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An Application of Hunter-Prey Optimization for Maximizing Photovoltaic Hosting Capacity Along with Multi-Objective Optimization in Radial Distribution Network

Sai Ram Inkollu[1]* **G.V. Prasanna Anjaneyulu[2]** **Kotaiah NC[2]** **Nagaraja Kumari.CH[3]**

[1]*Dhanekula Institute of Engineering & Technology, Vijayawada, Andhra Pradesh 521139, India*
[2]*R.V.R & J.C. College of Engineering, Chowdavaram, Guntur, Andhra Pradesh 522019, India*
[3]*Guru Nanak Institute of Technology, Ibrahimpatnam, Telangana 501506, India*
*Corresponding author's Email: inkollusiaram@gmail.com

Abstract: Currently global warming is increasing significantly around the world and become one of the typical issues for sustainability. In this connection, many sectors are transforming towards sustainable solutions. Integration of renewable energy (RE) is one such adaption in electrical power systems, by which the burden on conventional plants as well as their greenhouse gas (GHG) emission can be reduced significantly. However, due to radial structure, electrical distribution networks (EDNs) may not support for RE integration inappropriately. There are numerous methods have been introduced on optimal allocation of RE sources in radial distribution networks (RDNs), but not highly focused on maximizing their RE hosting capacity (HC). In this paper, a recent and efficient meta-heuristic algorithm, hunter-prey optimization (HPO) is introduced for finding the optimal locations and sizes of photovoltaic (PV) systems in RDNs. In addition to the loss minimization and voltage profile improvement, maximization of PV hosting capacity (HC) is focused as a major objective. Simulation results are done on IEEE 33-bus RDNs for different scenarios. The computational efficiency of proposed HPO is compared with other recent algorithms and it is observed that the results of HPO are better than other compared methods in terms of global optima. In addition, the enhanced HC of PV systems in RDNs is ensured improved performance in terms of reduced grid-dependency, GHG emission and distribution losses along with improved voltage profile.

Keywords: Radial distribution network, Hunter-prey optimization, Photovoltaic system, Hosting capacity, Multi-objective optimization.

1. Introduction

Currently, most electrical distribution networks (EDNs) are transforming into more clean and green technologies by integrating various types of renewable energy (RE) based distributed generation (DG), electric vehicles (EVs), and energy storage systems (ESSs), in response to continuously increasing global warming and declining fuel for conventional power sources [1]. However, the stochastic and intermittent nature of REs has presented the EDNs' operators with a number of difficult tasks. In particular, radial distribution networks (RDNs) are designed with high X/R ratio distribution losses and to cover larger areas, which results in high distribution losses and an inadequate voltage profile. To overcome these issues, optimal network reconfiguration (ONR) [2], optimal integration of DG [3], optimal integration of ESSs [4], optimal allocation of EV charging infrastructure [5], and their simultaneous solutions can provide a variety of technological-economical benefits such as reduced distribution losses, improved voltage profile, increased voltage stability margins, and increased reliability. Many researchers are focused on optimal integration of RE in EDNs, considering different technological, economic, and environmental objectives [6]. However, in order to achieve the global target of net-zero carbon by 2050 [7], maximization of RE hosting capacity (HC) is essential in EDNs [8]. However, the difficulty involved in moving towards a net-zero carbon electricity system is to be understood [9]. Since photovoltaic (PV) technology is one of the most highly adapted technologies among various RE technologies, even at small consumer sites, many researchers are focused on assessment [10] and enhancement of its HC in EDNs [11]. With these conditions, optimal integration of RE-based DGs in EDNs becomes one of the most actively pursued optimization problems in electrical engineering. Some of such recent works are discussed here.

