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Optimal Integration of Distributed Energy Resources in Distribution Networks Utilizing 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, intending to improve system performance and meet ancillary service requirements. This study employs Metaheuristic Optimization Techniques, especially a hybrid PSO-EHO 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 PSO-EHO-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, PSO-EHO 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 PSO-EHO to address the issue.

PSO-EHO 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. PSO-EHO together with an analytical method is used to address the issue. The authors concluded that bigger systems are better suited for the heuristic method[7]. 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 [8]. 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 [9].

appropriate placement of DERs in DN requires determining the appropriate quantity, size, and location. [10] 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[11], [12]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[13].

2. BACKGROUND

1.1 Particle Swam Optimization (PSO)

The conventional PSO method considers each particle as a possible solution to the job inside the search space. In D-dimensional space, the location and velocity vectors of the ith particle may be written as $x_i = (x_{i1}, x_{i2}, \ldots, x_{iD})$ and $v_i = (v_{i1}, v_{i2}, \ldots, v_{iD})$, respectively. After random particle initialization, the ith particle's velocity and location are updated as shown below.

$$v_i(t+1) = wv_i(t) + c_1 r_1 (p_i - x_i(t)) + c_2 r_2 (p_g - x_i(t)) \quad (1)$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (2)$$

The inertia weight (w) may adjust the effect of prior velocity on the present one. The weights of $p_g; p_i$ are determined by two constants, c_1 and c_2. p_i indicates the best prior position of the ith individual, whereas p_g represents the best previous position of all particles in the current generation. r_1 and r_2 are two randomly generated variables that have a uniform distribution in the range [0, 1].

Table -1: PSO algorithm

```
Step1: Randomly initialize Swarm population of N particles
Xi ( i=1, 2, …, n)
Step2: Select hyperparameter values
   w, c1 and c2
Step 3: For Iter in range(max_iter):  # loop max_iter times
      For i in range(N):  # for each particle:
         a. Compute new velocity of ith particle
            swarm[i].velocity =
               w*swarm[i].velocity +
               r1*c1*(swarm[i].bestPos -swarm[i].position) +
               r2*c2*( best_pos_swarm -swarm[i].position)
         b. Compute new position of ith particle using its new
velocity
            swarm[i].position += swarm[i].velocity
         c. If position is not in range [minx, maxx] then clip it
            if swarm[i].position < minx:
               swarm[i].position = minx
            elif swarm[i].position > maxx:
               swarm[i].position = maxx
         d. Update new best of this particle and new best of
Swarm
            if swaInsensitive to scaling of design
variables.rm[i].fitness < swarm[i].bestFitness:
               swarm[i].bestFitness = swarm[i].fitness
               swarm[i].bestPos = swarm[i].position

            if swarm[i].fitness < best_fitness_swarm
               best_fitness_swarm = swarm[i].fitness
               best_pos_swarm = swarm[i].position
      End-for
   End -for
Step 4: Return best particle of Swarm
```

1.2 Elephant Herding Optimization (EHO)

To overcome global optimization challenges, we simplified elephant herding behavior into the idealized guidelines below.

1) The elephant population consists of clans, each with a certain number of elephants.

2) Each generation, a certain number of male elephants leave their family group to live alone distant from the main group.

3) Each tribe of elephants is led by a matriarch.

A. Clan updating operator

As mentioned before, all the elephants live together under the leadership of a matriarch in each clan. Therefore, for each elephant in clan ci, its next position is influenced by matriarch ci. For the elephant j in clan ci, it can be updated as

$$x_{new,ci,j} = x_{ci,j} + \alpha \times \left(x_{best,ci} - x_{ci,j}\right) \times r \quad (3)$$

$x_{new,ci,j}$ and $x_{ci,j}$ represent the updated and old positions of elephant j in clan ci, respectively. The scale factor $\alpha \in [0,1]$ defines the impact of matriarch ci on $x_{ci,j}$. $x_{best,ci}$ signifies matriarch ci, the fittest elephant in clan ci. $r \in [0,1]$. Here, uniform distribution is applied.

