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# A Novel Hybrid Optimization Approach for Allocation of Distributed Generation in Distribution Power Network

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**Abstract**
***This study aims to assimilate distributed generation (DG) unit using a novel hybrid technique to improve the efficiency of electric power distribution networks by minimizing the real power losses (RPL) and enhancing the bus voltages (BV). A hybrid technique has been implemented by combining the features of nature-inspired algorithms namely hunter-prey optimizer (HPO) and ant lion optimizer (ALO) algorithms. The exploitation characteristic of ALO and exploration characteristic of HPO is utilized to optimize single DG in radial distribution power network (DPN). The efficacy of the suggested hybrid optimization technique is validated using MATLAB/Simulink software tool. The proposed hybrid technique was executed to optimize type I and type III DG in a balanced IEEE 69-bus radial DPN. The optimized type I and type III DG placement minimized the real power losses of a test system to 71.23 kW and 20.38 kW, respectively. Additionally, the least bus voltage of the test system improved to 0.9776p.u and 0.9843p.u following type I and type III DG allocation. The optimized allocation of type I DG and type III DG has resulted in 68.34% and 90.94% power loss reduction, respectively and enhanced the minimum bus voltage of the test system by 7.5% and 8.3%, respectively.*** **The efficacy of the proposed hybrid methodology was investigated by relating its simulation outcome with other optimization methodologies present in the literature. The comparative results revealed that the proposed hybrid optimization technique provided better RPL minimization at improved BV than the compared optimization techniques.**

**Keywords**
**Distributed generation, radial distribution power network, power losses, bus voltage.**

## I. Introduction

Electricity has become a primary component for developing a global economic infrastructure to ensure sustainable economic growth. In the recent past, the depreciation of conventional resources and the rise of the global population have led to electricity deficiency. Electricity customers are powered through power distribution networks (PDNs). A typical radial distribution network (RDN) is a passive network. The RDN faces numerous problems including high power losses (PL) and voltage reduction because of the large numbers of consumers and higher R/X ratio. In addition to that, the performance of RDN gets limited due to unscheduled interruptions, harmonic distortions and voltage instability [1]. This situation creates a necessity to improve the performance of RDN to provide a reliable and secure system to end users.

Various methodologies suggested in the literature includ-


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ing capacitor placement, network reconfiguration, distributed generation (DG) allocation and FACTS device integration to improve RDN performance [2, 3]. However, in recent times, DG assimilation has been highly recommended over other methodologies since it supports DS with real power (P) and reactive power (Q) support. DG is a small-scale power-generating unit that can produce electrical power near the load site [4]. Optimal assimilation of DG units favors both the power system utility and end users including power loss reduction, voltage improvement, reduced energy cost and improved system reliability [5].

However, DG's location and size need to be optimized for accomplishing promising outcomes. Different methods were suggested by the researchers to optimize DG into DPN and grouped into four categories such as analytical, sensitivity approach, artificial intelligence and meta-heuristic technique [6]. In addition to the above methods, an integrated methodology using a sensitivity approach and meta-heuristic algorithm is also proposed in the literature. These techniques optimize the appropriate site and size for the DG unit in DPN to achieve economic, technical and environmental benefits.

A novel integrated single and multi-objective optimization technique was proposed [7] to optimize DG units into electrical power distribution networks. An analytical optimization approach was presented in [8] to optimize the solar PV systems for PL reduction and voltage profile (VP) enhancement. The proposed approach employed a fixed step size variation to optimize DG size in a 33-bus balanced radial DS. Four distinctive meta-heuristic optimization techniques using PSO, TLBO, WOA and GWO were applied [9] for solving a DG optimization problem. In addition, the performance of these techniques was compared concerning the percentage of power loss reduction. A hybrid optimization method was proposed [10] using a sine cosine algorithm (SCA) and an analytical approach for figuring out the optimal positions and sizes for multiple DG units in radial DPN. The proposed hybrid methodology used a loss sensitivity factor (LSF) to curtail the size of the search space. An optimization technique using grey wolf optimizer (GWO) was applied in [6] for optimally engaging a DG in a standard IEEE 33 bus radial DS to reduce total RPL and enhance voltage stability. A hybrid optimization approach using power loss index and salp swarm algorithm (SSA) was proposed in [11] for optimally accommodating solar PV systems and wind turbines (WTs) in the radial DPN for voltage improvement and RPL minimization.

From the above literature, it was inferred that the analytical and sensitivity factor approaches optimized DG placement have provided significant results but often these techniques are prone to inaccuracy problems because of the complex mathematical expression. Likewise, most of the meta-heuristic algorithms have been associated with slow convergence rates and local optima stagnation problems. For example, PSO and WOA have suffered slow convergence for a complex and high-dimensional search problem [9]. Furthermore, the majority of algorithmic-based techniques including ALO have given encouraging outcomes for an optimal DG allocation problem but are often trapped to local optima solutions due to their narrow exploitation feature. Therefore, a hybrid optimization technique can be a suitable alternative to evade the local optima stagnation and to improve the quality of the optimal solution. In addition, the hybrid technique can provide a near-optimal solution with a considerable rate of convergence. In the present study, a novel hybrid technique using ALO and HPO algorithms is proposed to optimize DG into DPN.

