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Optimal Positioning and Sizing of Distributed Energy Sources in Distribution System Using Hunter-Prey Optimizer Algorithm

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KEYWORDS

distributed generators; distribution power networks; hunter-prey optimization; photovoltaic system; wind turbine

ABSTRACT

The integration of distributed generation (DG) based on renewable energy (RE), in distribution power networks (DPN) has become indispensable for reducing power losses and voltage deviation along the DPN. Typical DGs are placed adjacent to the load in DPN and locally distribute adequate active and reactive power. However, the appropriate placement of DG in DPN at the right location and size is essential to achieve the desired objectives. In this paper, DG is optimized into radial DPN with the aid of a recent bio-inspired hunter-prey optimization (HPO) algorithm. HPO is a bio-inspired and population-based optimization algorithm that mimics the hunting action of an animal. The HPO algorithm evades the local optimal stagnation and reaches the optimal solution rapidly. HPO optimizes solar photovoltaic (PV) and wind turbine (WT) DG systems to minimize multi-objective functions (MOFs) including active power loss (APL) and voltage deviation (VD), and to enhance voltage stability (VS). An optimized solution has been obtained for a standard IEEE 69-bus radial DPN and the optimized simulation result of HPO has been compared with other optimization algorithms with the aim of assessing its effectiveness. The optimized PV and WT DG integration via the proposed HPO algorithm has yielded a power loss reduction of 67.10 % and 90.4 %, respectively. Furthermore, a considerable enhancement in bus voltage and voltage stability has been seen in radial DPN after the inclusion of DG.

1. Introduction

In recent times, distributed generation (DG), particularly that based on renewable energy sources (RESs), has been increasingly integrated in distribution power networks (DPNs) to locally provide the necessary active (P) and reactive (Q) power support. DG placement is considered as the most effective method for increasing the reliability and power quality of DPN. P and Q injection of DG near the load helps to meet electricity demand, reduce power losses, minimize voltage deviation and improve system stability. The influence of DG placement over DPN critically relies on site, size and type of DG. The best selection of DG position and size produces better performance in terms of improved bus voltage profile (VP), active power loss (APL) reduction and operating cost savings. Contrarily, inappropriate DG assimilation in DPN results in poor bus VP, greater line power loss and high operating costs (Oree et al., 2017). Also, the performance of DPN is improved only up to a certain penetration level of DG. The unconstrained penetration of DG causes higher voltage deviations and greater power losses along the lines. This problem constitutes a challenge amongst researchers in terms of determining the optimal size and site for DG, with which the desired objectives can be achieved, including active power loss (APL) and reactive power loss (RPL) minimization, VP improvement, voltage stability enhancement, power quality and reliability enhancement. Over the years, numerous methodologies have been proposed by researchers as solutions to the problem of optimal DG placement.

A simplified analytical method based DG optimization approach was implemented to curb the total APL in DPN (Sa'ed et al., 2019). A novel methodology was presented for optimizing the position and capacity of DG to curtail power loss (PL) and enhance VS (Essallah et al., 2019). An integrated methodology using analytical and heuristic approaches was proposed for optimizing DG units to cut down total APL (Kansal et al., 2016). An improved gravitational search algorithm (GSA) was proposed to figure out the ideal position and capacity of PV DG for minimizing overall operating cost (Abdul Kadir et al., 2019). Quasi-oppositional chaotic symbiotic organisms search (QOCSOS) based DG optimization was implemented so as to curtail total APL, enrich VP, and enhance the VS of a radial DPN (Truong et al., 2020). The DG optimization problem was solved using the electrostatic discharge algorithm (ESDA) for minimizing MOF, including PL reduction and VS improvement (Khasanov et al., 2019). The grey wolf optimization (GWO) technique was applied to solve the optimal DG problem in a standard IEEE 33 bus radial DPN to reduce total APL and enhance voltage stability (Kamel et al., 2019). The ant lion optimization (ALO) technique has been adopted to optimize multiple DG units for multiple objectives of RPL reduction, VP improvement and voltage stability enhancement (Palanisamy et al., 2021). The proposed work was implemented over standard IEEE 84 bus and 119 bus radial DPN. A hybrid DG optimization approach using power loss index and salp swarm algorithm (SSA) was proposed to accommodate PV and WT DGs into radial DPN with the purpose of VP improvement and APL minimization (Abdel-Mawgoud et al., 2022). An integrated optimization technique was introduced using fuzzy logic controller with PSO and ALO (Samala et al., 2020). The proposed technique effectively reduced the operating cost and enhanced the voltage stability. The hybrid optimization technique using the loss sensitivity factor (LSF), simulated annealing (SA) and PSO algorithms was proposed to locate the suitable site and size for DG in radial DPN in order to reduce total APL and improve VP (Ali et al., 2020a). The proposed hybrid optimization technique recorded better results than SA and PSO in a shorter time. The water cycle algorithm (WCA) was adopted for PV and WT DG optimal allocation into standard radial DPNs to achieve better VP, APL reduction, VS enhancement and operating cost minimization (Abou El-Ela et al., 2018). A multi-objective DG optimization problem using improved differential search algorithm (IDSA) was presented to optimally position PV and WT

DGs with suitable size in radial DPNs (Injeti, 2018). Radial DPN performance was improved through the optimal integration of DGs via multi-objective modified symbiotic organisms search (MOSOS) algorithm (Saha et al., 2021).

