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Multi-objective hunter prey optimizer technique for distributed generation placement

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ABSTRACT

Accommodation of distributed generation (DG) units in the distribution power network (DPN) reduces the power losses (PL), improves the voltage profile (VP), and enhances the stability. The size and site for distribution generations have to be optimized to avail favorable results. Otherwise, the DPN may experience greater power losses, higher voltage deviation, and voltage instability issues. This article implements an optimization technique using a hunter-prey optimizer (HPO) algorithm to optimize single and multiple (two) DG units in the radial DPN to minimize total real power losses (RPL) and total voltage deviation (TVD). The effectiveness of the HPO algorithm is assessed on the IEEE benchmark 69-bus radial DPN and a real-world Cairo-59 bus RDS. The simulation outcome after the optimized inclusion of DGs shown significant RPL reduction and considerable voltage enhancement. Furthermore, the optimized results of HPO algorithm were compared to the different algorithms and the comparison proved that the HPO can provide a more promising and authentic outcome than other algorithms.

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1. INTRODUCTION

Distribution power networks (DPNs) have endured higher power demand in recent times due to rapid advancements in technology and globalization. The increased power demand can create several problems, including power quality, reliability, power losses, and environmental degradation [1]. Distributed generation (DG) integration is one of the promising methods for nullifying the issues in DPN [2]. A typical DG employs small-scale power-generating units (especially renewable energy DGs) to produce electricity locally into the DPN. DG allocations improve power quality, reduce power losses (PL), enhance reliability, and reduce environmental pollution [3]. However, DG allocation is a difficult and non-linear problem. Hence, an efficient methodology is essential to optimize the DG in DPN for securing maximum benefits. Many meta-heuristics (MH) and bio-inspired (BI) algorithms were introduced to find the optimal solution for this complex and dynamic DG allocation problem.

Differential evolution (DE) [4], genetic algorithm (GA) [5], and cuckoo search algorithms (CSA) [6] were applied to optimize DG for PL reduction and voltage deviation (VD) minimization. Different types of DGs were optimized using whale optimization algorithm (WOA) [7], manta ray foraging optimization (MRFO) algorithm [8], BAT algorithm [9], salp swarm algorithm (SSA) [10], sine cosine algorithm (SCA) [11], adaptive particle swarm optimization (APSO) [12], modified gravitational search algorithm (MGSA) [12], grey wolf algorithm (GWA) [13], ALO algorithm [14], Harris hawk optimization (HHO) [15] and turbulent water flow optimization (TWFO) [16] to enhance the performance of DPN. The authors [17] utilized a teaching-learning algorithm to optimize offshore WT in the 33-bus system. Multi-objective PSO was used to optimize inverter-based DG allocation in *Unit Layanan Pelaksana* (ULP) Way Halim 88-bus DPN [18]. An integrated optimization approach using a teaching-learning algorithm and PSO algorithm was proposed and simultaneously optimized the DGs and STATCOMs [19]. A multi-objective firefly analytical hierarchy algorithm was applied to optimally allocate type-1 DG units for PL reduction, VP enhancement, and stability improvement [20]. A multi-objective energy management problem was solved using the golden jackal optimization (GJO) algorithm in a microgrid system powered by hybrid energy sources [21].

Several algorithms are often trapped in local optima solutions and offer poor convergence (LOS) due to the complexity of the DG allocation problem. For instance, GA and CSA offer slow convergence and hence require regular parameter tuning. BAT algorithm often produces unstable results because of its poor exploration capability. GWO and ALO algorithms grieve from inaccuracy and slow convergence. The shortcomings of these popular algorithms have led to an opportunity for the development of new BI and MH algorithms. Hunter prey optimizer (HPO) is a novel bio-inspired algorithm that characterizes the hunting behavior of an animal to solve a wide range of optimization problems [22]. The HPO algorithm has a diverse exploration capability to cover the entire search space of the optimization problem and can evade local optima stagnation issues. Also, it can proportionately tune its parameters according to the problem definition. Importantly, the dynamic hunting behavior between the hunter and prey offers faster convergence [23]. Hence, this study implements an optimization technique using the HPO algorithm to optimize the site and size of PV and WT in the radial DPN. The proposed study is presented in different sections as follows. Section 2 presents the mathematical framework of the multi-objective DG placement problem. Section 3 describes the proposed HPO-DG optimization technique. Section 4 discusses the simulation findings for optimized single and two DG placements. Section 5 summarizes the significant contribution of the research study as a conclusion.