The hybrid technique makes use of the exploration and exploitation features of ALO and HPO to compensate for the drawbacks of individual algorithms. Ant Lion Optimizer (ALO) and Hunter Prey Optimizer (HPO) are simple and effective meta-heuristic algorithms used for solving a vast number of optimization problems. HPO algorithm compensates for the poor convergence characteristics of ALO and helps to track down global optima solutions [12]. Moreover, ALO and HPO require only a few control variables for execution. The contribution of the proposed work is outlined as follows:

1. A new hybrid optimization technique using ALO and HPO algorithms is proposed to optimize the site and size of a single DG unit in the RDPN to reduce RPL and enhance VP. The performance of the proposed hybrid technique is tested on a balanced IEEE 69-bus RDPN.

2. The simulation outcomes are obtained and analyzed for type-I and type-III DG allocation.

3. The optimized outcomes are compared with other known optimization techniques for investigating the effectiveness of the proposed hybrid technique. The RPL and minimum bus voltage are taken as comparison metrics.

Excluding the introduction section, the remaining parts of the work are elaborated in five sections. Section II. presents the objective function framework and essential power flow constraints. Section **??** briefs about DG modelling and distribution test network. Section IV. explains the proposed hybrid optimization technique for the DG allocation problem. Section V. discusses the research findings and section 6 concludes the research outcome.

## II. OBJECTIVE FUNCTION FRAMEWORK

The proposed hybrid optimization methodology is implemented to find the ideal position & size of Type-I DG & Type-III DG to minimize RPL and enhance VP of DPN.

### A. Objective(s)

#### 1) Real power loss minimization ($f_1$)

Total real power loss (RPLT) along the feeder of RDPN is expressed in (1).

$$RPL_T = \left( \sum_{k=1}^{nb} R_k * I_k^2 \right) \tag{1}$$

Where, $R_k$ denotes per unit (p.u.) resistance of the distribution line, $I_k$ designates the current through a distribution line and $nb$ points to the total number of branches in RDS.

The $RPL_T$ reduction is ensured by minimizing the power loss index (PLI) expressed in (2) [13].

$$f_1 = PLI = \frac{RPL_{TDG}}{RPL_{TnoDG}} \tag{2}$$

Where $RPL_{TDG}$ and $RPL_{TnoDG}$ denote the total RPL of RDPN with and without DG unit, respectively.

#### 2) Voltage profile improvement ($f_2$)

The voltage profile enhancement ($f_2$) of RDS is measured by evaluating the voltage deviation index (VDI) [13].

$$f_2 = VDI = \left( \sum_{i=1}^{N} (|V_n - V_i|) \right) \tag{3}$$

Where $N$ refers total no. of buses, $V_n$ and $V_i$ imply nominal (1.0 p.u.) and actual bus voltages, respectively.

The multi-objective function (MOF) of the single DG placement problem is expressed in (4) and is solved using the weighted sum method.

$$MOF = min(w_1 f_1 * w_2 f_2) \tag{4}$$

Here, the sum of $w_1$ and $w_2$ should be one.

### B. Constraints

The optimal solution for the DG placement problem should satisfy several constraints [14] of radial DS listed below.

#### 1) Power Balance Constraints

$$P_S + P_{DG} = \left( \sum_{i=1}^{N} P_i + \sum_{j=1}^{nb} P_{loss}(j) \right) \tag{5}$$

and

$$Q_S + Q_{DG} = \left( \sum_{i=1}^{N} Q_i + \sum_{j=1}^{nb} Q_{loss}(j) \right) \tag{6}$$

Where $P_S$ and $Q_S$ denote real power (P) and reactive power (Q) support of substation; $P_{DG}$ and $Q_{DG}$ correspond to the P & Q rating of DG; $P_L$ and $Q_L$ point to the P & Q demand connected to radial DS respectively; $P_{loss}$ and $Q_{loss}$ denote real and reactive power loss along the distribution line, respectively.

#### 2) Bus Voltage Constraint

$$V_{min} \leq V_i \leq V_{max} \tag{7}$$

Where $V_{max}$ and $V_{min}$ are the desired maximum and minimum bus voltages for a secure and reliable operation of RDS. A typical RDS is assumed to be safe and secured when bus voltages are between 0.95p.u ($V_{min}$) and 1.05p.u ($V_{max}$) [14].