The EDNs performance is improved by optimally integrating PV and WT type RE sources using ant lion optimization (ALO). Simulations are performed on IEEE 69-bus EDN for reducing distribution losses (f_1), improving voltage profile (f_2), and enhancing voltage stability index (f_3) [12]. Water cycle algorithm (WCA) is introduced for integrating PV, WT and CBs optimally. Simulations are done on IEEE 33-bus and 69-bus EDNs by considering f_1, f_2 and f_3 along with operating cost of DGs (f_4) and reduction of GHG emission from conventional power plant (f_5) [13]. Total harmonic distortion (THD) including total voltage harmonic distortion and individual harmonic distortion are reduced along with f_1 by integrating PV based DGs using biogeography-based optimization (BBO), genetic algorithm (GA), artificial bee colony (ABC), and particle swarm optimization (PSO) [14]. Multi-objective improved differential search algorithm (MOIDSA) with Pareto optimal approach is introduced for optimizing f_1, f_2, f_3 and f_4 via optimally locating and sizing PV and WT (which operates fixed power factor 0.866) based DGs in IEEE 33-bus and IEEE 69-bus EDNs. A comparison is done for two different penetration levels of DGs and highlighted that the maximum penetration level of DGs can result for better performance [15]. ALO is utilized for minimizing multi-economic objective function which includes grid power purchase cost, reliability cost, and cost of DGs installation cost. In addition, the impact of DGs allocation is quantified on f_1 and f_2 [16]. Continuous power flow (CPF) approach is used to maximize the DG penetration by integrating different types DGs (synchronous generators, synchronous compensator, fuel cells, and WTs) optimally. The major objective functions solved simultaneously are f_1, f_2, f_3 and f_4 along with voltage stability margin (f_5) and network transfer capability (f_6) [17]. Multi-objective modified symbiotic organisms search (MOSOS) algorithm is proposed for solving DGs in RDNs towards minimizing the annual energy cost, annual investment and operation cost of DGs and total voltage deviation [18]. Manta ray foraging optimization (MRFO) [19], Pareto multi-objective sine cosine algorithm (MOSCA) [20], hybrid grey wolf optimizer (HGWO) [21], whale optimization algorithm (WOA) [22], stud krill herd algorithm (SKHA) [23], krill herd algorithm (KHA) [23] and pathfinder algorithm (PFA) [24], some of such recent meta-heuristic approaches adapted for solving the DG allocation problem in RDNs.

From these works, it can be realized that the allocation of DGs at improper locations and sizes can result for negative impact on EDNs performance. Also, oversized DG penetration or HC can result for excessive installation and operational cost along with negative impact on EDNs performance. Thus, finding optimal locations, sizes and optimal HC of DGs can be treated as a complex multi-objective optimization problem with multi-type (discrete and continuous) search variables and different equal and unequal constraints and attained much attention among various researchers [25]. Besides, the above reviewed literature is exploring the various meta-heuristic optimization algorithms for solving this problem and has been treated as a continuous challenge. However, according to o Free Lunch (NFL) theorem [26], optimization algorithm's ability to solve one set of problems doesn't guarantee it can solve another. All optimizers average all optimization problems, despite some being superior. The NFL theorem enables academics suggest innovative optimization algorithms or improve existing ones. Some of such recent algorithms are: mixed leader based optimizer (MLBO) [27], three influential members based optimizer (TIMBO) [28], darts game optimizer (DGO) [29], mixed best members based optimizer (MBMBO) [30], multi leader optimizer (MLO) [31], and random selected leader based optimizer (RSLBO) [32]. In this context, the following are the major contributions for this paper.

- First time, a novel hunter-prey optimization (HPO) [33] is introduced in this paper for exploring its computation efficiency while solving optimal allocation of PV location and sizes for different multi-objectives.
- In addition, finding optimal number of DG locations is not paid much attention to attain maximum HC of DGs and considered as another major contribution of this work.

Rest of the paper is arranged as follows: In section 2, the mathematical modelling of PV based DGs and their hosting capacities (HC) are modelled.

In section 3, the mathematical formulation of proposed multi-objective function with different constrained is explained. In section 4, the concept of HPO is explained with its modelling. Section 5 discussed the effectiveness of proposed approach based on simulation results on IEEE 33-bus RDN considering different scenarios. At last, section 6 presents the overall research findings of this work comprehensively.

2. Modelling of theoretical concepts

In this section, the effect of a PV system at a location is modelled suitably for load flow study, and defined the PV HC mathematically.

2.1 Photovoltaic systems

According to different types of DGs definitions and technologies [17], PV systems can be mainly treated as a real power compensator at a location in the network. Thus, the effect of PV system at a location can be realized by off-setting its capacity from the connected load, mathematically,

$$\overline{P_{d(k)}} = P_{d(k)} - PV_{IC(k)} \tag{1}$$

where $\overline{P_{d(k)}}$ is the net effective load demand after integrating a PV system at bus-*k*, $P_{d(k)}$ is the connected peak load demand at bus-*k*, $PV_{IC(k)}$ is the installed capacity of PV system at bus-*k*.

