each solution in ABC population **do**
4: Employ bee for exploration
5: Evaluate fitness
6: Update solution
7: **end for**
8: **for** each solution in WOA population **do**
9: Update position using WOA equations
10: Evaluate fitness

11: **end for**
12: Select best solutions from both ABC and WOA populations
13: Update hyper parameters of VGG19 model
14: Check for convergence
15: **end while**

3.PROBLEM FORMULATION

The optimal allocation of DERs aims to maximize annual savings and profit by reducing charges for energy losses, peak power losses, and substation capacity release, while maintaining better node voltage and feeder current profiles under multi-level loads. A penalty function technique is given for determining the maximum node voltage variation and temperature limit of distribution feeders. The objective function is expressed as follows:

$$Max.\,F=\lambda\left(K_e\left(\sum_{j=1}^{N_L}P_{loss,bj}H_j-\sum_{j=1}^{N_L}P_{loss,aj}H_j\right)+\zeta K_p(P_{loss,b}^{P}-P_{loss,a}^{P})\right.$$
$$\left.+\zeta K_S\,(S_b^p-S_a^p)\right)-\zeta K_{SC}\sum_{n=1}^{loc}Q_{SC,n}-\zeta K_{DG}\sum_{n=1}^{loc}P_{DG,n;}$$
$$\forall n\in N,\ \forall j\in L \qquad (5)$$

where N and L represent the number of system nodes and load levels, respectively. The multi-level piece-wise yearly load profile considers the number of load levels and their durations (N_L and H_j respectively). $P_{loss,bj}$ and $P_{loss,aj}$ represent power losses for uncompensated and compensated systems at the j_{th} load level, respectively. $P_{loss,b}$ and $P_{loss,a}$ represent peak power losses for uncompensated and compensated systems. S_b^p represents the base case sub-station capacity, while S_a^p represents the sub-station capacity after DER allocation and reconfiguration. Q_{SC} and P_{DG} represent reactive and active compensation at a candidate node. $K_eK_pK_SK_{SC}K_{DG}$ are the unit costs of energy, peak power losses, sub-station capacity release, shunt capacitor installation, and DG installation, respectively. The first and second terms reflect the costs of reducing yearly energy loss and peak power loss, respectively. The third term covers the yearly costs for substation capacity release. The fourth and final periods represent the yearly costs for installing SCs and DGs, respectively. The penalty function λ is designed to address node voltage variations and feeder current constraints. It is defined as the geometric mean of the node voltage penalty function V_{pf} and the feeder current penalty function I_{pf} , as seen below:

$$\lambda=\sqrt{\left(V_{pf}\times I_{pf}\right)} \qquad (6)$$

Where

$$V_{pf}=\frac{1}{1+Max(\Delta V_{nj})};\quad \forall n\in L,\ \forall j\in L \qquad (7)$$

$$I_{pf}=\frac{1}{1+Max(\Delta I_{nj})};\quad \forall n\in N,\ \forall j\in L \qquad (8)$$

Equation (3) demonstrates that V_{pf} is derived by assessing the highest deviation in node voltage across all system nodes, considering all load levels. Here, ΔV_{nj} represents the voltage deviation of the n_{th} node from the source voltage at the j[th] load level. Similarly, the value of I_{pf} is calculated using equation (4), where ΔI_{nj} represents the deviation of the current in the n_{th} feeder from its rated ampacity during the j_{th} load level. The values of $\Delta I_{nj} and \Delta V_{nj}$ are determined by using equations (5) and (6), respectively. A soft voltage limitation is implemented in (5) by establishing a minimum specified node voltage, $V_{\min S}$, which must be maintained below the minimum allowable node voltage, $V_{\min}$, as determined by the power regulating authority. $V_{\max}$ refers to the highest allowable voltage at a node as determined by regulatory bodies, whereas $I_n^{\max}$ represents the designated line ampacity for the nth line.