#### 3) DG Power Injection Limit

The power injection capacity of DG is restricted to 60% of the total connected load plus power losses of RDS [14]. The optimized capacity of a DG must be equal to or less than the load power demand of RDS to avoid security issues.

$$P_{DG} \leq 0.6 * (P_L + P_{loss}) \tag{8}$$

and

$$Q_{DG} \leq 0.6 * (Q_L + Q_{loss}) \tag{9}$$

#### 4) Thermal Limit

$$I_k \leq I_{max(k)} \tag{10}$$

Where k = 1, 2, ...., nb

### C. Power Flow for Distribution System

Power flow (PF) in electrical power networks is essential to compute line power losses, voltage profiles, etc. Additionally, PF is a crucial tool for assessing the stability, reliability and economic state of power networks. The customary PF methods of transmission power networks like Gauss-Seidel (GS) and Newton Raphson (NR) techniques produce inadequate results for DPN because of its complex radial structure, more no. of load buses and high R/X ratio. Hence, for accurate PF assessment, a typical DPN employs a unique power flow methodology using the Backward/Forward Sweep (BFS) algorithm [15]. The BFS algorithm provides efficient and effective PF results at better convergence than GS and NR techniques [15].

For n-bus RDS shown in Fig.1, consider 'i' and 'i+1' are the load buses connected by a branch 'k'.

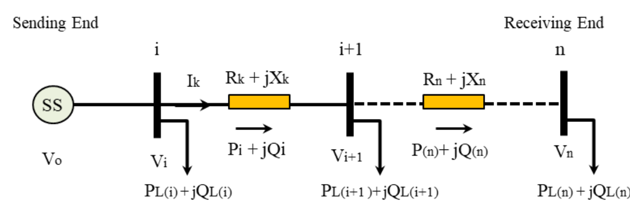


Fig. 1. n bus RDS

The real power loss (RPL) along the branch 'k' is expressed in (11).

$$RPL = I_k^2 * R_k \tag{11}$$

## III. DG Modelling in Distribution Network

This section describes the DG modelling and a radial bus test system (IEEE 69-bus RDPN).

### A. Test System: IEEE 69 bus RPDN

It has a single feeder, 68 no. of load buses (or nodes) and 68 no. of branches. Figure 2 shows the one-line schematic for 69-bus RDS. The feeder of the test system cumulatively supplies 3.8 MW and 2.69 MVAr of real and reactive power at a base voltage of 12.66 kV.

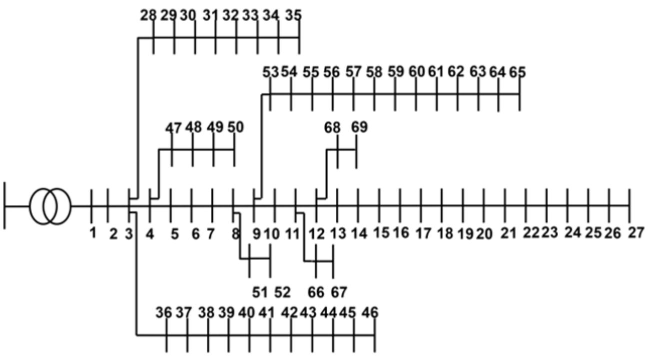

Fig. 2. One line schematic of 69-bus RDS

### B. DG Modelling

DG units are modelled either as a constant P-Q type or a constant P-V type [16]. If $P_{Li}$ and $Q_{Li}$ refer to active and reactive power absorption before DG placement, then the updated real $(P_{Ni})$ and reactive $(Q_{Ni})$ power absorption following a DG placement is calculated as:

$$P_{Ni} = P_{Li} - P_{DG} \tag{12}$$

and

$$Q_{Ni} = Q_{Li} - Q_{DG} \tag{13}$$

For Type I (solar PV) DG unit, $Q_{DG}$ is zero since it is assumed to operate at unity p.f. The output power of $P-Q$ DG is expressed with a negative polarity since it injects current into RDS. The constant $P-V$ DG adjusts the reactive power flow to control the bus voltage.

#### 1) Type I DG Modelling

In this study, the solar PV system is demonstrated as type I DG. Equation (14) describes the output power (P) rating of a type I DG unit [17]. In the present work, the solar PV system is modelled as type I DG.

$$P = \begin{cases} P_r * \left(\frac{G}{G_r}\right), & 0 \le G \le G_r \\ P_r, & G_r \le G \end{cases} \tag{14}$$

Where $P_r$ is the rated output power, $G$ is the solar irradiance at the optimal site(s) and $G_r$ is the rated solar irradiance of the earth's surface.

#### 2) Type III DG Modelling

The wind turbine (WT) system is represented as type III DG in this study. Equations (15) and (16) illustrate the real (P) and reactive (Q) power output of type III DG respectively [17].

$$P = \begin{cases} 0, & 0 \le v \le v_{cin} \\ P_r * \left(\frac{v-v_{cin}}{v_r-v_{cin}}\right), & v_{cin} \le v \le v_r \\ P_r, & v_r \le v \le v_{cout} \end{cases} \tag{15}$$

and

$$Q = P * tan\left(cos^{-1}(p.f._{DG})\right) \tag{16}$$

Where $v_r$ and $v$ are the rated and actual wind velocity (WV) of a WT system. $v_{cin}$ and $v_{cout}$ are the cut-in and cut-out WV.

## IV. Methodology: ALO - HPO Hybrid Technique

This section presents mathematical modeling of ALO, HPO and hybrid ALO-HPO optimization methods.

### A. Ant Lion Optimizer (ALO)

ALO simulates the hunting activity between ants and ant lions. ALO incorporates five steps to solve an engineering optimization problem.