2.2 Hosting capacity of PV systems

As defined in literature, HC is the ratio of installed capacity of PV systems to the network peak load demand [11]. Mathematically,

$$PV_{HC} = \left(\sum_{i=1}^{nPV} PV_{IC(i)} / \sum_{k=1}^{nbus} P_{d(k)}\right) \tag{2}$$

where PV_{HC} is the total hosting capacity (HC) of PV systems in the network, nPV and $nbus$ are the number of PV systems and number of buses in the networks, respectively.

3. Problem formulation

The proposed multi-objective function includes maximization of PV HC, minimization of distribution losses, voltage profile improvement, and reduction of GHG emission from conventional power plants. Mathematically,

$$OF = min\left(P_{gr} + P_{loss} + AVD_{pr} + GHG_{em}\right) \tag{3}$$

$$P_{loss} = \sum_{br=1}^{nbr} I_{br}^2 \times r_{br} \tag{4}$$

$$AVD_{pr} = \frac{1}{nbus} \sum_1^{nus} \left(|V|_{(r)} - |V|_{(i)}\right) \tag{5}$$

$$GHG_{em} = (CO_2 + SO_2 + NO_x) \times \left[P_{gr}\right] \tag{6}$$

$$P_{gr} = P_{loss} + \left(\sum_{k=1}^{nbus} P_{d(k)} - \sum_{i=1}^{nPV} PV_{IC(i)}\right) \tag{7}$$

where OF is the overall objective function, P_{loss} is the real power distribution loss, AVD_{pr} is the average of network voltage profile, GHG_{em} is the GHG emission form conventional plant, $|V|_{(r)}$ and $|V|_{(i)}$ are the voltage magnitudes of reference/sub-station bus and bus-i, respectively, CO_2, SO_2 and NO_x are the major pollutants from conventional power plants, P_{gr} is the net-effective grid-dependency of the network after installing PV systems. Here, by maximizing PV_{HC}, the grid-dependency of the network can be reduced significantly.

The multi-objective function expressed in Eq. (3) is constrained by the following equal and unequal planning and operational constants.

$$|V|_{(i),min} \leq |V|_{(i)} \leq |V|_{(i),max} \tag{8}$$

$$I_{br} \leq I_{br,max} \tag{9}$$

$$PV_{HC} \leq \sum_{k=1}^{nbus} P_{d(k)} \tag{10}$$

$$PV_{IC(i),min} \leq PV_{IC(i)} \leq PV_{IC(i),max} \tag{11}$$

Here, Eq. (8) is used to maintain the voltage profile of a bus within minimum and maximum tolerable limits, Eq. (9) is defined to maintain all branch currents less than their maximum limits, Eq. (10) is defined for avoiding over compensation, and Eq. (11) is used to define the DG capacity limits in the optimization problem.

4. Hunter-prey optimization

Nature may be able to help us solve challenges. In nature, creatures interact in numerous ways. Hunter–prey interaction is one of such and the most fascinating phenomena in population biology. Animals utilize a variety of tools and methods to hunt. Because prey is usually crowded, the hunter chooses prey that isn't near the swarms (average herd position). After finding his target, the hunter pursues and hunts it down. Meanwhile, the prey looks for food, escapes a predator attack, and finds safety. This protected area is ideal for prey in terms of safety or fitness in optimization problems. With this background, a simple meta-heuristic algorithm namely hunter-prey optimization (HPO) is developed uniquely [33]. In the same way that other algorithms have initialization, exploration, and exploration phases, HPO has these phases as well. Their modelling is shown here.

4.1 Initialization

In a search space, a uniformly distributed random number theory is used to generate the initial population of prey or hunters inside the lower and higher bounds of their respective populations.

$$hp_i = rand(1, n_v).* \left(u_{hp} - l_{hp}\right) + l_{hp} \quad (12)$$

where hp_i is the position of hunter/prey, l_{hp} and u_{hp} are the lower and upper limits of hunter/prey, respectively; $rand$ is uniformly distributed random number, n_v is the number of variables or dimension of the problem.

At this step, the fitness of each population is evaluated in terms of the proposed objective function, and the population with the best fitness is advanced to the pre-iterative stage as the current iterative global best.