$$\Delta V_{nj}=\left\{\begin{matrix}1-|V_{nj}|; & V_{\min S}<V_{nj}\le V_{\min}\\ 0; & V_{\min}\le V_{nj}\le V_{\max}\\ a\ very\ l\arg e\ number;\ \ else & \end{matrix}\right\};\forall n\in N,\quad \forall j\in L \qquad (9)$$

$$\Delta I_{nj}=\left\{\begin{matrix}0; & I_{nj}\le I_n^{\max}\\ a\ very\ l\arg e\ number;\ \ else & \end{matrix}\right\};\forall n\in N,\quad \forall j\in L \qquad (10)$$

As follows, the capital recovery factor ζ for DER investments are calculated:

$$\zeta=(d(1+d)^Y)/((1+d)^Y-1) \qquad (11)$$

where d represents the discount rate and Y denotes the DER allocation project's planning horizon. The subsequent operational limitations are implemented:

$$g_j(h) = 0; \quad \forall j \in L \tag{12}$$

where $g_j(h)$ denotes the collection of power flow equations applicable to the j_{th} load level.

At each node, the aggregate active and reactive power introduced by DG and SCs must remain within the permissible range, which is delineated as follows:

$$Q_{SC,\min} \le Q_{SC,n} \le Q_{SC,\max}; \quad \forall n \in N \tag{13}$$

$$P_{DG,\min} \le P_{DG,n} \le P_{DG,\max}; \quad \forall n \in N \tag{14}$$

where $P_{DG,\min}$ and $P_{DG,\max}$ represent, respectively, the minimum and maximum active power generation limits at a node. In the same manner, the minimum and maximum limits on reactive power generation at a node are denoted as $Q_{SC,\min}$ and $Q_{SC,\max}$, respectively.

The following are the defined system power generation limits for SCs and DGs:

$$\sum_{n=1}^{loc} Q_{SC,n} \le Q_D; \quad \forall n \in N \tag{15}$$

$$\sum_{n=1}^{loc} P_{DG,n} \le P_D; \quad \forall n \in N \tag{16}$$

It is postulated that the combined active and reactive power injected by DGs and SCs at every candidate node location should be in excess of the system's nominal active power demand Q_D and reactive power demand P_D, respectively.

Prohibited by equations (13) and (14) is the duplication of candidate sites for DERs.

$$N_{SC,a} \ne N_{SC,b}; \quad a,b \in N \tag{17}$$

$$N_{DG,a} \ne N_{DG,b}; \quad a,b \in N \tag{18}$$

where NDG and SC refer, correspondingly, to candidate sites for DGs and SCs. Given that discrete sizes of DERs are commercially available, they are modeled as follows:

$$Q_{SC} \le K_b Q_b; \quad K_b = 0,1,2,\ldots,nsc \tag{19}$$

$$P_{DG} \le K_d P_d; \quad K_d = 0,1,2,\ldots,ndg \tag{20}$$

Q_b and P_d denote the unit size of SCs and DGs, respectively.

K_b and K_d denote the quantity of capacitor banks and discrete dispatches of DG, respectively.

Initially optimizing the solution, it determines the ideal location and dimensions of Distributed Energy Resources (DERs), considering the yearly demand profile.

Next, the optimization process is performed individually for each demand level to find the most efficient power distribution of the deployed Distributed Energy Resources (DERs). Nevertheless, the locations for Distributed Energy Resources (DERs) remain fixed and their capacity is limited to the size determined by the solution reached. The supplementary limitations necessary to ascertain the most efficient allocations of SCs and DGs are represented as follows:

$$Q_{SC,n} = K_t \Delta Q; \quad K_t = 0,1,2,\ldots,Q_{SC,n}/\Delta Q \tag{21}$$

$$P_{DG,n} = K_{md} \Delta P; \quad K_{md} = 0,1,2,\ldots,P_{DG,n}/\Delta P \tag{22}$$

ΔP and ΔQ indicate the relative discrete sizes of available commercial SCs and DGs.