#### 1) Random Walk

Random walk (RW) of an ant configured mathematically as in (17).

$$X(t) = \left\{ \begin{array}{ll} 0, & \text{cums}(2r(t_1)-1), \\ \text{cums}(2r(t_2)-1), \ldots, & \text{cums}(2r(t_n)-1) \end{array} \right\} \tag{17}$$

Where *cums* refers to the cumulative sum and $t$ points to iteration. A stochastic function r(t) is used to represent the RW of an ant.

$$r(t) = \left\{ \begin{array}{ll} 1, & \text{if} \quad \text{rand} > 0.5 \\ 0, & \text{if} \quad \text{rand} \le 0.5 \end{array} \right\} \tag{18}$$

Where *rand* is a randomly generated number between zero and one. The RW of ant normalized within boundary conditions using (19).

$$X_i^t = \frac{(X_i^t - a_i) * (d_i^t - c_i^t)}{b_i - a_i} + c_i^t \tag{19}$$

Where $X_i^t$ points to the position of ant, $a_i$ and $b_i$ represent variables corresponding to minimum and maximum RW and $t$ is an iteration number.

#### 2) Ant Lion Trap

The characteristics of the ant lion trap are mathematically presented in (20) and (21):

$$c_i^t = Antlion_j^t + c^t \tag{20}$$

and

$$d_i^t = Antlion_j^t + d^t \tag{21}$$

Where $Antlion_j^t$ refers to the position of ant lion, $(c^t, d^t)$ are the vectors corresponding to the minimum and maximum values of variables.

#### 3) Trap Building

Ant lion builds a trap to hunt an ant. Traps are set using roulette wheels to increase the probability of a successful hunt.

#### 4) Sliding Ants toward the Ant Lion

Once the prey fell inside a pit, the ant lion made the prey slide towards it. Equations (22) and (23) illustrate the sliding process of ants.

$$c^t = \frac{c^t}{I} \tag{22}$$

and

$$d^t = \frac{d^t}{I} \tag{23}$$

Where $I$ is a ratio. Here, the radius of the ant's position decreased exemplifying the sliding of an ant.

#### 5) Catching Prey and Rebuilding Traps

The ant lion consumes the trapped ant and rebuilds the pit for the next hunt. Equation (24) exemplifies this phase of the ALO algorithm.

$$Antlion_j^t = Ant_i^t \ if \ f(Ant_i^t) > f(Antlion_j^t) \tag{24}$$

#### 6) Elitism

The ant lion with the best solution is set as elite. The elite solution controls the ant's movement throughout the search space.

$$Ant_i^t = \frac{R_A^t + R_E^t}{2} \tag{25}$$

Where $R_A^t$ and $R_E^t$ are the movements of ant around the ant lion and elite.

### B. Hunter Prey Optimizer

HPO is a bio-inspired optimization algorithm, which impersonates the hunting action of an animal [12]. The population is randomly set as follows:

$$x_i = rand(1,d) * (u-l) + 1 \tag{26}$$

Where $i = 1,2,...,npop$ and $d = 1,2,...,M$. Here, $x_i$ refers to the hunter position, $npop$ point's population size; $M$ points search space size; $l$ and $u$ denote the lower and upper limit of search space. The position of the hunter location is updated as follows:

$$x_{ij}^{t+1} = x_{ij}^t + \frac{1}{2}(2*C*Z*P_{pos(j)} - x_{ij}^t) + (2(1-C)*Z*\delta_j - x_{ij}^t) \tag{27}$$

Where $x(t)$ and $x(t+1)$ are the present and future position of the hunter respectively; $P_{pos(j)}$ points to the prey position and $\delta_j$ refers to the average location. Where,

$$\delta_j = \frac{1}{n}\sum_{j=1}^{npop} x_j \tag{28}$$

And, the adaptive parameter (Z) is computed using (29) and (30).

$$P = r_1 < C;\ IDX = (P == 0) \tag{29}$$

and

$$Z = r_2 \otimes IDX + r_3 \otimes (\approx IDX) \tag{30}$$

Where $r_1$ and $r_2$ are the vectors of random values lie between zero and one. Similarly, $r_2$ is a random number that lies between 0 and 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 one to 0.02 during the iterative process.

$$C = 1 - it * \frac{0.98}{it_{max}} \tag{31}$$

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

$$P_{pos} = x_i | i \ is \ index \ of \ Max(end) \ sort \ (Deuc) \tag{32}$$

The Euclidean distance ($Deuc$) is computed from an average location of search space using (33).

$$Deuc_j = \sqrt{\sum_{j=1}^{d} (x_{ij} - \delta_j)^2} \tag{33}$$

The convergence of HPO is poor when the distance between the search agent and $\mu$ between consecutive iterations is large. Therefore, the hunter should look forward to the next prey once the trapped prey is hunted. This scenario is simulated in (34) and (35).