4.2 Exploration phase for updating hunter position

To help search variables identify the optimum place, a searching process must repeated. Exploration and exploitation are two stages of the search process. Exploration is the algorithm's inclination to function randomly, causing many changes in solutions. Large changes in solutions make it more vital to keep seeking for new places to look. Thus, in exploitation phase, there is a need to reduce randomness so the algorithm can search for global optima. The exploration phase of HPO for updating hunter position at an iteration k is defined by,

$$hp_{ij}(k+1) = hp_{ij}(k) + 0.5\left\{\left[2B_pA_pP_{pr(j)} - hp_{ij}(k)\right] + \left[2\left(1 - B_p\right)A_p\gamma_j - hp_{ij}(k)\right]\right\} \quad (13)$$

where $hp_{ij}(k+1)$ is the modified position of hunter for next iteration, $P_{pr(j)}$ is the position of prey, γ_j is the mean of all prey positions , A_p is the adaptive parameter, B_p is the parameter used for balancing exploration and exploitation phases.

The following relations are employed for defining the A_p, and B_p,

$$B_p = 1 - \frac{0.98 \times k}{k_{max}} \text{ and}$$

$$A_p = r_2 \otimes idx + r_3 \otimes (\sim idx) \quad (14)$$

where $\overline{r_1} = rand(1, n_v) < B_p$, $r_2 = rand()$, $\overline{r_3} = rand(1, n_v)$, $idx = (r_1 == 0)$, $\overline{r_1}$ and $\overline{r_3}$ are the random vectors in [0, 1] with a size equals to number of variables, respectively, r_2 is a random number, idx is the index number of the $\overline{r_1}$ when it satisfies $r_1 = 0$, $\otimes$ is element by element multiplication, k and k_{max} are the current iteration number and maximum iterations, respectively.

The position of a prey P_{pr} is calculated first using average of all prey positions γ_j , and the Euclidean distance between of each search variable to this mean position, as given by,

$$\gamma_j = mean\left(hp_{ij}\right) \text{ and}$$

$$D_{euc(i)} = \sqrt{\sum_{j=1}^{n_v}\left(hp_{ij} - \gamma_j\right)^2} \quad (15)$$

According to Eq. (16), the prey which has maximum distance from mean distance γ_j , is considered as the prey for hunting $P_{pr(j)}$ as given by,

$$\overline{P_{pr}} = \overline{hp_i} \middle| i \; is \; index \; of \; \max(end) sort(D_{euc}) \quad (16)$$

The method will approach slow convergence rate if we always consider the search agent with the largest distance from the average position (γ_j) in each iteration. When the hunter kills his target, he may moves on to the next victim in the chain of events, as described in the hunting scenario. HPO is investigating a reduction strategy in order to address this issue, as follows:

$$\overline{P_{pr}} = \overline{hp_i} \middle| i \; is \; sorted \; oD_{euc}(p_{best}) \, ,$$
$$p_{best} = round\left(B_p \times n_v\right) \quad (17)$$

4.3 Exploitation phase for updating prey position

In the event of an attack, prey seeks to flee and find a safe haven assuming that the prey has a better probability of surviving, HPO assume that the optimum safe place is the best global position.

$$hp_{ij}(k+1) = G_{pr(j)} + B_pA_p cos(2\pi r_4) \times \left(G_{pr(j)} - hp_{ij}\right) \quad (18)$$

where $hp_{ij}(k+1)$ is the prey position for the next

Table 1. Comparison of literature for single PV allocation

Method	PV Sizes (kW) and Locations	GHG_{em} (lb/h) $\times 10^3$	P_{loss} (kW)	AVD_{per} (p.u.)	P_{loss} Reduction (%)	GHG Reduction (%)	HC (%)	Grid Dependency (%)
MRFO [19]	2590.217 (6)	2530.48	111.03	0.972	47.378	68.52	69.72	32.30
HGWO [21]	2590 (6)	2530.48	111.03	0.972	47.378	68.52	69.72	32.30
WOA [22]	2589.6 (6)	2530.48	111.03	0.972	47.378	68.52	69.72	32.30
SKHA [23]	2590.215 (6)	2530.48	111.03	0.972	47.378	68.52	69.72	32.30
KHA [23]	2590.216 (6)	2530.48	111.03	0.972	47.378	68.52	69.72	32.30
PFA [24]	**2590.264 (6)**	**2530.48**	**111.03**	**0.972**	**47.378**	**68.52**	**69.72**	**32.30**
HPO	**2590 (6)**	**2530.48**	**111.03**	**0.972**	**47.378**	**68.52**	**69.72**	**32.30**