After properly locating Distributed Energy Resources (DERs), the distribution network is changed individually for each demand level. The reconfiguration issue aims to reduce actual power loss P_{loss} at the j_{th} load level, while ensuring compliance with different operational restrictions of the network. The mathematical framework for the DNR issue is expressed as:

$$Min.P_{loss.j} = \sum_{n=1}^{E} R_n \frac{P_{nj}^2 + Q_{nj}^2}{|V_{nj}|^2}; \quad \forall n \in N, \quad \forall j \in L \tag{23}$$

The active and reactive power flows in the nth branch of the system are denoted by P_{nj} and Q_{nj}, respectively, where E indicates the total number of branches. The symbol R_n represents the resistance of the n_{th} branch, whereas V_{nj} represents the voltage at the n_{th} node at the j_{th} load level.

Equation (19) is bound by the following limitations:

1. Radial topology constraint

The revised network configuration must be radial, meaning that it should not have any closed paths. Thus, the radiality constraint for the rth radial topology is defined as:

$$\phi_j(r) = 0; \quad \forall j \in L \tag{24}$$

$\phi_j(r)$ represents the symbolic representation of a closed loop.

2. Node voltage constraint

During the DNR, a stringent voltage limit is implemented as a crucial operating strategy for the network. During the optimization process, it is necessary to ensure that all node voltages V_{nj} of the system remain within the specified minimum ($V_{\min}$) and maximum ($V_{\max}$) limits.

$$V_{\min} \le V_{nj} \le V_{\max}; \quad \forall n \in N, \quad \forall j \in L \tag{25}$$

The power flow constraint is determined by equation (8).

The radiality limitation is the most significant obstacle when addressing the issue of network reconfiguration. The issue is solved using the codification described in[17] in the current study. This is a rule-based method for detecting and correcting radial topologies that are not practical. Based on this codification, three criteria have been formulated using graph theory to detect and rectify infeasible individuals that may arise throughout the computing process.

Simulation results:

The proposed approach is tested using IEEE 33-bus and 69-bus test distribution systems. In matlab 2021a, the obtained results are briefed out in this section as follows.

IEEE-69 and 33 bus system:

The IEEE 69,33 BUS systems are utilized by using mat power 7.1 toolkit and the optimal locations for DG's and capacities are obtained using a hybrid ABC-WOA algorithm. figure1 &2 shows the objective function value converges over the given number of iterations.