Eq. (1) does not update the fittest elephant in each clan $x_{ci,j} = x_{best,ci}$. The fittest one may be upgraded as follows:

$$x_{new,ci,j} = \beta \times x_{cener,ci} \quad (4)$$

where the impact of the $x_{cener,ci}$ on the $x_{new,ci,j}$ is determined by a factor $\beta \in [0,1]$. As we can see, the knowledge gathered by every elephant in clan ci is what creates the new individual $x_{new,ci,j}$ in Equation (4). The center of clan ci is denoted by $x_{center,ci}$ and its d-th dimension may be computed as

$$x_{center,ci,d} = \frac{1}{n_{ci}} \times \sum_{j=1}^{n_{ci}} x_{ci,j,d} \quad (5)$$

where $1 \le d \le D$ signifies the d-th dimension and D is the total dimension. n_{ci} represents the number of elephants in clan ci. $x_{ci,j,d}$ represents the d-th elephant individual $x_{ci,j}$. Eq. (5) calculates the center of clan $ci, x_{center,ci}$ using D computations.

B. Separating operator

In elephant group, male elephants will leave their family group and live alone when they reach puberty. This separating process can be modelled into separating operator when solving optimization problems. In order to further improve the search ability of EHO method, let us assume that the elephant individuals with the worst fitness will implement the separating operator at each generation as shown in Eq. (6).

$$x_{worst,ci} = x_{\min} + (x_{\max} - x_{\min} + 1) \times rand \quad (6)$$

$x_{\max}$ and $x_{\min}$ represent the maximum and lower bounds of an elephant's location. The worst elephant in clan ci is represented by $x_{worst,ci}$. We employ a uniform distribution in the range $[0,1]$ rather than a stochastic distribution in $rand \in [0,1]$.

Table -2: Elephant Herding Optimization (EHO)

Algorithm 1 Elephant Herding Optimization (EHO)

1: Initialize population of elephants with random positions
2: Define parameters: number of clans (C), number of elephants per clan (N), maximum number of generations (G), scale factor (σ), separating probability (p_{sep}), and maximum mutation step size (Δ_{max})
3**: while** not reached maximum generations **do**
4: Evaluate fitness of each elephant
5: **for** each clan c_i **do**
6: Find the fittest elephant $x_{best,c}i$ in clan c_i
7: Calculate the center $x_{center,c}i$ of clan c_i
8: **for** each elephant j in clan c_i **do**
9: **if** elephant j is not the fittest in clan c_i **then**
10: Generate a random scale factor r
11: Update elephant j's position:
12: $xnew,ci,j = xci,j + \sigma \cdot (xbest,ci - xci,j) \cdot r$
13: **else**
14: Generate a random factor η
15: Calculate the new position based on the center of the clan:
16 $xnew,ci,j = xcenter,ci + \eta \cdot (xci,j - xcenter,ci)$
17: **end if**
18: **end for**
19: **end for**
20: **for** each clan ci **do**
21: Find the elephant with the worst fitness $x_{worst,c}i$ in clan ci
22: **if** random probability $p < p_{sep}$ **then**
23: Generate a random value rand
24: Update $x_{worst,c}i$'s position:
25: $xworst,ci = xworst,ci + rand \cdot \Delta max$
26: **end if**
27: **end for**
28: Ensure that all elephant positions are within the feasible range
29: Increment generation count
30: **end while**
31: Select the best solution from the final population

1.3 Objective Function

In a hybrid EH-PSO method, the objective function f(x) represents the function to be optimized. This function assesses the quality or fitness of a solution represented by the vector x in the search space.

The objective function, denoted as $f(x)$, is defined depending on the issue being addressed. In a minimization problem, the objective is to discover the smallest possible value for the function $f(x)$, whereas in a maximization issue, the objective is to find the largest possible value.

The objective function may be mathematically expressed as:

Minimize $f(x)$
Or
Maximize $f(x)$
Where:

- x is a vector that represents a possible solution in the search space.
- The objective function $f(x)$ examines the quality of a solution (x).

In a hybrid EH-PSO method, the optimization process combines EHO's exploration and PSO's exploitation capabilities. This combination seeks to strike a better balance between exploration and exploitation, resulting in enhanced convergence characteristics and solution quality.

The hybrid method repeatedly adjusts particle locations (represented by x) using a mix of EHO and PSO processes. These systems are often built around mathematical equations that regulate particle movement in the search space.