Table 2. Comparison of literature for two PVs allocation

Method	PV Sizes (kW) and Locations	HC (kW)	GHG_{em} (lb/h) $\times 10^3$	P_{loss} (kW)	AVD_{per} (p.u.)
ALO [16]	487.18 (33), 498.3 (15)	985	5824.69	115.037	0.9643
PSO [16]	500 (32), 500 (15)	1000	5792.26	113.720	0.9645
GA [16]	491.45 (32), 500 (15)	991	5810.73	114.191	0.9644
ALO [16]	474.67 (17), 493.86 (16)	969	5905.61	137.605	0.9678
PSO [16]	461.49 (16), 485.33 (33)	947	5908.85	117.480	0.9637
GA [16]	469.77 (17), 470.93 (15)	941	5957.81	135.269	0.9671
MRFO [19]	1157.6 (30), 851.5089 (13)	2009	3671.57	87.167	0.9795
HPO	**1157.81 (30), 852.2 (13)**	**2010.01**	**3671.57**	**87.167**	**0.9795**

Table 3. Comparison of literature for three PVs allocation

Method	PV Sizes (kW) and Locations	HC (kW)	GHG_{em} (lb/h) $\times 10^3$	P_{loss} (kW)	AVD_{per} (p.u.)
WCA [13]*	854.6(14), 1101.7(24), 1181(29)	3137	1334.84	51.808	0.9840
GA [14]*	694.7(14), 1184.4(24), 1462.8(28)	3342	921.80	54.511	0.9833
ABC [14]*	1137.2(9), 1067.4(24), 803.1(32)	3008	1605.80	53.299	0.9803
PSO [14]*	1062.5(9), 1044.7(24), 951.8(30)	3059	1498.64	52.461	0.9804
BBO [14]*	753.9(14), 1009.4(24), 1071.4(30)	2835	1951.84	50.697	0.9807
MOSCA [20]*	609.8(33), 629.3(13), 1159.4(6)	2399	2859.74	56.362	0.9798
SPEA2 [20]*	1151.9(9), 774.2(25), 750.4(33)	2677	2288.54	55.351	0.9788
MOIDSA [15]	968.7(30), 800(13), 1036.3(25)	2805	2015.43	51.622	0.9802
MOIDSA [15]	793.4(31), 396(25), 933.1(14)	2123	3426.67	55.309	0.9790
MRFO [19]	792(13), 1068(24), 1027(30)	2887	1844.60	50.646	0.9807
HPO	**802(13), 1091(24), 1054(30)**	**2947**	**1721.64**	**50.653**	**0.9813**

**Revised answers w.r.t base case load flow*

iteration, G_{pr} is the global best position of prey, r_4 is the random number between 0 and 1.

4.4 Identification of hunter or prey from the updated variables

In order to use Eqs. (13) and (18) to update the hunter and prey positions, the search variables must first be used to identify the hunter and prey. According to Eq. (19), if $r_5 < R_p$, then hp_{ij} will be treated as a hunter else, as a prey.

$$hp_{ij}(k+1) = \begin{cases} Eq(13) & if\ r_5 < R_p \\ Eq(17) & else \end{cases} \quad (19)$$

where r_5 is the random number between 0 and 1, R_p is a regulating parameter, which is set to 0.1.

As seen in the different phases of HPO, it is a highly efficient and competitive algorithm in real-time applications because of its unique ability to solve both unimodal and multimodal issues while maintaining a good balance between exploration and exploitation [26].

Table 4. Comparison of network performance in different case studies with HPO results

No. of PVs	**P_{loss} (kW)**	**Loss Reduction (%)**	**GHG Emission (lb/h) $\times 10^3$**	**GHG Reduction (%)**	**Q_{loss} (kVAr)**	**V_{min} (p.u)**	**AVD_{pr} (p.u)**
0	**210.99**	**-**	8039.1	**-**	143.03	0.9038 (18)	0.9453
1	111.03	47.38	2530.48	68.52	81.68	0.9424 (18)	0.972
2	87.25	58.65	3671.5	54.33	59.773	0.9685	0.9795
3	72.79	65.50	1722.3	78.59	50.65	0.9687	0.9813
4	67.64	67.94	1138.4	85.84	47.1681	0.9703	0.9828