$$kbest = round(C * npop) \tag{34}$$

and

$$P_{pop} = x_i|\ i\ is\ sorted\ D_{euc}(best) \tag{35}$$

Where $n$ points to the number of search agents. At the beginning of the algorithm, *kbest* is set equal to *npop*. The hunter picks the farthest search agent (prey) and captures while steadily decreasing the *kbest* value. At the end of the HPO algorithm, the *kbest* value points to the first search agent (least distance from $\delta$). Therefore, equation (24) is replaced by (36) to locate the prey.

$$x_{ij}^{t+1} = T_{pos(j)} + (C * Z * cos(2\pi r_4) * (T_{pos(j)}^{t} - x_{ij}^{t}) \tag{36}$$

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 $r_4$ is a random variable between [0,1]. The position of hunter or prey is updated using (37) if $r_5$¡$\beta$.

$$x_{ij}^{t+1} = x_{ij}^{t} + \frac{1}{2}((2 * C * Z * P_{pos(j)} - x_{ij}^{t}) + (2(1 - C) * Z * \delta_j - x_{ij}^{t})) \tag{37}$$

Where $r_5$ refers to a random number between zero and one; $\beta$ is an adjusting factor equal to 0.1. For $r_5 < \beta$, the search agent is treated as a hunter. Otherwise, the search agent is a prey.

### C. Hybrid ALO-HPO Algorithm

The hybrid technique intends to use the exploitation feature of HPO and the exploration feature of the ALO algorithm to enrich the quality of optimal solutions for a DG placement problem. HPO algorithm supports ALO algorithm to evade the local optima trap. The ALO algorithm updates the initial population and then the HPO algorithm upgrades the optimal solution. The implementation and execution of the proposed ALO-HPO hybrid technique are presented in various steps as follows.

**ALO Operation**

1. Initialize the number of DG, population size, maximum number of iterations and boundary conditions.
2. Randomize the population size of the DG unit using (38).

$$Population = (DG_{max} - DG_{min}) * rand() + DG_{min} \tag{38}$$

3. Set iteration count ‘it’ = 0 and calculate the fitness value of MOF for the randomly generated population size.
4. Save the population size which gives the least fitness value as the best solution (present).
5. Update the ant lion’s position using (17)–(19).
6. Repeat the above steps for different positions of search agents.

**HPO Operation**

7. Initialize the number of search agents, $r_5$, and $\beta$.
8. Assign the population of ALO as an initial population of HPO.
9. Compute the fitness values for the search agent.
10. Find the individual and global best solution.
11. Update adaptive parameter (Z) and ‘C’ factor using (30) and (31).
12. For $r_5 < \beta$, compute the population size using (32) – (35) and update the position of a hunter using (27).
13. Update the position using (36), otherwise.
14. Compute the fitness value for the updated population size and position.
15. Repeat steps 13 and 14 for $it < it_{max}$.
16. Assign the updated position of HPO’s search agent to ALO.
17. Repeat the steps from 3 to 16 till $it < it_{max}$.
18. Print the best solution.

The flowchart for the hybrid ALO-HPO algorithm is shown in Fig.3.

## V. Test Results and Discussion

The proposed hybrid optimization method simulation study has been executed using MATLAB/Simulink software version 2020b. This section investigates the simulation outcomes for type I and type III DG placement in IEEE 69-bus RDPN. The simulation is performed considering the following control parameters.

- Number of iterations, $it_{max}$ - 100
- Population count (both ALO and HPO) – 30

