DOI: 10.36108/ujees/2202.40.0132

UNIOSUN Journal of Engineering and Environmental Sciences. Vol. 4 No. 1. March. 2022

Single and Multiple Placements of Different DG Types On the Power Distribution System

Oladepo, O., Awofolaju, T.T. and Lasisi, H.O.

Abstract: Integration of distributed generation on power distribution system impacts the network for improved voltage stability and power quality. However, inaccurate sizing and placement of the energy sources can worsen the network performance. This paper proposes a hybrid particle swarm optimization/whale optimization algorithm for the optimal placement of different distribution generation types on a power network. Standalone metaheuristics are efficient and robust optimization tools but are mostly challenged with convergence and sub-optimal solutions. The exploration potential of particle swarm optimization with the selection of higher inertial weight is annexed with the exploitation phase of the whale optimization algorithm. The proposed technique is verified on IEEE 33 – bus distribution system. Results show 86.12% and 89.84% improvement in voltage deviation for Type I and Type III DG injection respectively. Besides, the convergence is achieved in less than 50 iterations compared to standalone methods.

Keywords: Particle swarm optimization, Whale optimization algorithm, Distributed generation, Distribution network, Voltage deviation and power loss.

I. Introduction

Distributed generations (DGs) such as photovoltaic and small hydropower are embedded in an electrical distribution system (DS) to supply power within the vicinity of generation. The energy resources to accomplish power generation are known as distributed energy resources (DER). It performs a significant role in modern electrical power networks. Researchers had predicted that DG would take a dominant percentage of all new generations [1]. To tackle the rapidly increasing energy demand, integrating distributed generators into distribution systems has become a more economical alternative to traditional solutions such as transmission expansion, network reconfiguration and substation upgrades. DG can be embedded in DSs to improve the system's voltage profiles and power quality. It also provides ancillary services like spinning reserve, reactive power compensation, and frequency control [2]. Besides, there is the ease of rural electrification because power is generated at the point of use. The economic benefits are reduction in power transmission, distribution maintenance, operating cost due to the decline in line losses, reduction in health challenges charges due to polluted environmental conditions, reduction in fuel cost and distributed power tariff. Ecological benefits include a decrease in the rate of emission of dangerous gasses toxic to plants and animals [3].

Oladepo, O., Awofolaju, T.T. and Lasisi, H.O. (Department of Electrical and Electronic Engineering, Osun State University, Osogbo, Osun State, Nigeria)
Corresponding author: ooladepo@yahoo.com.
Phone Number: +2347035665642
Submitted: 01-02-2022
Accepted: 26-03-2022

Despite benefits, poorly sized DG units and improperly operated utility connected energy sources lead to reverse power flow, excessive losses, increased network capital and operating costs, demand-supply imbalance, the decline in power quality and subsequent feeder overloads [4,5]. In [6], the most significant benefit of DG application in DS depends on the technical selection of the optimal site and capacity of DG.

Different researchers have introduced several methods, objectives and constraints. Techniques used include the classical or numerical method, as presented in [7,8]. The analytical approach, as shown by [9–14]. Another technique used is the heuristic approach, as proposed in the works of [15,16]. Some researchers also used mixed solution methods involving more than one approach, as shown by [17,18]. These methods have also presented different objectives varying from single to multiple objectives with varying optimization constraints. The analytical method offers the benefit of short computation time, but as the problem becomes complex, the assumption for simplifying the problem may override the accuracy of the solution [19]. The numerical method proved effective with a limited number of busses [20]. Linear programming is proficient in tackling optimization problems in DS, such as evaluating the optimal capacity of DG units [21]. However, it can only apply to linear objective functions, massive decision variables and high computation time [20,22].