Table 5. Comparison of different algorithms for scenario 4

Algorithm	**Worst**	**best**	**Mean**	**Median**	**Std.**
TLBO	137.01	67.64	70.84	67.67	11.02
BOA	100.96	67.64	71.22	67.82	6.92
BES	96.42	67.63	**69.87**	67.74	5.86
COA	85.15	67.75	71.27	68.27	4.84
HPO	**90.94**	**67.63**	69.96	**67.64**	**4.73**

5. Results and discussion

As mentioned earlier, the major objective of this work is to integrate PV systems optimally in RDN using a new hunter-prey optimization (HPO) for maximizing the hosting capacity (HC), minimizing the losses, improving the voltage profile and reducing the GHG emission from conventional plants. The computational efficiency of HPO is evaluated using four scenarios. The simulations are performed on IEEE 33-bus RDN and its bus data and branch data are taken from [27]. For the HPO and other algorithms, the maximum number of iterations and number of population are considered as 50 and 30, respectively. And, the number of search variables is equal to 2 times of the number of PV systems to be integrated optimally.

By performing load flow [28], it is observed that the network is suffering by total real and reactive power losses equal to 210.99 kW and 143.03 kVAr, respectively for serving a total real and reactive power loadings of 3715 kW and 2300 kVAr, respectively. Also, the minimum voltage magnitude is registered at bus-18 as 0.9038 p.u. and the average voltage magnitude of the network is determined as 0.9453 p.u. Since, there are no PV systems/ DGs available in the standard network, the total load and losses have been supplied by main-grid only and consequently grid-dependency is 100 %. Thus, by assuming the grid-supply is from conventional power plants, the GHG emission is determined as 8039.1×10^3 lb/h. This operating state is treated as base case, and compared with the forthcoming cases in each scenario.

5.1 Maximum HC with single PV location

In this scenario, the maximum capacity of PV system along with its location is optimized using HPO algorithm. The results of HPO are as follows: location is bus-6 and size is 2590.241 kW. Thus the network performance is improved as follows: the real and reactive power losses are 111.023 kW and 81.684 kVAr, respectively. The minimum voltage magnitude at bus-18 is raised to 0.9424 p.u and the average voltage magnitude is increased to 0.972 p.u. By having this optimized PV system, the GHG emission is determined as 2530.48×10^3 lb/h.

In comparison to base case, the losses and GHG emission are reduced by 47.38 % and 68.52 %, respectively. On the other hand, the HC and grid-dependency are become 69.72 % and 32.3 %, respectively.

The results of HPO are compared with literature works and given in Table 1. From this, it can be seen that the HPO is behaved as well competitive algorithm to MRFO [19], HGWO [21], WOA [22], SKHA [23], KHA [23], and PFA [24]. All these algorithms have resulted for almost same HC of PV system and correspondingly network performance.

5.2 Maximum HC with two PV locations

In this scenario, the maximum capacities of two PV systems along with their location are optimized. The results of HPO are as follows: the locations are buses 30 and 13 and the sizes are 1157.64 kW and 851.5 kW, respectively. Thus the network performance is improved as follows: the real and reactive power losses are 87.1669 kW and 59.773

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kVAr, respectively. The minimum voltage magnitude at bus-18 is raised to 0.9685 p.u and the average voltage magnitude is increased to 0.9795 p.u. By having this optimized PV system, the GHG emission is determined as 3671.5×10^3 lb/h. In comparison to the base case, the losses and GHG emission are reduced by 58.69 % and 54.33 %, respectively. On the other hand, the HC and grid-dependency are become 54.11 % and 48.24 %, respectively.

The results of HPO are compared with literature works and given in Table 2. From this, it can be seen that the HPO is outperformed than ALO, PSO and GA [16], and MRFO [19] by its global optima.

5.3 Maximum HC with three PV locations

In this scenario, the maximum capacities of three PV systems along with their location are optimized. The results of HPO are as follows: the locations are buses 24, 30 and 13 and the sizes are 1091.33 kW, 1053.64 kW, and 801.7 kW, respectively. Thus the network performance is improved as follows: the real and reactive power losses are 72.7865 kW and 50.6529 kVAr, respectively. The minimum voltage magnitude at bus-33 is raised to 0.9687 p.u and the average voltage magnitude is increased to 0.9813 p.u. By having this optimized PV system, the GHG emission is determined as 1722.3×10^3 lb/h

In comparison to base case, the losses and GHG emission are reduced by 65.5 % and 78.59 %, respectively. On the other hand, the HC and grid-dependency are become 79.33 % and 22.63 %, respectively. The results of HPO are compared with literature works and given in Table 3. From this, it can be seen that the HPO is outperformed than WCA [13], GA [14], ABC [14], PSO [14], BBO [14], MOSCA [20], SPEA2 [20], MOIDSA [15], MOIDSA [15], and MRFO [19], by its global optima.