2. OBJECTIVE FUNCTION FRAMEWORK

This section presents the objectives of the DG allocation problem, power flow constraints and DG modelling. The HPO algorithm is implemented to optimize the bus location(s) and size(s) of PV and WT DG unit(s) to minimize total RPL and improve VP of DPN. The primary objective (f_1) is the minimization of total real power loss (P_{Tloss}). (1) expresses the objective function for f_1.

$$f_1 = \min(P_{\text{Tloss}}) \tag{1}$$

P_{Tloss} in a DPN is computed through power flow execution using a backward/forward sweep (BFS) algorithm [24]. For a DPN with ‘n’ number of nodes, the real power loss ‘$P_{loss,k}$’ along a branch ‘k’ is given in (2). Where, R_k denotes to p.u. resistance.

$$P_{\text{loss,k}} = I_k^2 R_k \tag{2}$$

P_{Tloss} of a RDS with ‘nb’ number of branches can be expressed as in (3).

$$P_{\text{Tloss}} = \sum_{k=1}^{nb} P_{\text{loss,k}} \tag{3}$$

The voltage profile (VP) improvement is the secondary objective (f_2) and can be achieved by minimizing the total voltage deviation (TVD) of RDS. The (4) expresses the objective function of TVD minimization.

$$f_2 = \min\left(\sum_{i=1}^{N} \left|1 - |V_i|\right|\right) \tag{4}$$

Where, ‘*N*’ refers a total no. of buses in RDS.

2.1. DG optimization: Weighted sum method

The optimal solution for the multi-objective (f_1 and f_2) DG allocation problem is obtained using the weighted sum method (WSM). (5) presents the objective function (MOF) for a DG optimization problem using weightage factors.

$$f_{\text{obj}} = \omega_1 f_1 + \omega_2 f_2 \tag{5}$$

Where ω_1 and ω_2 referred to weightage factors. And, $\omega_1+\omega_2=1$. The values of f_1 and f_2 should be normalized according to their corresponding base values during the optimization process.

2.2. Constraints

The optimal solution for the multi-objective DG placement problem must satisfy several operational limits or constraints of RDS. The list of equality and inequality operational constraints considered in the present study is presented below.

2.2.1. Power balance constraints

This is an equality constraint that relates to the incoming and outgoing power flow of RDS. The optimized solution must ensure that the total incoming power flow is equal to the total outgoing power. The mathematical expressions for power balance constraints [25] are presented in (6) and (7).

$$P_S + P_{\text{DG}} = \sum_{i=1}^{N} P_L(i) + \sum_{j=1}^{\text{nb}} P_{\text{loss}}(j) \tag{6}$$

$$Q_S + Q_{\text{DG}} = \sum_{i=1}^{N} Q_L(i) + \sum_{j=1}^{\text{nb}} Q_{\text{loss}}(j) \tag{7}$$

Where, 'P_{DG}' and 'Q_{DG}' correspond to optimal active and reactive power rating of DG unit(s), respectively; 'P_L' and 'Q_L' point to active and reactive power demand respectively.

2.2.2. Bus voltage constraint

The optimal outcome for DG placement should not violate the voltage constraint expressed in (8). For ensuring a secure and reliable operation of RDS, bus voltage (V_i) variation must be kept within ±5% of the substation voltage (slack bus).

$$V_{\text{min}} \leq V_i \leq V_{\text{max}} \tag{8}$$

Where, 'V_{max}' and 'V_{min}' are the maximum and minimum bus voltages, respectively.