The development of the metaheuristic algorithm solves some of the problems associated with conventional analytical and numerical methods. However, they still have significant drawbacks in the inability to guarantee an optimal solution. A tabu search optimization algorithm was presented in [23] for the best placement of DG to minimize the annual cost of energy and voltage profile. The results show improvement in the performance indicator selected. However, it is challenged with high time-consumption. The genetic algorithm is also robust in complex problems and has a higher degree of global optimum solutions. However, it is challenged by substantial computation time. To overcome the shortcomings in metaheuristics, two significant properties need to be considered: exploration and exploitation properties. Exploration is the ability to extensively navigate and search the whole problem space while exploitation determines the algorithm convergence speed to fit the best solution [24,25]. However, most metaheuristic algorithms do not possess the ability to balance both properties. Hence, the need to hybridize two metaheuristics to take complementary advantages of the combining algorithms to solve optimization problems [26,27]. In [28], particle swarm optimization (PSO) is applied for the sizing and placement of fuel cells while considering cost, voltage profile and emission as objective functions. However, the approach is challenged with the inability to balance exploration and exploitation property. The PSO is sound in its exploration phase but weak in the exploitation phase, with premature trapping into the local minimum. The whale optimization algorithm (WOA) is robust and can handle a complex optimization problem. However, it could be challenged with a low convergence. Therefore, it can be enhanced by hybridizing it with other meta-heuristics and adjusting its coefficient and random vectors in both the exploration and exploitation phases.

In this study, a hybrid of PSO and WOA algorithms (PSOWOA) is presented to balance two crucial properties (exploration and exploitation) to improve convergence and time. A new optimization technique based on a hybrid PSO and WOA algorithm for sitting and sizing distribution generation on the distribution network is presented for voltage minimization and power loss reduction. The paper is structured as follows: Section 1 presents the introduction with the literature review, Section 2 presents the material and method, Section 3 presents the results and discussion. Finally, section 4 presents the conclusion.

II. Materials and Method

The optimization programming is coded in Matlab m-file for computation and visualization. The algorithm is presented as follows;

A. Particle Swarm Optimization

PSO is a stochastic population-based optimization algorithm that mimics the social activities of fish or herd of birds. Swarm behaviour is modelled based on simple guiding rules using schools of fishes and the swarm of a bird. Velocity modification for each agent can be expressed by the following equations [29]:

$$V_{ij}^{k+1} = wv_{ij}^{k+1} + c_1 rand_1 \times \left(pbest_{ij} - x_{ij}^k \right) + c_2 rand_2 \times \left(gbest - x_{ij}^k \right) \quad (1)$$

Where V_i^{k+1} is agent *i* velocity at iteration *k*, w is the weight of maximum and minimum value ($w_{\max} = 0.9, w_{\min} = 0.4$), c_1 and c_2 are acceleration coefficients, rand is a random number between 0 and 1, x_i^k and x_j^k are agent *i* and agent *j* current position of at iteration *k* respectively, $pbest_i$ is agent *i* pbest, and $gbest$ is gbest of the group. The position is updated according to the following expression:

$$x_i^{k+1} = x_i^k + v_i^{k+1} \quad (2)$$

The weighting function is expressed as:

$$w = w_{\max} - Itre\left(w_{\max} - w_{\min}\right) / Itre_{\max} \quad (3)$$

Where $w_{\max}$ and $w_{\min}$ are maximum and minimum weights, $Itre_{\max}$ and $Itre$ are maximum and current iteration respectively. The movement of the particle is illustrated in Figure 1.

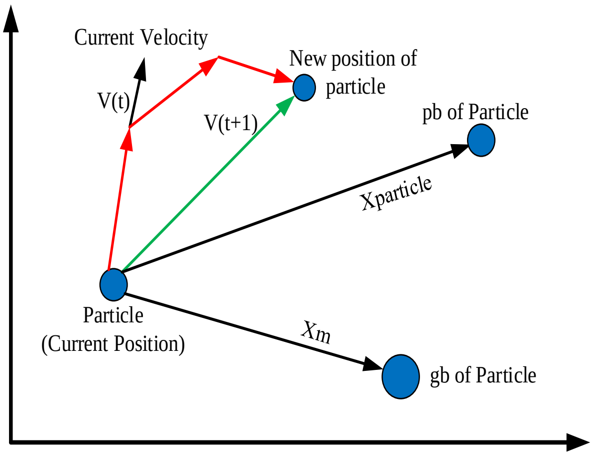

Figure 1: Movement of PSO particles

B. Whale Optimization Algorithm

The algorithm's inspiration is from the hunting pattern of humpback whales and its model is made up of the following stages: Encircling prey, bubbling net and search for prey [30]. Their track to prey (krill and small fishes) is illustrated in Figure 2.