The different methodologies highlighted in the above literature reported favorable results in DPN by optimizing DG at appropriate site and size. However, according to the no free lunch (NFL) theorem, all optimization algorithms may not have the ability to produce the expected outcomes for different optimization problems (Ho et al., 2002). This opens up an opportunity for researchers to propose a new or modified optimization technique to achieve a potentially better or improved solution to this optimization problem. In this paper, the DG is optimized into radial DPN with the aid of the recent bio-inspired hunter-prey optimization (HPO) algorithm. Also, the performance of the HPO algorithm has been tested for different benchmark functions and produced a better optimal solution at rapid convergence (Dash et al., 2021).

The contribution of the proposed research work is summarized below.

- An optimization technique is applied using the HPO algorithm to optimize a PV and WT DG unit in DPN.
- The proposed HPO based technique is implemented to locate the optimal site and size of DG in DPN with the aim of finding the optimal solution for multi-objective fitness function, including APL reduction, VP enhancement and VSI enrichment.
- The robustness of the proposed technique is investigated for IEEE 69-bus radial DPN and the optimized research findings are compared with other techniques.

The remaining parts of the manuscript are presented under different sections. Section 2 deals with objective framework. Section 3 describes the concept of the HPO algorithm. Section 4 presents the simulation test results of the HPO optimized DG unit for a standard IEEE 69 bus radial DPN. Finally, conclusions are drawn from the HPO-based DG optimization in Section 5.

2. Objective Function Framework

The appropriate location and size for a PV and WT DG is optimized to minimize total APL, improve VP, and enhance the voltage stability (VS) of radial DPN. The total APL minimization (f_1) is achieved by minimizing the power loss index (PLI), VP improvement is attained by minimizing the voltage deviation index (VDI), and VS enhancement is attained by minimizing the reciprocal value of voltage stability index (VSI).

2.1. Objective Function Definition

A multi-objective function (MoF) DG optimization problem is framed to minimize the total APL and VDI and maximize the VS of radial DPN. The mathematical expression for MoF is given below:

$$\mathrm{MOF} = \min(\delta_1 f_1 + \delta_2 f_2 + \delta_3 f_3) \tag{1}$$

where, f_1, f_2 and f_3 are the objective functions of total APL reduction, VD minimization and VS improvement, respectively. Also, δ_1, δ_2, and δ_3 are the weighting factors of respective objective functions f_1, f_2 and f_3. The value for these factors must be picked as per the significance of individual objective functions. Also, their cumulative sum should always equal 1.

The total APL of the test system is computed as follows:

$$APL_T = \sum_{k=1}^{L} R_k * I_k^2 \tag{2}$$

where, R_k is p.u. line resistance and I_k is line or branch current.

APL_T reduction (f_1) is achieved by reducing the ratio given below:

$$f_1 = \left(\frac{P_{DG,Tloss}}{P_{Tloss}} \right) \tag{3}$$

where, $P_{DG,Tloss}$ refers to the total APL after DG inclusion and P_{Tloss} points to the total APL before DG inclusion.

VD minimization (f_2) is achieved by minimizing VDI (Abu-Mouti et al., 2011, Kowsalya, 2014):

$$f_2 = VDI = (V_1 - V_i) \tag{4}$$

where, V_1 is the voltage of a substation.

The VS of RDS can be assessed by evaluating the voltage stability index (VSI). The mathematical expression for VSI is given below (Gandomkar et al., 2005):

$$VSI = \left\{ |V_i|^4 \right\} - 4\left\{ P_{i+1} X_k - Q_{i+1} R_k \right\}^2 - 4\left\{ P_{i+1} R_k + Q_{i+1} X_k \right\} |V_i|^2 \tag{5}$$

where, V_i is the voltage magnitude of a bus, (R_k , X_k) are the distribution line resistance and reactance, respectively. (P_{i+1}, Q_{i+1}) refers to real power demand and reactive power demand, respectively.

Since, MoF is a minimization function, VS enhancement is obtained by minimizing its reciprocal value.

Therefore, $$f_3 = \frac{1}{VSI} \tag{6}$$

2.2. Constraints

The optimized solution for a MoF DG problem is attained by meeting several constraints of radial DPN. The constraints taken into account are briefed below:

2.2.1. DG Real Power Balance Constraint

$$P_{DG} \leq P_i + P_{loss} \tag{7}$$

Where, P_i is the total AP of connected load and P_{loss} is the total APL along DPN.

2.2.2. DG Size Limit (P_{DG})

$$P_{DG,min} \leq P_{DG} \leq P_{DG,max} \tag{8}$$

Where,

$$P_{DG,min} = 0.1 \times P_i \tag{9}$$

$$P_{DG,max} = 0.6 \times P_i \tag{10}$$

Here, ($P_{DG,min}$ and $P_{DG,max}$) are the permissible least and maximum size for DG.

2.2.3. Bus Voltage Constraint (V_i)

$$V_{min} \leq V_i \leq V_{max} \tag{11}$$

Where, V_{min} = 0.95p.u & V_{max} = 1.05p.u are the desired minimum and maximum voltages of DPN, respectively.

2.3. DG Modelling

2.3.1. PV DG Model

PV DG injects active power into the radial DPN. The output power of PV DG (P_{pv}) is expressed in the following equation (Kayal et al., 2013):

$$P_{pv} = \begin{cases} P_{pvr} \times \left(\frac{G}{G_r}\right), 0 \leq G \leq G_r \\ P_{pvr}, G_r \leq G \end{cases} \tag{12}$$

where, P_{pvr} is the rated PV output power, (G, G_r) represent the solar insolation at optimal site and rated solar insolation of earth's surface in W/m^2. P_{pv} relies on environmental parameters such as solar radiation and temperature since they are exposed to the atmosphere.