2.2.3. DG capacity limit

The optimized capacity of DG units (single or multiple) must be less than the total power demand of RDS to avoid security issues [25].

$$P_{\text{DG}} \leq P_D \tag{9}$$

$$Q_{\text{DG}} \leq Q_D \tag{10}$$

2.3 DG modelling

In this study, solar PV and WT are represented as P type and P-Q type models, respectively. (11) mathematically describes the characteristics of a solar PV [25]. Here, Q_{DG} is assumed zero.

$$P_{\text{DG}} = \begin{Bmatrix} P_r \times \left(\frac{G}{G_r}\right), & 0 \leq G \leq G_r \\ P_{\text{r},} & G_r \leq G \end{Bmatrix} \tag{11}$$

The output characteristic equation for WT is presented in (12) and (13) [23], [22].

$$P_{\text{DG}} = \begin{Bmatrix} 0, & 0 \leq v \leq v_{\text{cin}} \\ P_r \times \left(\frac{v-v_{\text{cin}}}{v_r-v_{\text{cin}}}\right), & v_{\text{cin}} \leq v \leq v_r \\ P_r, & v_r \leq v \leq v_{\text{cout}} \end{Bmatrix} \tag{12}$$

$$Q_{\text{DG}} = P \times \tan(\cos^{-1}(\text{p.f.}_{\text{DG}})) \tag{13}$$

Where 'P_r' is the rated output power of a solar PV, 'G' is a solar irradiance at the optimal site(s), 'Gr' is the rated solar irradiance at earth's surface, 'P_r' is the rated output power of WT, 'V_r', and 'V' is the rated and actual wind velocity (WV) in meter/sec at the optimal sites. 'V_{cin}' and 'V_{cout}' are the cut-in and cut-out WV in meter/sec.

3. HPO ALGORITHM: SOLUTION TECHNIQUE FOR DG ALLOCATION

This section outlines the mathematical modeling of the HPO algorithm and its application in optimal DG allocation. HPO is a novel bio-inspired algorithm and is modeled to characterize the hunting behavior of an animal.

3.1. Mathematical modelling

HPO is a bio-inspired and population-based optimization algorithm that characterizes the hunting behavior of an animal. The population position is randomly set in search space and is expressed in (14).

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

Where, i = 1, 2, … npop and d = 1, 2, … M. Here, x_i refers the hunter position, 'npop' point's the population size, M points the search space size, 'l' and 'u' denotes the lower and upper limit of search space.

The position of hunter is updated using (15).

$$x_{\text{i,j}}^{(t+1)} = x_{\text{i,j}}^{(t)} + {}^{1}\!/_{2}\left\{\left(2 * C * Z * P_{\text{pos}(j)} - x_{\text{i,j}}^{(t)}\right) + \left(2(1 - C) * Z * \mu_j - x_{\text{i,j}}^{(t)}\right)\right\} \tag{15}$$

Where, $x^{(t)}$ and $x^{(t+1)}$ represent the present and future position of the hunter, respectively. $P_{pos(j)}$ points the prey position. μ_j is the average of the locations and is expressed as (16).

$$\mu_j = {}^{1}\!/_{n} \sum_{j=1}^{\text{npop}} x_j \tag{16}$$

Adaptive parameter (Z) is computed using (17) and (18).

$$P = r_1 < \text{C;IDX} = (P == 0) \tag{17}$$

$$Z = r_2 \otimes IDX + r_3 \otimes (\approx \text{IDX}) \tag{18}$$

Where, r_1 and r_2 are the vectors represent a random value 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, the value of C is reduced from 1 to 0.02 during the course of the iterative process and it is expressed in (19).

$$C = 1 - \text{it} * \left(\frac{0.98}{\text{it}_{\text{max}}}\right) \tag{19}$$

Where 'it_{max}' and 'it' points to maximum iteration and present iteration number respectively. The prey (P_{pos}) is chosen referring to a search agent located far from μ.