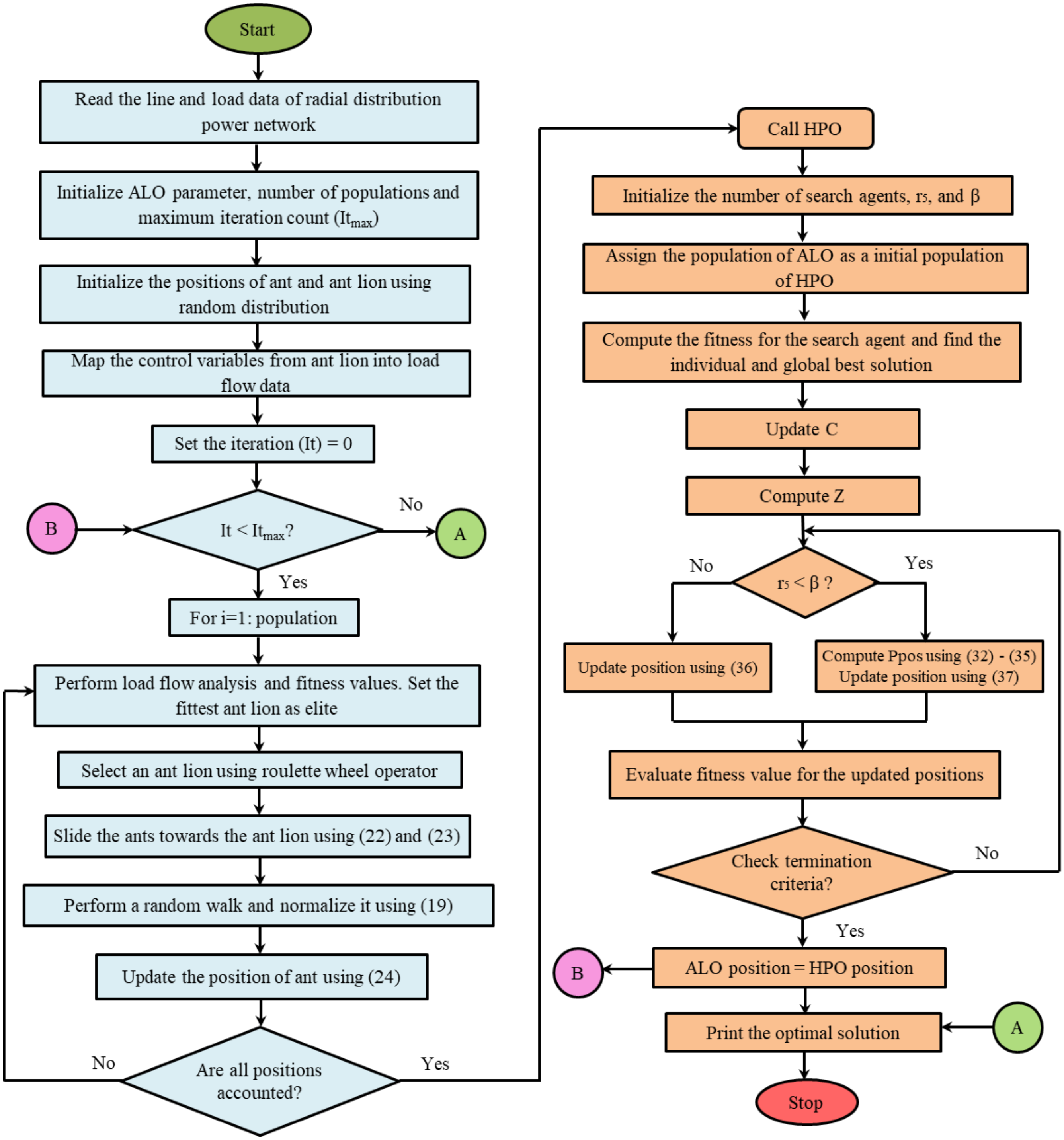

Fig. 3. Flowchart for hybrid ALO and HPO optimization algorithm

- Maximum DG capacity boundary – 2300 kW for type I DG and 3000 kVA for type III DG
- p.f. – 1 for type 1 DG and 0.866 for type III DG

The value for weightage factors ($w_1$ and $w_2$) is approximated based on the significance of $f_1$ and $f_2$. In the present work, $f_1$ is given more significance than $f_2$; hence, the value of $w_1$ chosen is greater than $w_2$. To approximate the values for

TABLE I.
CHOICE OF WEIGHTAGE FACTORS

| $w_1$ | $w_2$ | **Fitness value** |
|---|---|---|
| 0.6 | 0.4 | 0.1988 |
| 0.65 | 0.35 | 0.2199 |
| 0.7 | 0.3 | 0.2375 |
| 0.75 | 0.25 | 0.2541 |
| 0.8 | 0.2 | 0.2700 |
| 0.85 | 0.15 | 0.2857 |
| 0.9 | 0.1 | 0.2752 |
| 0.95 | 0.05 | 0.2970 |

weightage factors, the proposed hybrid method was executed for type I DG unit placement and the fitness values for MOF were computed. Table I lists the fitness value obtained for various combinations of $w_1$ and $w_2$. The values of $w_1$ and $w_2$ that result in the lowest fitness function value are picked as suitable weightage factors. From Table I , $w_1$=0.6, and $w_2$=0.4 were picked as suitable weightage factors since they provided the least fitness value.

### *A. Test Result: without DG*

Initially, the $RPL_T$ and VP of the test system before DG allocation were computed via the BFS PF assessment method. The PF was executed assuming,

- A symmetrical test system
- Base power - 100 MVA and base voltage - 12.66 kV

The PF assessment without DG placement results in the least VP of 0.9092p.u at $65^{th}$ bus and RPLT of 225 kW.

### *B. Test Result: with DG Placement*

Table II presents the optimized test results of the proposed hybrid method. The proposed technique optimizes type I and type III DG units at the $57^{th}$ bus with the capacity of 1835.38 kW and 1665.56 kVA, respectively. Following a type I and type III DG placement, the $RPL_T$ of the test system reduced from 225 kW to 71.23 kW and 20.38 kW, respectively. Figures 4 and 5 show the RPL of the 69-bus radial test system prior and after DG placement, respectively.