2.3.2. WT DG Model

The output power (P_w) of WT is expressed as follows (Kayal et al., 2013):

$$P_w = \begin{cases} 0, & 0 \leq V \leq V_{cin} or v \geq v_{cout} \\ P_{wr} \times \left(\frac{V - V_{cin}}{V_r - V_{cin}}\right), & V_{cin} \leq V \leq V_r \\ P_{wr}, & V_r \leq V \leq V_{cout} \end{cases} \tag{13}$$

where, P_{wr} is the rated power delivered by WT for a rated speed. (v_r, v) are the rated and actual speeds of a wind stream at optimal site. Likewise, (v_{cin} and v_{cout}) are cut-in and cut-out speeds of a wind stream.

3. Hunter-Prey Optimization Algorithm

HPO is a bio-inspired and population based optimization algorithm proposed in 2022 (Naruei et al., 2022). HPO mimics the hunting action of an animal. The population position is randomly set in the search space as follows:

$$X_i = \text{rand}\ (1,d) \times (u-l) + l \tag{14}$$

where, $i = 1, 2\ldots.n_{pop}$ and $d = 1, 2\ldots.M$.

Here, x_i refers to the hunter position, n_{pop} to the population size, M to the search space size, l and u to the lower and upper limit of the search space.

The position of the hunter's location is updated as follows:

$$X_{i,j}^{(t+1)} = X_{i,j}^{(t)} + \frac{1}{2}\left\{\left(2 * C * Z * P_{pos(j)} - X_{i,j}^{(t)}\right) + \left(2(1-C) * Z * \mu_j - X_{i,j}^{(t)}\right)\right\} \tag{15}$$

where, $x^{(t)}$ and $x^{(t+1)}$ represent the present and future positions of the hunter, respectively. $P_{pos(j)}$ points to prey position. μ_j indicates the average locations and is obtained by $\mu_j = \frac{1}{n}\sum_{j=1}^{n_{pop}} x_j$. The adaptive parameter (Z) is computed using Eq. (16) and Eq. (17).

$$P = r_1 < C; IDX = (P == 0) \tag{16}$$

$$Z = r_2 \otimes IDX + r_3 \otimes (\approx IDX) \tag{17}$$

where, r_1 and r_2 are the vectors of random values which lie between [0, 1]; similarly, r_2 is a random number which lies between [0, 1]. IDX corresponds to an index number of r_1 that satisfies the condition (P==0); C is a factor that helps to balance exploitation and exploration. Typically, a value of C gets reduced from 1 to 0.02 in the course of the iterative process and it is illustrated as follows:

$$C = 1 - it * \left(\frac{0.98}{it_{max}}\right) \tag{18}$$

where, it_{max} and it points to maximum iteration and present iteration numbers, respectively.

The prey (P_{pos}) is chosen by referring to a search agent that is located far from μ.

$$P_{pos} = X_i \mid i \text{ is index of Max(end) sort (Deuc)} \tag{19}$$

The Euclidean distance is computed from an average location of the search space, using Eq. (20).

$$D_{euc(j)} = \left(\sum_{j=1}^{d}(x_{i,j} - \mu_j)^2\right)^{\frac{1}{2}} \tag{20}$$

The convergence of HPO is poor when the distance between the search agent and μ, between consecutive iterations, is large. Therefore, once the prey is caught in a hunting scene, the hunter should look forward to the next prey. This scenario is simulated as follows:

$$\mathrm{kbest} = \mathrm{round}(C \times n_{pop}) \tag{21}$$

$$P_{pos} = x_i \mid i \text{ is sorted } D_{euc}(\mathrm{kbest}) \tag{22}$$

where, n points to the number of search agents.

At the beginning of the algorithm, kbest is set equal to n_{pop}. The hunter picks the farthest search agent (prey) and captures it while steadily decreasing kbest value. At the end of the HPO algorithm, the kbest value points to the first search agent (the least distance from μ). Therefore, Eq. (15) is replaced by Eq. (23) in order to locate the prey as follows:

$$X_{i,j}^{(t+1)} = T_{pos(j)} + C * Z * \cos(2\pi\pi_4) \times \left(T_{pos(j)}^{(t)} - X_{i,j}^{(t)}\right) \tag{23}$$

where, $x^{(t+1)}$ is located by a function of *cos* and its input variables for different radii and angles from optimal position (global). $T_{pos(j)}$ and r_4 are random variables between [0,1]. The position of the hunter or the prey can be updated using the following equation:

$$x_{i,j}^{(t+1)} = \begin{cases} x_{i,j}^{(t)} + \frac{1}{2}\left\{\left(2 * C * Z * P_{pos(j)} - x_{i,j}^{(t)}\right) + \left(2(1-C) * Z * \mu_j - x_{i,j}^{(t)}\right)\right\} & if \quad r_5 < \beta \qquad 24(a) \\ T_{pos(j)} + C * Z * \cos(2\pi r_4) \times \left(T_{pos(j)}^{(t)} - X_{i,j}^{(t)}\right) & else, \qquad 24(b) \end{cases}$$

If r_5<β then the search agent is treated as hunter (Eq. 24a) and if $r_5 \geq \beta$ then the search agent is treated as prey (Eq. 24b). Here r5 refers to a random number between 0 and 1; β is an adjusting factor equal to 0.1. The flowchart for the HPO algorithm is shown in Figure 1.