In PSO, the update equation for a particle's location at iteration t+1 may be stated as follows:

$$x_i^{(t+1)} = x_i^{(t)} + v_i^{(t+1)}$$

- $x_i^{(t)}$ is the position of particle i at iteration t.
- $v_i^{(t+1)}$ is the velocity of particle i at iteration t+1

Similarly, in EHO, the update equation for an elephant's location may be represented in numerous ways depending on its dynamics and exploration approach.

The hybrid EH-PSO method combines the update equations from EHO and PSO in a manner that takes use of each algorithms' capabilities. The objective function $f(x)$ directs the optimization process and ensures high-quality solutions for the issue.

Table -3: Proposed Algorithm

Algorithm 1 Hybrid PSO-EHO Algorithm for Hyper parameter Tuning

Initialize population of elephants and swarm of particles with random positions

Define parameters for both algorithms:

- For EHO: number of clans (C), number of elephants per clan (N), maximum generations (G), scale factor (σ), separating probability (p_{sep}), and maximum mutation step size (Δ_{max})
- For PSO: maximum number of iterations (*max iter*), inertia weight (*w*), cognitive weight (*c1*), and social weight (*c2*)

while not reached maximum generations (for EHO) or maximum iterations (for PSO) **do**

Perform EHO steps:

Evaluate fitness of each elephant

for each clan c_i **do**

Find the fittest elephant $x_{best,c}i$ in clan c_i

Calculate the center $x_{center,c}i$ of clan c_i

for each elephant *j* in clan c_i **do**

if elephant *j* is not the fittest in clan c_i **then**

Generate a random scale factor *r*

Update elephant *j*'s position:

$xnew,ci,j = xci,j + \sigma \; (xbest,ci \quad xci,j) \; r$

else

Generate a random factor η

Calculate the new position based on the center of the clan:

$xnew,ci,j = xcenter,ci + \eta \; (xci,j \quad xcenter,ci)$

end if

end for

end for

Perform separating operator

Ensure that all elephant positions are within the feasible range

Perform PSO steps:

for Iter in range (max iter) **do**

for each particle in swarm **do**

Compute new velocity of particle

27: Compute new position of particle using its new velocity

28: Clip position if out of range

29: Update best position of particle and best position of swarm

30: **end for**

31: **end for**

32: Increment generation count or iteration count

33: **end while**

34: Return the best solution found by EH-PSO

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:

$$Max.\ F = \lambda\left(K_e\left(\sum_{j=1}^{N_L} P_{loss,bj}H_j - \sum_{j=1}^{N_L} P_{loss,aj}H_j\right) + \zeta K_p(P^P_{loss,b} - P^P_{loss,a}) + \zeta K_S\,(S_b^p - S_a^p)\right) - \zeta K_{SC}\sum_{n=1}^{loc} Q_{SC,n} - \zeta K_{DG}\sum_{n=1}^{loc} P_{DG,n};\quad \forall n \in N,\ \forall j \in L \tag{7}$$

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. $K_e K_p K_S K_{SC} K_{DG}$ 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:

$$\lambda = \sqrt{\left(V_{pf} \times I_{pf}\right)} \tag{8}$$

Where

$$V_{pf} = \frac{1}{1 + Max(\Delta V_{nj})};\quad \forall n \in L,\ \forall j \in L \tag{9}$$

$$I_{pf} = \frac{1}{1 + Max(\Delta I_{nj})};\quad \forall n \in N,\ \forall j \in L \tag{10}$$

Equation (9) 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 jth load level. Similarly, the value of I_{pf} is calculated using equation (10), 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 (11) and (12), 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.

$$\Delta V_{nj} = \begin{cases} 1 - |V_{nj}|; & V_{\min S} < V_{nj} \le V_{\min} \\ 0; & V_{\min} \le V_{nj} \le V_{\max} \\ a\ very\ large\ number; & else \end{cases};\ \forall n \in N,\quad \forall j \in L \tag{11}$$

$$\Delta I_{nj} = \begin{cases} 0; & I_{nj} \le I_n^{\max} \\ a\ very\ large\ number; & else \end{cases};\ \forall n \in N,\quad \forall j \in L \tag{12}$$