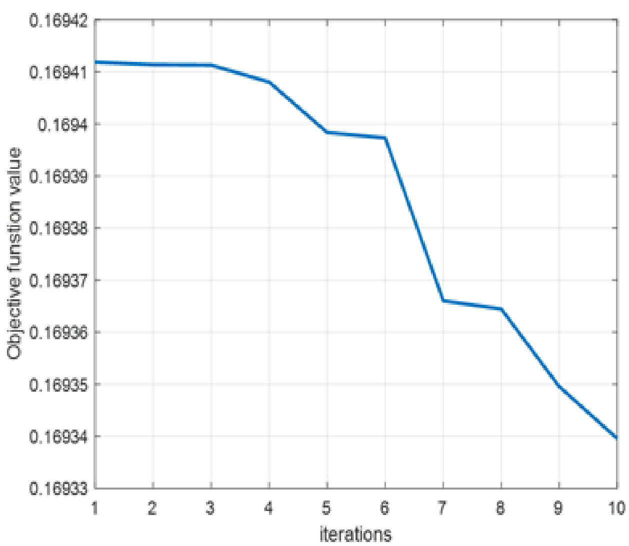

Figure 1:69-Bus convergence plot

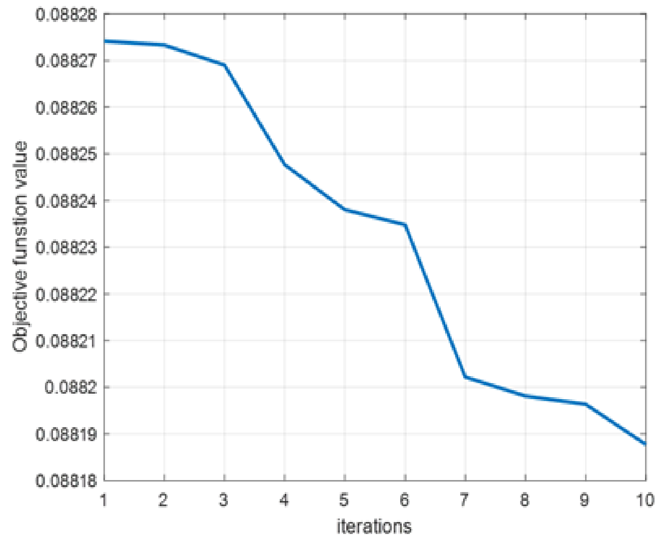

Figure 2:33-Bus convergence plot

The obtained voltage magnitudes with and without DG placement of a 69 and 33 bus system is shown in fig 3 and 4. It is observed that is voltage profile enhances due to the placement of DG's.

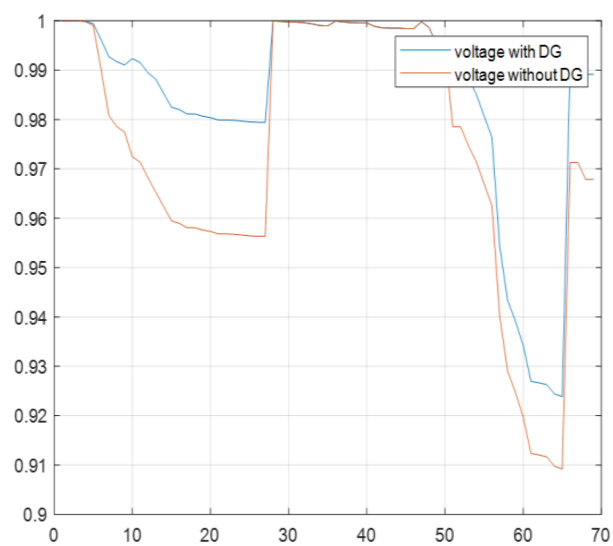

Figure 3:69-Bus voltage profile

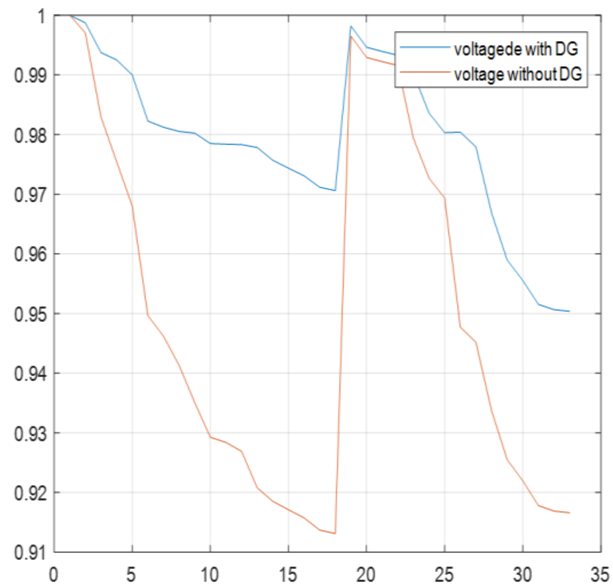

Figure 4:33-Bus voltage profile

In figure 5 and 6 depicts the active power loss of the 33 and 69 bus systems, and it is observable that the loss is significantly reduces due to the placements of DG's.