$$P_{\text{pos}} = x_i | \text{i } is \text{ index of Max(end) sort (Deuc)} \tag{20}$$

The Euclidean distance is computed from an average location of search space using (21).

$$D_{\text{euc}(j)} = \left(\sum_{j=1}^{d}\left(x_{\text{i,j}} - \mu_j\right)^2\right)^{1/2} \tag{21}$$

The convergence of HPO is a concern 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 expressed in (22) and (23). Where, 'n' points to number of search agents.

$$kbest = round(C \times npop) \tag{22}$$

$$P_{pos} = x_i | i \text{ } is \text{ } sorted \text{ } D_{euc}(kbest) \tag{23}$$

At the beginning of the algorithm, 'kbest' is set equal to 'npop'. The 'kbest' value is progressively decreased after the hunter picks a farthest search agent (prey) and captures it. At the end of the algorithm, 'kbest' value points to the first search agent (least distance from μ). Therefore, (15) is replaced by (24) in order to locate the position of prey.

$$x_{i,j}^{(t+1)} = T_{pos(j)} + C * Z * \cos(r_4 2\pi) \times \left(T_{pos(j)}^{(t)} - x_{i,j}^{(t)}\right) \quad (24)$$

Where, $x^{(t+1)}$ is updated location of next prey, $T_{pos(j)}$ is the optimal position of prey (global) and r_4 is a random variable between [0,1]. The positions of hunter and prey after the update are expressed in (25) and (26):

$$x_{i,j}^{(t+1)} = x_{i,j}^{(t)} + {}^1\!/_2 \left\{\left(2 * C * Z * P_{pos(j)} - x_{i,j}^{(t)}\right) + \left(2(1-C) * Z * \mu_j - x_{i,j}^{(t)}\right)\right\} \quad \text{if} \quad r_5 < \beta \quad (25)$$

else

$$x_{i,j}^{(t+1)} = T_{pos(j)} + C * Z * \cos(r_4 2\pi) \times \left(T_{pos(j)}^{(t)} - x_{i,j}^{(t)}\right) \quad (26)$$

If $r_5<\beta$, then the search agent is treated as a hunter (25), else the search agent is a prey (26). Here r_5 refers to a random number between 0 and 1; β is a regulating factor equal to 0.1.

3.2. Implementation

The proposed HPO algorithm finds the best solution (DG location and size) for the DG allocation problem by executing the following steps.

- Step 1: Define the optimization problem parameters including the site, size, and type (PV and WT) of the DG. Also, initialize the HPO algorithm operational parameters such as population size and maximum iterations.
- Step 2: At first, perform a random walk to generate the initial solution of the DG placement problem.
- Step 3: Run power flow for the test system for the random solution and determine the fitness level of MOF expressed in (5). Assign the computed fitness level as 'kbest'.
- Step 4: Update the locations of the hunter (DG size) according to the present location and the optimal location (DG site) explored so far. The updated position denotes a possible best solution for the DG placement problem.
- Step 5: Update the adaptive (Z) and balance (C) parameters expressed in (18) and (19).
- Step 6: Compare r_5 with regulating parameter β. If $r_5 < \beta$, then compute the new position of the hunter (DG size) using (25). Otherwise, update the position of prey (DG site) using (26).
- Step 7: Run power flow for the updated hunter position and compute the fitness level for the MOF.
- Step 8: Replace 'kbest' if the fitness level computed in Step 7 is less than the previous best value.
- Step 9: Increase the iteration count and repeat the above steps until the stopping criteria is reached.
- Step 10: Print the optimal solution.

4. TEST RESULTS AND DISCUSSION

The simulation outcomes for the test systems under study are investigated for a single and multiple (two) DG placement. The necessary programming was coded in MATLAB software version-2022b and executed using an Intel i3, 4.10 GHz processor personal computer. Since, the objective function is proposed to solve using the weightage factors approach, approximation of ω_1 and ω_2 is vital for achieving a better solution. The combinations of weightage factors that give minimum fitness value for the objective function are considered as appropriate values [26]. In this study, weightage factors are approximated for a single PV-optimized allocation. The combination $\omega_1 = 0.6$ and $\omega_2 = 0.4$ are chosen as appropriate weightage factors since they provided the least fitness value for the optimized single PV allocation.