4. Results and Discussion

The effectiveness of the proposed HPO-based optimization technique was tested for single PV and WT DG placement in a standard IEEE 69-bus radial DPN. The simulation was executed considering the number of iterations (max.) and population size (n_{pop}) as 50 and 30, respectively. Except slack bus (bus no.1), all the remaining buses were considered as candidate locations for DG accommodation. The necessary codes for the simulation were written and executed in MATLAB software version 2021b on an Intel i3, 4.10 GHz processor personal computer.

The weightage factors (δ_1, δ_2 and δ_3) for f_1, f_2 and f_3 were appropriately selected as per the significance. In the present work, more significance was given to APL_T reduction (f_1), hence, the weightage factor (δ_1) corresponding to f_1 was more than that of f_2 and f_3. The suitable weightage factors for Eq. (1) were found by executing the HPO algorithm for PV DG unit placement. The factors that result in the lowest fitness function value were picked as suitable weightage factors. Table 1 lists the obtained fitness function value for various choices of weightage factors.

From Table 1, the following combinations, δ_1=0.5, δ_2=0.1 and δ_3=0.4 were chosen as suitable weightage factors since they provided the least value for MoF (Eq.1).

Table 1. Selection of weightage factors for MoF

δ_1	δ_2	δ_3	**Fitness value**
0.5	0.1	0.4	0.6140
0.5	0.2	0.3	0.7241
0.5	0.3	0.2	0.7496
0.5	0.4	0.1	0.7651
0.5	0.25	0.25	0.7169
0.6	0.1	0.3	0.710
0.6	0.2	0.2	0.7253
0.6	0.3	0.1	0.7308
0.6	0.25	0.15	0.7280
0.6	0.15	0.25	0.7125
0.7	0.1	0.2	0.7509
0.7	0.2	0.1	0.7864
0.7	0.15	0.15	0.7637
0.8	0.1	0.1	0.8021

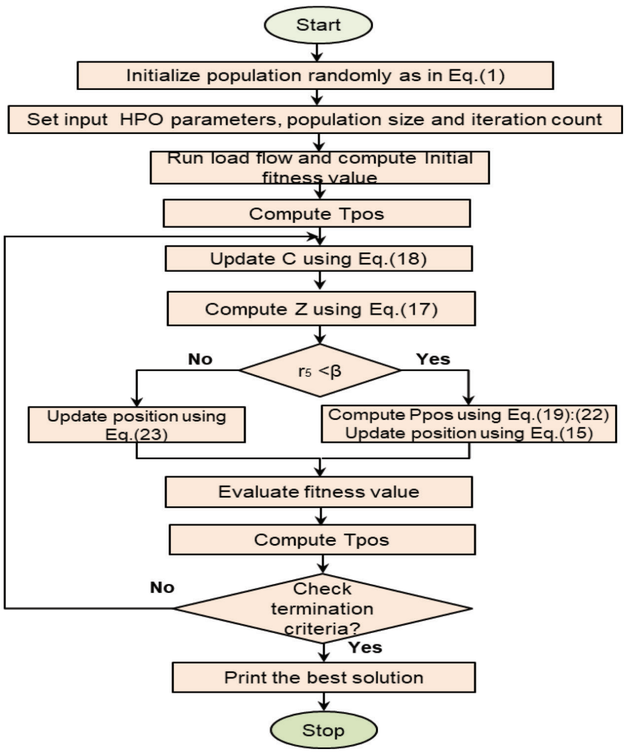

Figure 1. HPO flowchart

4.1. Backward Forward Sweep (BFS) Algorithm

Load flow (LF) study is a key tool for assessing the stability, reliability, and economy of a power system network. Also, LF analysis is a fundamental tool for the design and operation of electric power systems. However, the LF techniques of transmission networks, including Gauss–Seidel (GS) and Newton Raphson (NR), are not recommended for radial DPN because of i) a greater no. load buses and branches of DPN and ii) a greater R/X ratio. Hence, for adequate and accurate LF assessment in radial DPN, a backward-forward sweep (BFS) algorithm-based approach has been employed (Ali et al., 2020b). The BFS algorithm was executed in two phases as explained in the subsections that follow.

4.1.1. Forward Sweep

This is the first phase of the BFS algorithm where the voltage profile of the bus is calculated. The calculation originates from the first node and moves forward towards the far end node. Initially, the primary node voltage is assumed to be 1p.u.

4.1.2. Backward Sweep

This is the second phase of the BFS algorithm where the currents, through all the branches, are computed. The calculation begins from the far end branch and proceeds towards the head node. The algorithm, for the BFS LF study and analysis, is illustrated as a flowchart in Figure 2.