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

$$\zeta = (d(1+d)^Y)/((1+d)^Y - 1) \tag{13}$$

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

$$g_j(h) = 0; \quad \forall j \in L \tag{14}$$

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:

$$Q_{SC,\min} \le Q_{SC,n} \le Q_{SC,\max}; \quad \forall n \in N \tag{15}$$

$$P_{DG,\min} \le P_{DG,n} \le P_{DG,\max}; \quad \forall n \in N \tag{16}$$

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:

$$\sum_{n=1}^{loc} Q_{SC,n} \le Q_D; \quad \forall n \in N \tag{17}$$

$$\sum_{n=1}^{loc} P_{DG,n} \le P_D; \quad \forall n \in N \tag{18}$$

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 (15) and (16) is the duplication of candidate sites for DERs.

$$N_{SC,a} \ne N_{SC,b}; \quad a,b \in N \tag{19}$$

$$N_{DG,a} \ne N_{DG,b}; \quad a,b \in N \tag{20}$$

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:

$$Q_{SC} \le K_b Q_b; \quad K_b = 0,1,2,\ldots,nsc \tag{21}$$

$$P_{DG} \le K_d P_d; \quad K_d = 0,1,2,\ldots,ndg \tag{22}$$

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:

$$Q_{SC,n} = K_t \Delta Q; \quad K_t = 0,1,2,\ldots,Q_{SC,n}/\Delta Q \tag{23}$$

$$P_{DG,n} = K_{md} \Delta P; \quad K_{md} = 0,1,2,\ldots,P_{DG,n}/\Delta P \tag{24}$$

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:

$$Min.P_{loss.j} = \sum_{n=1}^{E} R_n \frac{P_{nj}^2 + Q_{nj}^2}{|V_{nj}|^2}; \quad \forall n \in N, \quad \forall j \in L \tag{25}$$

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 (25) 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:

$$\phi_j(r) = 0; \quad \forall j \in L \tag{26}$$

$\phi_j(r)$ 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.

$$V_{\min} \le V_{nj} \le V_{\max}; \quad \forall n \in N, \quad \forall j \in L \tag{27}$$

The power flow constraint is determined by equation (27).

The radiality limitation is the most significant obstacle when addressing the issue of network reconfiguration. The issue is solved using the codification described in[14] 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 PSO-EHO algorithm. figure1 &2 shows the objective function value converges over the given number of iterations.

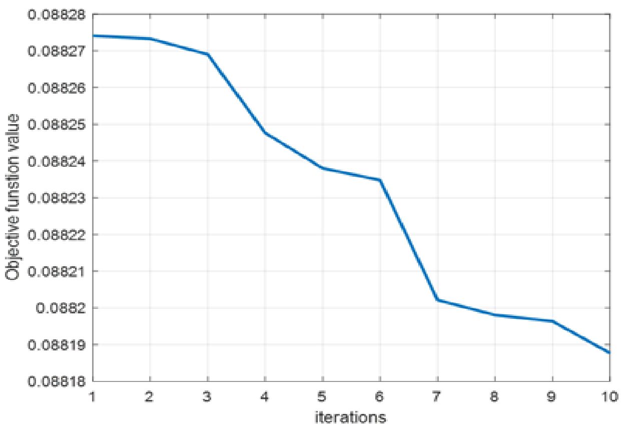

Fig-1: 69-Bus convergence plot

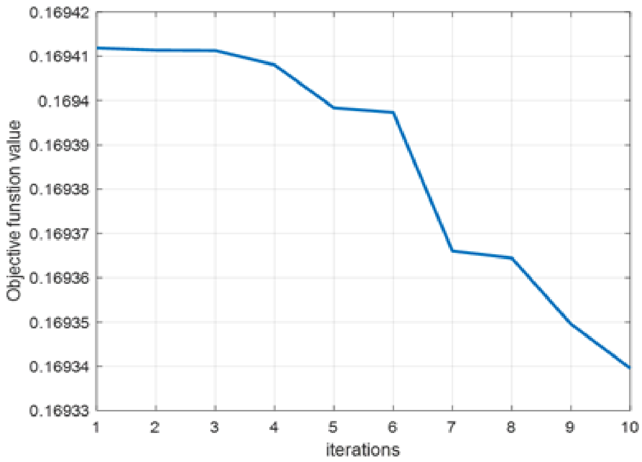

Fig- 2: 33-Bus convergence plot

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.