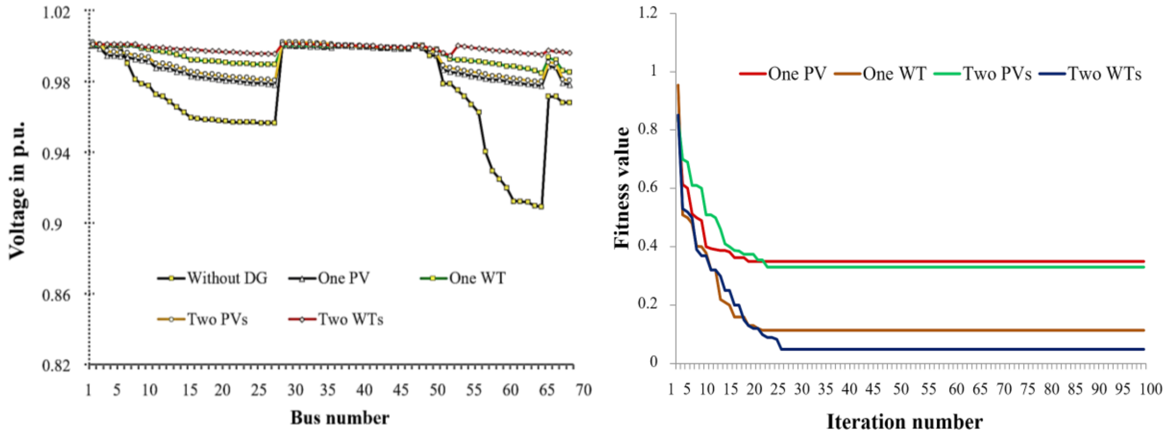
4.1. IEEE 69-bus RDS: Simulation results

The 69-bus DPN delivers 3.8 MW of real power and 2.69 MVAr of reactive power [27]. The simulation run results of the test system without and with DG insertion are presented in Table 1. Power flow (PF) results for the test system have been obtained via BFS algorithm. The test system with no DG placement accounted for 225 kW total real PL and 0.9092 p.u minimum voltage (V_{min}). Besides, a total of 9 buses have violated V_{min} constraint (< 0.95 p.u.). The optimized single PV and WT placement has reduced the total real PL to 71.12 kW and 13.67 kW and increased V_{min} to 0.9775 p.u and 0.9842 p.u, respectively. In the case of two PVs and WTs placements, the PL has been cut down to 70.45 kW and 7.68 kW, respectively. Simultaneously, V_{min} has been enhanced to 0.9798 p.u and 0.9951 p.u, respectively. Figure 1(a) illustrates the VP of the 69-bus test system after the allocation of DG units. It is obvious evident from the illustration that no buses in the test system record a voltage below 0.95 p.u after the DG allocations.

The optimized integration of DG systems had delivered a significant impact on PL reduction and VP improvement. But noticeably WT placement has provided superior results than the PV allocation since WT injects reactive power alongside real power support. Hence, higher PL reduction and better VP enhancement are achieved with WT placement. Moreover, the HPO algorithm reached the optimal solution in 10.23 and 11.8 seconds at 16th and 19th iterations for a single PV and WT placement, respectively. Whereas, for two PV and WT allocations, the HPO algorithm converged in 13.4 and 14.1 seconds and took 20 and 22 iterations, respectively. Figure 1(b) illustrates the convergence plot for the HPO algorithm for single and two DG placements. Furthermore, the HPO algorithm has not shown any sign of local optimal stagnation till the convergence.