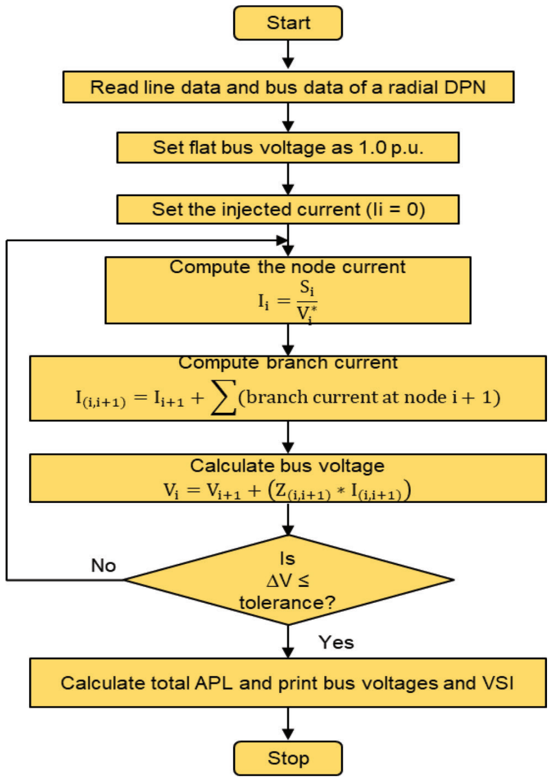

Figure 2. BFS algorithm for LF study

4.2. IEEE 69 Bus Radial DPN

The 69-bus radial DPN considered in this study is provided in Figure 3. The LF assessment of a standard IEEE 69 bus radial DPN without accommodating a DG unit resulted in a total APL of 225 kW for delivering a total active power demand of 3.8 MW and reactive power demand of 2.69 MVAr. Also, the test system experienced the lowest VP of 0.9092p.u and a minimum VSI of 0.6833 prior to DG placement. For the purpose of comparison, the LF result without DG unit is referred to as the base case.

The optimized test results for PV and WT DG placement for the considered multi-objective function is presented in Table 2.

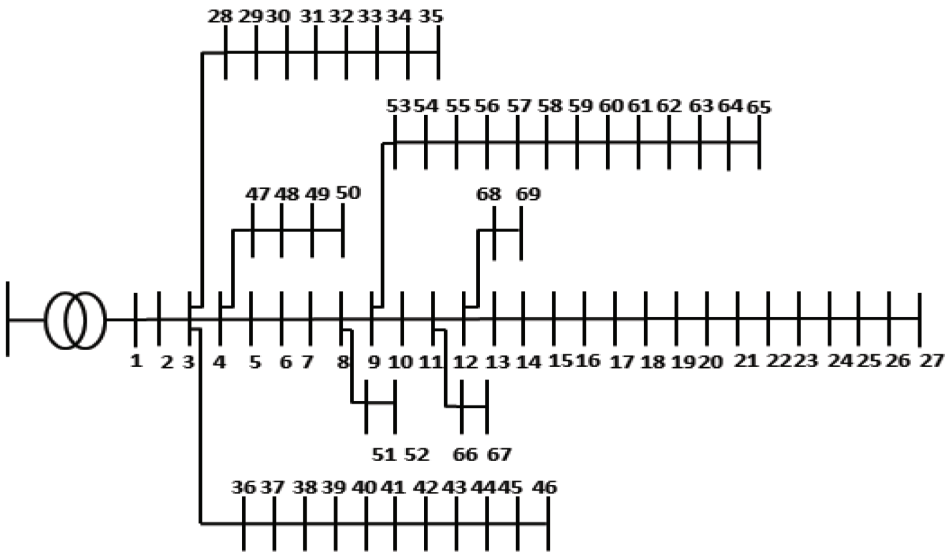

Figure 3. Standard IEEE 69 bus radial DPN

Table 2. Optimized simulation outcomes of IEEE 69-bus radial DPN

Parameter	PV DG unit	WT DG unit
Optimal bus site (no.)	61	61
Optimal size (in kW/kVA)	1856.78	1943.34
APL_T before DG placement (in kW)	225	
APL_T after DG placement (in kW)	74.01	21.58
V_{min} before DG placement (in p.u.)	0.9092	
V_{min} after DG placement (in p.u.)	0.9724	0.9788
VSI (min) before DG placement	0.6833	
VSI (min) after DG placement	0.8949	0.9187