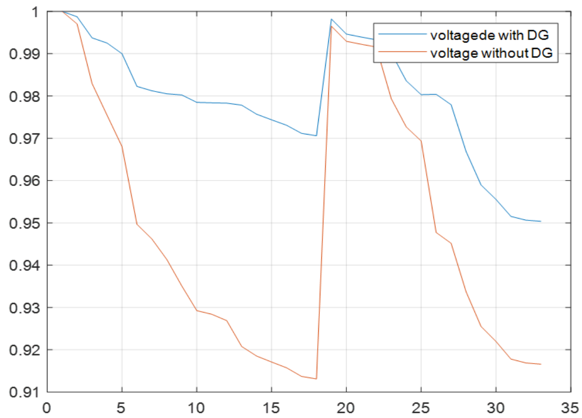

Fig - 3: 69-Bus voltage profile

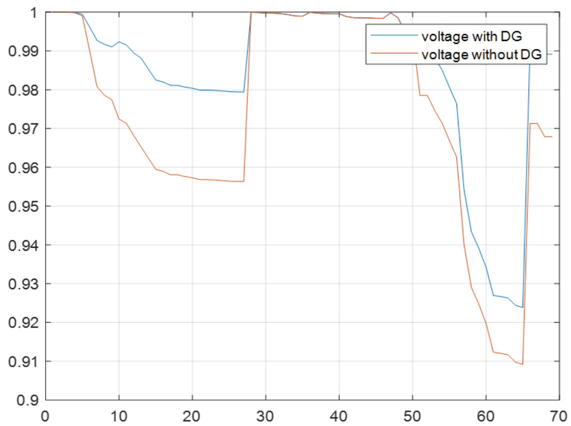

Fig- 4: 33-Bus voltage profile

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.

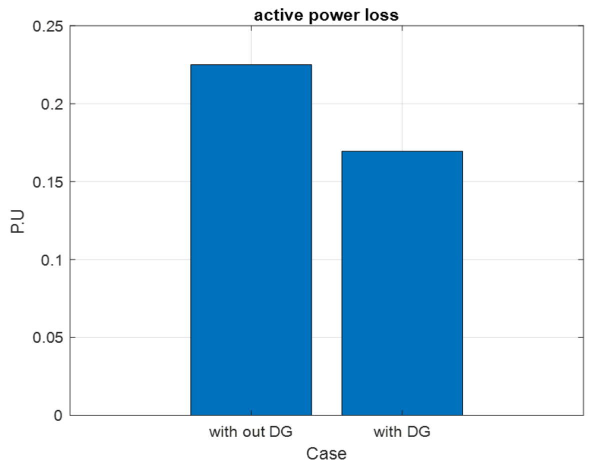

Fig- 5: bus active power loss

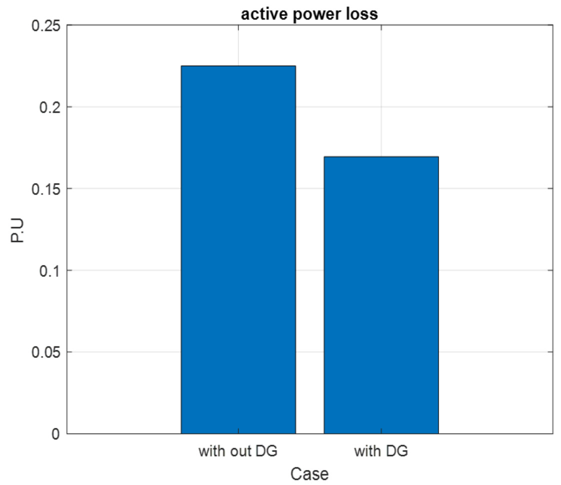

Fig- 6 : 33-bus active power loss

The location and capacity of placed DG's are given in table 4.

Table- 4 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. CONCLUSIONS

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 PSO-EHO 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 4 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 PSO-EHO 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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