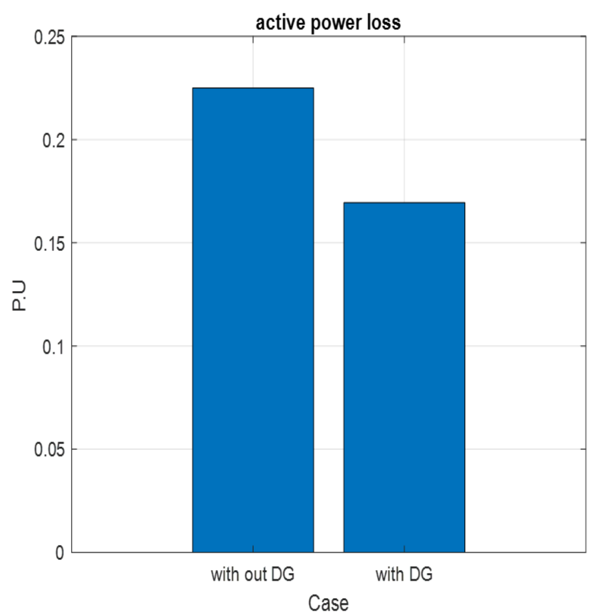

Figure 5-bus active power loss

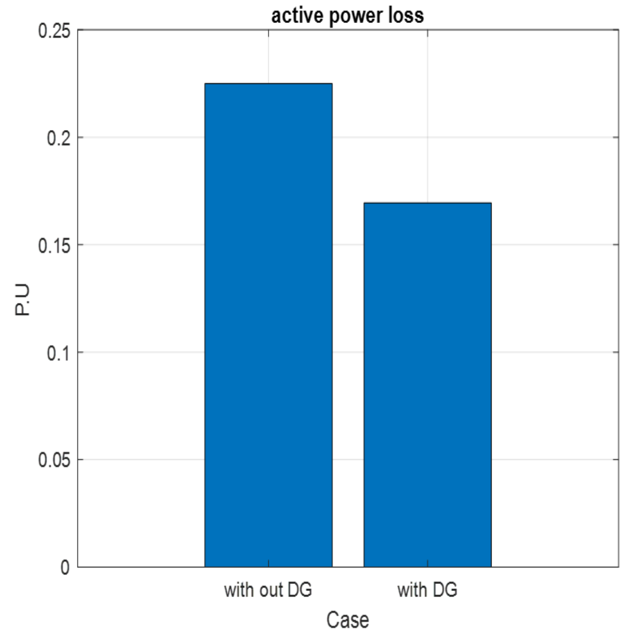

Figure 6:33-*bus active power loss*

The location and capacity of placed DG's are given in table 3.

Table 3 *Comparison table*

parameter	33-bus system					69-bus system				
DG-location	1	7	8	9	11	4	7	14	16	30
DG-capacity	0.4454	0.1570	0.4022	0.4376	0.9267	0.0439	0.1305	0.7079	0.6210	0.6676

4. CONCLUSION

The suggested technique, tested on both the IEEE 33-bus and 69-bus test distribution systems, yields encouraging results, as seen by simulation results. Using the MATLAB 2021a environment and the hybrid ABC-WOA method for optimum DG placement, the research successfully demonstrates system performance improvements. Figures 1 and 2 provide convergence graphs for objective function values across iterations, demonstrating the effectiveness of the optimization process. The subsequent examination of voltage profiles, shown in Figures 3 and 4, demonstrates the real advantages of DG deployment, with significant increases in voltage magnitudes throughout both systems. Furthermore, the decrease in active power losses, as shown in Figures 5 and 6, supports the suggested methodology's usefulness in improving system efficiency. Table 3 contains a thorough comparison of the locations and capabilities of the deployed DGs, which provides insights into their strategic deployment within the systems. Overall, these findings support the hybrid ABC-WOA algorithm's practicality and usefulness in optimizing DG placement, which contributes to improved system performance, voltage stability, and reduced power losses in both 33-bus and 69-bus distribution systems.

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