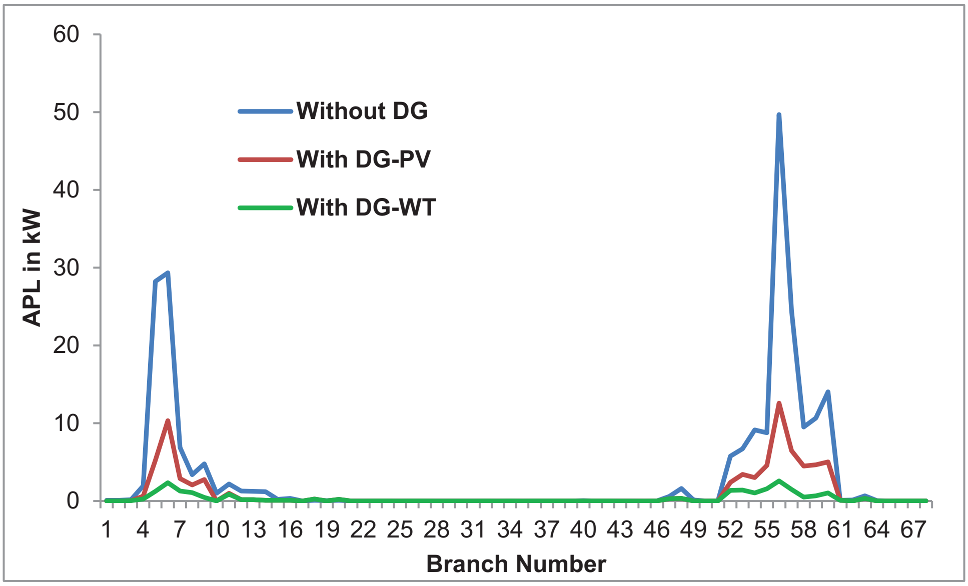

Figure 4. APL of IEEE 69-bus radial test system

4.2.1. Objective 1: APL_T Minimization

The HPO algorithm optimized the PV DG and WT DG with a capacity of 1856.78 kW and 1943.34 kVA at bus number 61. The optimized inclusion of PV DG minimized the APL_T to 74.01 kW. Likewise, the inclusion of WT DG reduced the APL_T to 21.58 kW. The addition of PV DG resulted in 67.10 % of APL_T from the base case value. On the other side, 90.04 % power loss minimization was achieved with WT DG integration. Figure 4 shows the APL of the IEEE 69-bus test system without and with a DG unit.

4.2.2. Objective 2: VP Improvement

The optimized accommodation of PV DG improved the minimum VP of the test system from 0.9092p.u to 0.9724p.u. Similarly, the integration of WT DG enhanced the V_{min} from 0.9092p.u to 0.9788p.u. The inclusion of DG has seen a considerable improvement in VP. PV DG accommodation increased the minimum VP by 0.0632p.u and WT DG improved it by 0.0696p.u from the base case. Figure 5 presents the VP of a 69-bus radial DPN before and after DG inclusion.

4.2.3. Objective 3: VSI Enhancement

The test system recorded a minimum VSI of 0.6833 before DG inclusion. However, after the addition of the PV DG unit, VSI_{min} was enhanced to 0.8949. Likewise, the addition of WT DG enhanced the VSI_{min} to 0.9187. With the addition of optimized PV and WT DG, the test system saw an improvement of 0.2116 and 0.2354 in VSI_{min} from the base case value. Figure 6 exhibits the VSI of 69-bus radial DPN after and before DG placement.

The HOP algorithm converges to a global optimal solution with MoF values 0.614 and 0.4853 for PV and WT DG placement, respectively, taking 15 and 18 iterations. The convergence curve for HPO is shown in Figure 7.