Table 1. IEEE 69-bus RDS: Test results with and without DG accommodations

Outcome	No DG	With single DG		With two DGs	
		PV	WT	PVs	WTs
Optimal site	-	57	57	17 61	17 61
Optimal size (kW/kVA)/p.f.	-	1776.54/1	1878.9/0.8211	621.54/1 1492.65/1	623.16/0.8293 2005.76/0.8234
RPL_T (kW)	225	71.12	13.67	70.45	7.68
V_{min} (p.u.)	0.9092	0.9775	0.9842	0.9798	0.9951
Simulation run time (sec)	-	10.23	11.8	13.4	14.1
No.of iterations	-	16	19	20	22



(a) (b)

Figure 1. Simulation results: (a) VP of 69-bus radial DPN and (b) convergence curve of HPO algorithm for 69-bus DPN

4.2. Comparative study

A comparative assessment between the simulation findings of HPO and other algorithms is cited in the literature and is graphically illustrated in Figure 2. The comparison is demonstrated in terms of percentage PL reduction and V_{min}. For a single PV optimized allocation, the HPO algorithm reduced PL of the test system by 68.39% which is 5.38%, 5.39%, 5.37%, and 41.09% more than DE [4], MRFO [8], WOA [7], and SSA [10], respectively. Likewise, HPO-optimized single WT placement cut down the PL by 93.92% which is 11.02%, 17.32%, 4.22%, and 4.21% more than GA [5], CSA [6], ALO [14], and WOA [7], respectively. Similarly, for two PV and WT placements, the HPO algorithm achieved better PL reduction than SCA [11], APSO [12], and MGSA [12]. In the case of VP enhancement, HPO algorithm-optimized DG integration resulted in better V_{min} than WOA, SCA, ALO, APSO, and MGSA. The HPO algorithm-optimized DG integration provides superior results than the other algorithms with a significant rate of convergence.

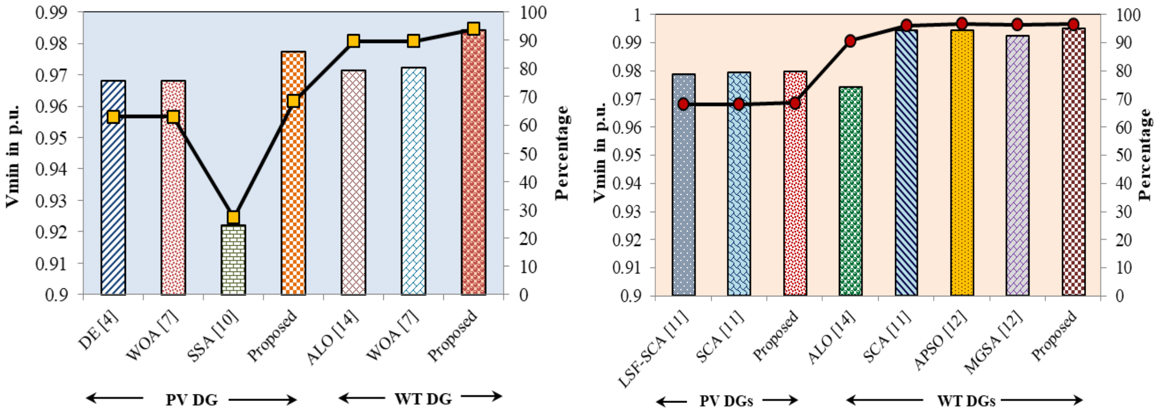
4.3 Cairo-59 bus RDS: Simulation results

Cairo-59 bus RDS is a real-world power network model that operates at 11 kV and supplies 50.348 MW and 21.448 MVAr of real and reactive power, respectively. The simulation run outcomes of Cairo-59 bus RDS with and without DG accommodation are presented in Table 2. The test system recorded 218.99 kW of RPL_T and 0.9864p.u of V_{min} before DG optimization.