TABLE II.
OPTIMIZED TEST RESULTS

| **Outcome Parameter** | **Prior DG Placement** | **Type I DG** | **Type III DG** |
|---|---|---|---|
| Optimal site | - | 57 | 57 |
| Optimal size (kW/kVA) | - | 1835.38 | 1665.56 |
| $RPL_T$ (kW) | 225 | 71.23 | 20.38 |
| $V_{min}$ (p.u.) | 0.9092 | 0.9776 | 0.9843 |

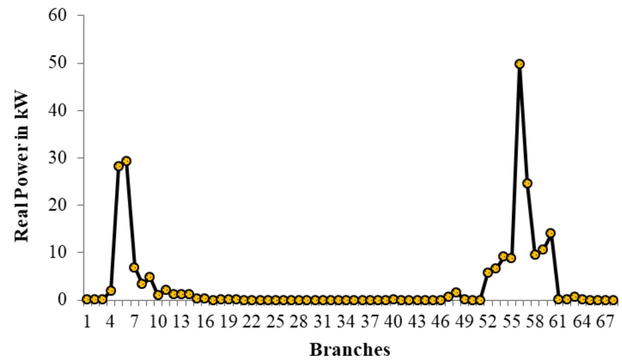


Fig. 4. RPL of 69-bus test system prior to DG placement

At the same time, the optimized accommodation of type I DG has improved the $V_{min}$ from 0.9092p.u to 0.9776p.u. And, type III DG placement has improved $V_{min}$ to 0.9843p.u. The test system has seen 0.0684p.u and 0.075p.u improvement in $V_{min}$ (base case) after type I and type III DG placement, respectively. Figures 6 and 7 exhibit the VP of 69-bus radial DS preceding and after the DG placement, respectively. Referring to Table II , type III DG placement produced a superior outcome than type I since type III DG injects reactive power besides real power supply. In addition, the suggested hybrid methodology took 10 and 12 iterations to converge to an optimal solution for type-I and type-III DG placement, respectively. Figure 8 illustrates the convergence characteristic of the hybrid ALO-HPO optimization method.

The potency level of the outcome obtained by the proposed hybrid methodology verified with the outcome of the popular methodology cited in the literature. Tables III and IV present the comparative results of different optimization methods. The comparison was quantified in terms of $RPL_T$ reduction and $V_{min}$. For type I DG placement, the suggested

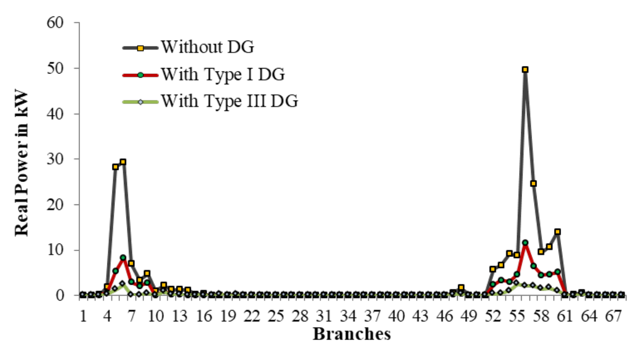


Fig. 5. RPL of 69-bus test system after DG placement

TABLE III.
COMPARISON OF TEST RESULTS: TYPE I DG ACCOMMODATION

| Parameter | Optimization Technique | | | | |
|---|---|---|---|---|---|
| | Classical DE [18] | MRFO [19] | WOA [20] | SSA [11] | Proposed |
| Optimal Position | 61 | 61 | 61 | 31 | 57 |
| Capacity (kW/kVA) | 1872.71 | 1872.70 | 1872.8 | 1870.19 | 1835.38 |
| $RPL_T$ (kW) | 83.22 | 83.22 | 83.2 | 163.57 | 71.23 |
| Power loss reduction (%) | 63.01 | 63 | 63.02 | 27.30 | 68.34 |
| $V_{min}$ (p.u.) | 0.9683 | - | 0.9683 | 0.9223 | 0.9776 |

TABLE IV.
COMPARISON OF TEST RESULTS: TYPE III DG ACCOMMODATION

| Parameter | Optimization Technique | | | |
|---|---|---|---|---|
| | GA [10] | CSA [2] | WOA [20] | Proposed |
| Optimal Position | 61 | 61 | 61 | 57 |
| Capacity (kW/kVA) | 2155.6 | 2300 | 2239.48 | 1665.56 |
| $RPL_T$ (kW) | 38.45 | 52.60 | 23.15 | 20.38 |
| Power loss reduction (%) | 82.90 | 76.60 | 89.71 | 90.94 |
| $V_{min}$ (p.u.) | - | - | 0.9725 | 0.9843 |

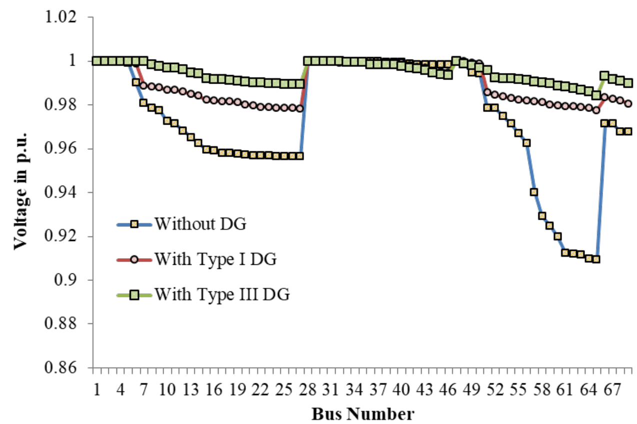


Fig. 7. Voltage magnitude of 69-bus radial DS after DG inclusion

hybrid optimization method has cut down $RPL_T$ by 68.34% from the base case value. Classical DE, MRFO, WOA and SSA methods prevailed in 63.01%, 63%, 63.02% and 27.30% of $RPL_T$ reduction, respectively. Adding to $RPL_T$ reduction, the proposed methodology also provided better voltage profile enrichment than other methods. Likewise, for type III