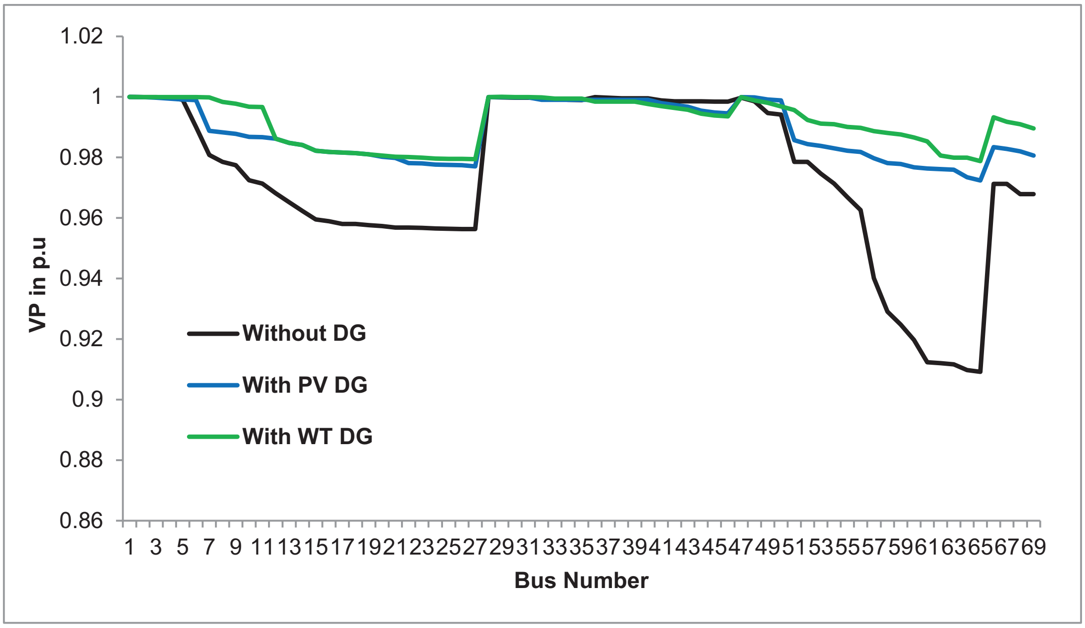

Figure 5. VP of a 69 bus radial DPN before and after DG inclusion

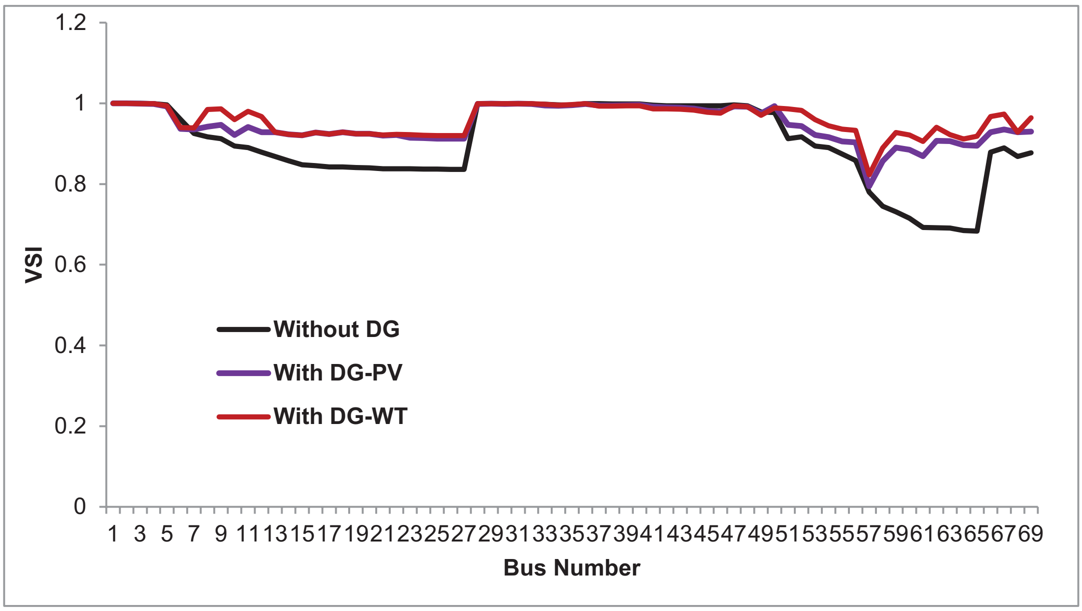

Figure 6. VSI of a 69bus radial DPN before and after DG inclusion

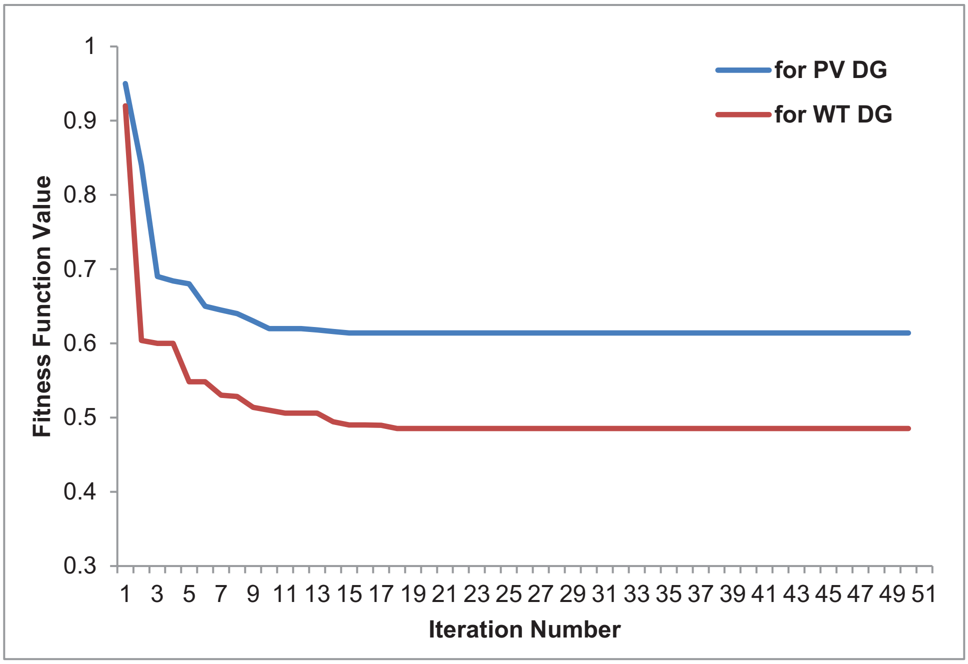

Figure 7. HPO convergence characteristics curve

Table 3. Test results comparison with PV DG placement

Parameters	Optimization Techniques					
	Classical DE (Kumar et al., 2019)	**LSA (Suresh et al., 2020)**	**GOA-CS (Subbaramaiah et al., 2023)**	**WOA (Subbaramaiah et al., 2023)**	**SSA (Suresh et al., 2020)]**	**HPO (Proposed)**
DG optimal position (no.)	61	61	6	61	31	61
DG capacity (in kW)	1872.71	1765.75	1990.71	1872.8	1870.19	1856.78
APL_T after DG placement (in kW)	83.22	183.40	147.66	83.2	163.57	74.01
% Power loss reduction	63.01	18.77	34.37	63.02	27.30	67.10
V_{min} after DG placement (in p.u.)	0.9683	0.9204	0.9236	0.9683	0.9223	0.9724

The efficacy of the proposed optimization methodology using the HPO algorithm has been examined by comparing its outcome with the outcomes of other optimization methodologies cited in the literature. Table 3 and Table 4 present the comparative test report for various optimization methodologies.

From the literature, classical DE, LSA, GOA-CS, WOA and SSA optimization techniques reported 63.01 %, 18.77 %, 34.37 %, 63.02 %, and 27.30 % of APL_T reduction for PV DG placement. However, the proposed technique resulted in a 67.10 % APL_T reduction with PV DG integration. Likewise, DE, LSA, GOA-CS, WOA and SSA optimization techniques reported a minimum VP (V_{min}) of 0.9683p.u, 0.9204p.u, 0.9236p.u, 0.9683p.u and 0.9223p.u, respectively, after PV DG accommodation in DPN. Whereas HPO-optimized PV DG achieved a V_{min} of 0.9724p.u. Likewise, for WT DG placement, GWO, ROA and ALOA optimization methodologies reported 73.86 %, 89.7 % and 89.7 % APL_T reduction, respectively. However, the proposed HPO methodology produced a 90.4 % APL_T reduction. From the comparative report presented in Table 3 and Table 4, the proposed HPO optimization technique achieved better APL reduction and a greater min. VP enhancement than other optimization techniques. Additionally, Figure 8 and Figure 9 graphically illustrate the comparative outcome of different methodologies for PV and WT DG, respectively.