For a single optimized PV and WT placement, the HPO algorithm converges to an optimal solution with 14328.2 kW and 13482.5 kVA capacity, respectively, and minimizes the RPL_T to 71.12 kW and 13.67 kW, respectively. At the same time, V_{min} of the test system improved to 0.9901p.u and 0.9925p.u, respectively. Likewise, for the optimized allocation of two PVs and WTs, PL has been reduced to 70.45 kW and 7.68 kW and V_{min} enhanced to 0.9923p.u and 0.9952p.u, respectively. Figure 3 illustrates the VP and convergence curve of the HPO algorithm for Cairo-59 bus RDS with optimized DGs integration.

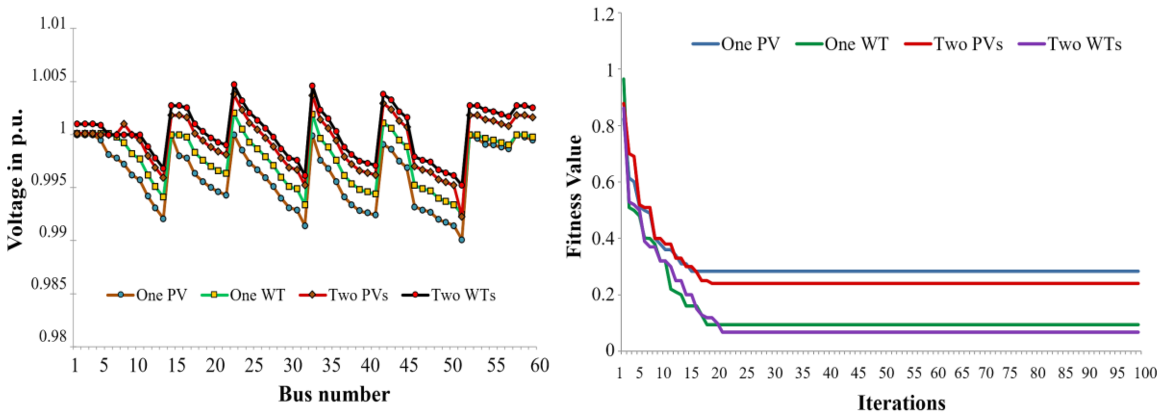
Table 2. Cairo-59 bus RDS: Test results with and without DG accommodations

Outcome	No DG	One PV	One WT	Two PVs	Two WTs
Optimal sites	-	3	3	25 41	25 41
Optimal sizes (kW/kVA)/p.f.	-	14328.2/ 1	13482.5/ 0.8303	10034.3/1 7894.8/1	8980.5/0.8134 9001.8/0.8218
RPL_T (kW)	218.99	71.12	13.67	70.45	7.68
V_{min} (p.u.)	0.9864	0.9901	0.9925	0.9923	0.9952



(a) (b)

Figure 2. Simulation results comparison for (a) single and (b) two DG placement



(a) (b)

Figure 3. Simulation results: (a) VP of Cairo-59 bus RDS and (b) convergence curve of HPO algorithm for Cairo-59 bus RDS

5. CONCLUSION

In this work, the HPO algorithm was implemented to solve a multi-objective DG placement problem in a DPN. The performance of the HPO algorithm was evaluated on a standard IEEE 69-bus benchmark radial DPN and a real-world Cairo-59 bus RDS. The PL in 69-bus RDS was reduced by 68.39% and 93.92% for the optimized single PV and WT placement and 68.68% and 96.59% for two PVs and WTs allocations, respectively. The minimum voltage (V_{min}) of the 69-bus RDS was significantly increased to 0.9775 p.u and 0.9798 p.u after a single and two PV allocations, respectively, and similarly, after single and two WT integrations V_{min} was increased to 0.9842 p.u and 0.9951 p.u, respectively. Likewise, the optimized allocation of single and two DG in Cairo-59 bus RDS has significantly reduced the PL and considerably improved the VP. Notably, the HPO algorithm effectively evaded the local optimal stagnation and converged to an optimal solution. Furthermore, the comparative study between the simulation findings of HPO and other algorithms signified its superiority in handling complex and nonlinear optimization problems.

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