5.4 Maximum HC with optimal PV locations

In addition to optimal number of PV systems, i.e., four, a comparison of all scenarios is given in Table 4. In optimal number of PV scenario, the maximum capacities of four PV systems along with their location are optimized. The results of HPO are as follows: the locations are buses 6, 14, 24, and 31 and the sizes are 926.4 kW, 646.82 kW, 967.22 kW and 686.25 kW, respectively. Thus the network performance is improved as follows: the real and reactive power losses are 67.6315 kW and 47.1681 kVAr, respectively. The minimum voltage magnitude at bus-18 is raised to 0.9703 p.u and the average voltage magnitude is increased to 0.9828 p.u. By having this optimized PV system, the GHG emission is determined as 1138.4×10^3 lb/h. In comparison to base case, the losses and GHG emission are reduced by 67.94 % and 85.84 %, respectively. On the other hand, the HC and grid-dependency are become x% and y%, respectively.

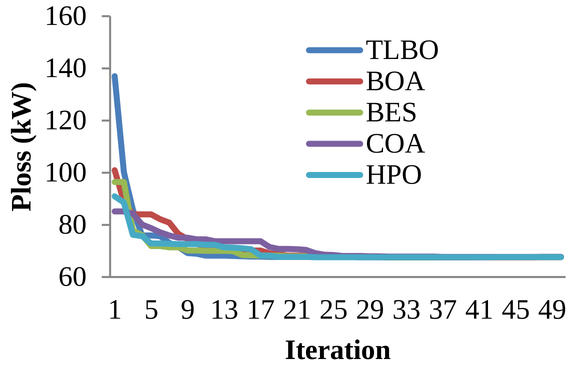

Figure. 1 Convergence characteristics of compared algorithms

As it can be seen that the HC of PV systems is increased significantly with four PV systems and thus, the network performance is also improved significantly. The four objectives functions are moderated as follows: grid-dependency is decreased, PV hosting capacity is increased, GHG emission reduced, losses are reduced, and voltage profile is increased.

The optimal number of PVs allocation is compared by implementing teaching-learning-based optimization (TLBO) [29], bald eagle search (BES) [30], coyote optimization algorithm (COA) [31], and butterfly optimization algorithm (BOA) [32]. Based on 50 independent runs, the performance of HPO is and other algorithms are compared in Table 5. From the lower values of worst, best, median and standard deviation, HPO is said to be high efficient and competitive algorithm to solve high-dimensional optimization problems. In addition, the convergence characteristics of all these algorithms are given in Fig. 1.

6. Conclusion

The integration of renewable energy (RE) into radial distribution networks (RDNs) is one such adaptation that can be made to electrical power systems in order to reduce the burden on conventional plants as well as their greenhouse gas (GHG) emissions. However, because of their radial structure, RDNs may be unable to provide adequate support for RE integration. A number of methods have been developed for the optimal allocation of renewable energy sources in radial distribution

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networks (RDNs), but none have been specifically designed to maximize the capacity of RDNs to host renewable energy sources (HC). It is discussed in this paper how a recent and efficient meta-heuristic algorithm, hunter-prey optimization (HPO), can be used to find the optimal locations and sizes of photovoltaic (PV) systems in renewable energy systems. The maximization of PV hosting capacity (HC), in addition to loss minimization and voltage profile improvement, has been identified as a major goal. The results of simulations are performed on IEEE 33-bus RDNs for a variety of scenarios. Comparing the computational efficiency of the proposed HPO with other recent algorithms, it is discovered that the results of the proposed HPO are superior to the results of the other compared methods in terms of global optima. Improved performance in terms of reduced grid-dependency, GHG emissions, and distribution losses, as well as an improved voltage profile, are also ensured by the increased HC of PV systems in RDNs, in addition to improved voltage profile.

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

The supervision, review of work and project administration, has been done by Sai Ram Inkollu. The paper background work, conceptualization, and methodology have been done by G.V. Prasanna Anjaneyulu. The dataset collection and editing draft is prepared by Kotaiah N.C. The program implementation, result analysis and comparison, and visualization have been done by Nagaraja Kumari.CH.

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