Table 4. Test results comparison with WT DG placement

Parameters	Optimization Techniques			
	GWO (Nowdeh et al., 2019)	ROA (Khasanov et al., 2021)	ALOA (Dinakara Prasasd Reddy et al., 2018)	HPO (Proposed)
DG optimal position (no.)	61	61	61	61
DG capacity (in kW)	1000	1828.47	2227.9	1943.34
APL_T after DG placement (in kW)	58.8	23.168	23.16	21.58
Power loss reduction (%)	73.86	89.7	89.7	90.4

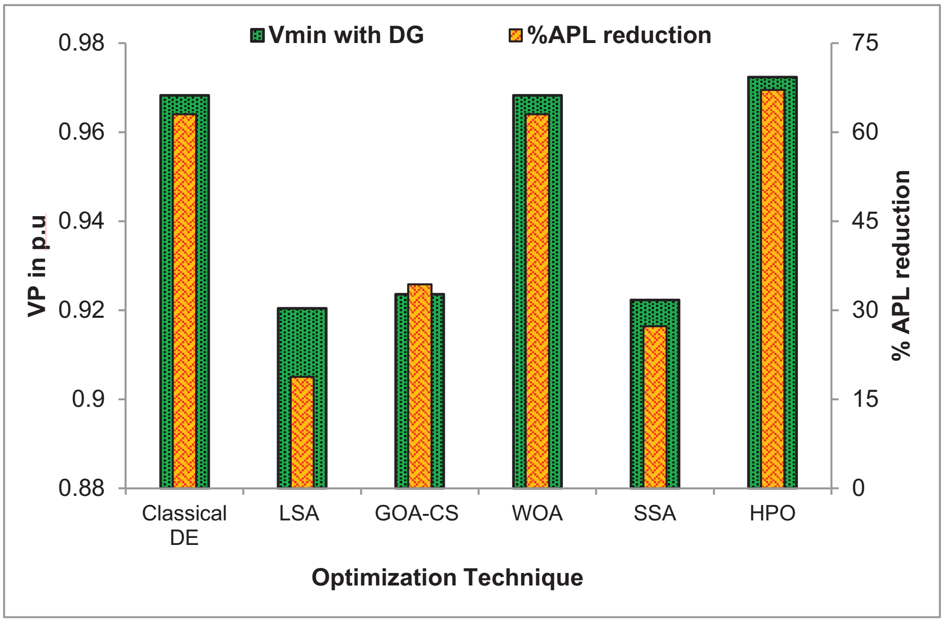

Figure 8. Comparative analysis of different optimization techniques for PV DG placement

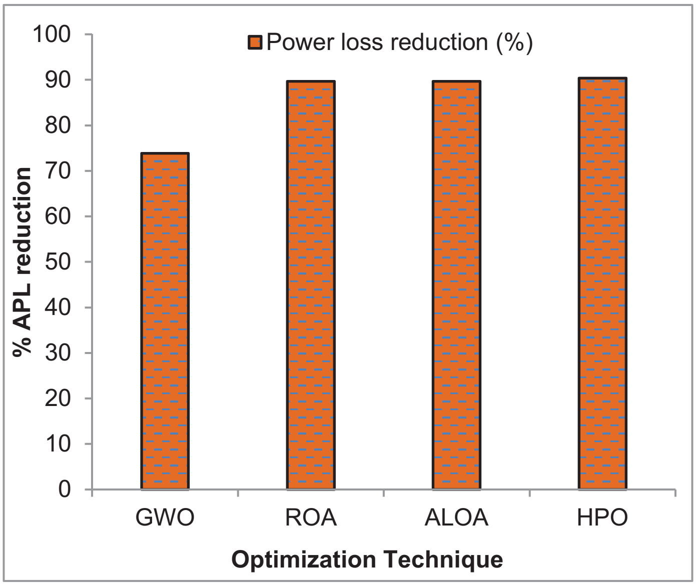

Figure 9. Comparative analysis of different optimization techniques for WT DG placement

5. Conclusion

In this article, an optimization technique using a recently developed bio-nature-inspired meta-heuristic optimization algorithm known as hunter-prey optimization (HPO) was proposed as a means of optimally integrating single PV and WT DG into a standard IEEE 69 bus radial DPN. DG was optimized to minimize a multi-objective framework including total APL reduction, VP improvement and voltage stability enhancement. The simulation study was executed for the optimal placement of PV and WT DG. The optimized PV and WT integration produced an APL_T reduction of 67.10 % and 90.4 %, respectively, from the base case value. Likewise, the optimized PV and WT DG positioning improved the minimum voltage of the test system by 0.0632p.u and 0.0696p.u, respectively, from the base case. Similarly, the minimum VSI was enhanced by a fraction of 0.2116 and 0.2354, from the base value for PV and WT placement, respectively. Besides this, the efficacy of HPO-optimized test results was examined comparatively with the optimization techniques cited in the literature. The comparison was made in terms of APL minimization and VP improvement. The comparative study showcased the domination of the HPO algorithm over other algorithms. Hence, the HPO algorithm can be recommended for DG placement in radial DPN.

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