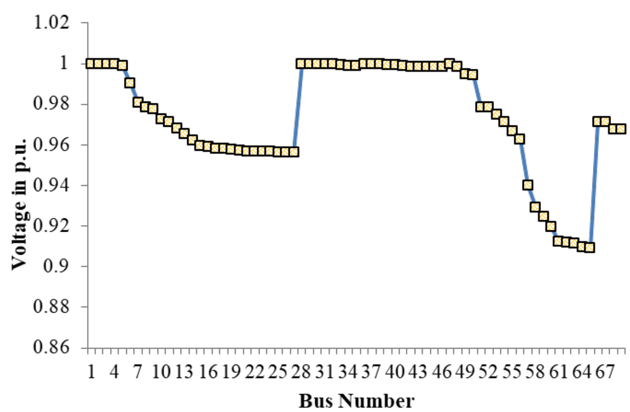


Fig. 6. Voltage magnitude of 69-bus radial DS prior to DG placement

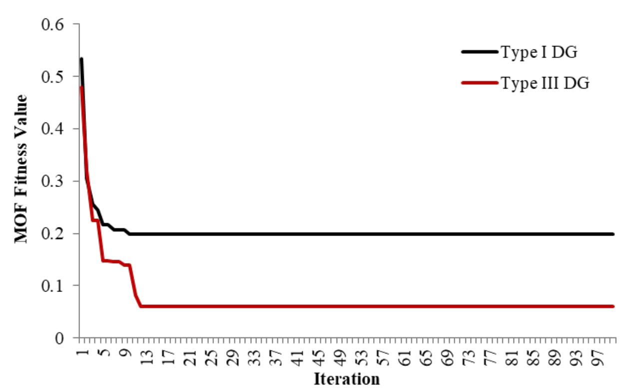


Fig. 8. Convergence curve of proposed ALO-HPO algorithm for IEEE 69 bus radial DS

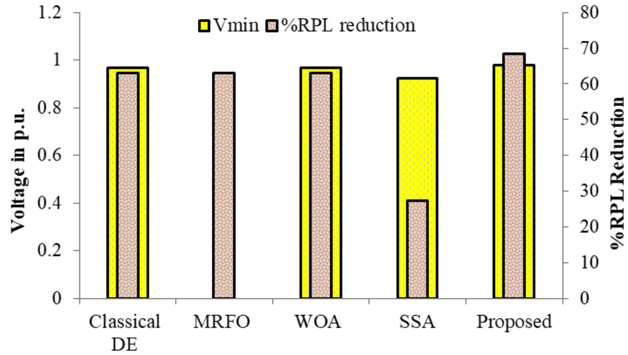


Fig. 9. Graphical representation of comparative results for Type I DG placement

DG allocation, the proposed hybrid methodology, GA, CSA and WOA accomplished 90.94%, 82.9%, 76.6% and 89.71%, respectively. Figures 9 and 10 present the graphical representation of comparative outcome.

## VI. Conclusion

In this study, an effort has been made to propose a new hybrid optimization method to optimize Type-I and Type-III DG into a radial DPN. The proposed hybrid optimization method has been developed using ALO and HPO algorithms. The performance of the hybrid technique was analyzed on IEEE 69 bus RDS for RPL minimization and voltage profile enhancement. The optimized DG Type-I and Type-III integration has yielded 68.34% and 90.94% RPL reduction with significant voltage enhancement. Furthermore, to investigate the level of simulation outcome of the proposed hybrid technique, the test results were compared with other methods keeping RPL reduction and $V_{min}$ as comparison metrics. The comparative outcome exhibited the dominance of the proposed novel hybrid method over other methods. Also, the proposed hybrid methodology could be recommended to optimize FACTS devices in distribution systems.

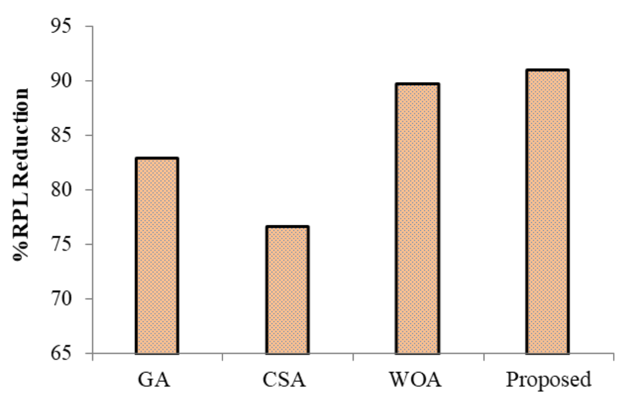


Fig. 10. Graphical representation of comparative results for Type III DG placement

## Conflict of Interest

The authors have no conflict of relevant interest to this article.

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