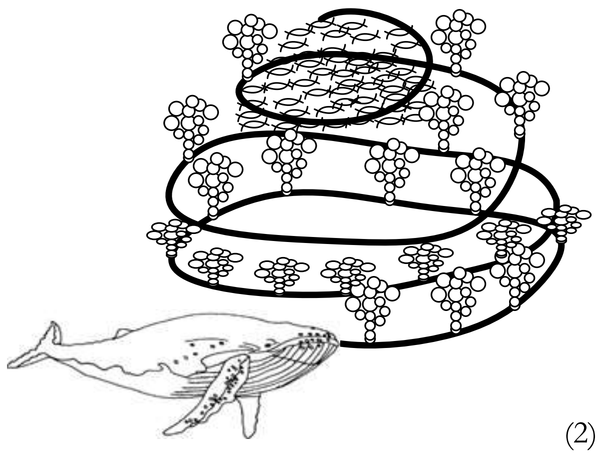

Figure 2: Bubbling-net tracking behaviour of humpback whales [30].

The humpback whale recognizes the prey's location in pray encircling and circles it. The behaviour is mathematically represented as follows [31]:

$$\vec{D} = \left| \vec{C}\vec{X}^*(t) - \vec{X}(t) \right| \quad (4)$$

$$\vec{X}(t+1) = \vec{X}^*(t) - \vec{A}\vec{D} \quad (5)$$

Where t is the present iteration, $\vec{A}$ and $\vec{C}$ are both coefficient vector, $\vec{X}*$ is the current position vector of the optimal solution so far, $\vec{X}$ represent the positional vector, | | is the modulus of the value consisting of elements product. The position $\vec{X}*$ is updated at each iteration when a better value is obtained. The vectors $\vec{A}$ and $\vec{C}$ are computed as follows:

$$\vec{A} = 2\vec{a}.\vec{r} - \vec{a} \tag{6}$$

$$\vec{C} = 2.\vec{r} \tag{7}$$

Where $\vec{a}$ decreases linearly from 2 to 0 for the first iteration to maximum iteration and $\vec{r}$ is a randomly selected vector of value [0,1].

The bubble-net prey searching method takes the exploitation phase of the algorithm and can be mathematically modelled as shrinking encircling prey and spiral position updating models. In the shrinking encircling model, the mechanism is achieved by the modification of the parameter $\vec{a}$ in the coefficient $\vec{A}$.

A spiral equation is then developed between the position of the whale and prey to replicate the helix-shaped navigation of the humpback whales as [31]:

$$\vec{X}(t+1) = \vec{D}'.e^{bl}\cos(2\pi l) + \vec{X}^*(t) \tag{8}$$

Where $\vec{D}' = \left|\vec{X}*(t) - \vec{X}(t)\right|$ and stands for the distance between an agent whale to the prey. b is a constant of the logarithmic spiral shape, l takes a random number in [-1,1]. The humpback whales simultaneously navigate the search space for prey within the shrinking circle and spiral-shaped route. The concurrent behaviour is modelled by assuming a probability of 0.5 swings between the shrinking encircling and the spiral updating model. This is mathematically defined as [31]:

$$\vec{X}(t+1) = \begin{cases} \vec{X}^*(t) - \vec{A}.\vec{D} & if \quad p < 0.5 \\ \vec{D}' \quad e^{bl}.\cos(2\pi l) + \vec{X}^*(t) & if \quad p \geq 0.5 \end{cases} \tag{9}$$

Where p denotes the random number in [0,1]. The search for prey takes the exploration phase of the WOA and vector $\vec{A}$ is also adapted for modification towards reaching the prey. The model is mathematically outlined as follows:

$$\vec{D} = \left|\vec{C}.\vec{X}_{rand} - \vec{X}\right| \tag{10}$$

$$\vec{X}(t+1) = \vec{X}_{rand} - \vec{A}.\vec{D} \tag{11}$$

Where $\vec{X}_{rand}$ represents the random position vector selected from the population at the current iteration.

C. Hybrid Particle Swarm Optimization-Whale Optimization Algorithm

The hybrid PSOWOA combines the PSO social swarm tracking and thinking capability with the WOA locally searching skill. Both algorithms are initialized at the same time. PSO is activated in its exploration phase and catalyzes with high inertial weight to reach its maximum tracking in the phase. The exploitation phase of the WOA finishes up the tracking initiated by PSO to obtain a global optimum. The problem to solve consists of two parts. The first is to solve for the optimal location of DG and secondly the optimal sizing.

i. Problem Formulation

The objective function considered is to minimize the power loss and voltage deviation. The decision variables are the sizing and location of the DG. The power loss in the system is calculated and computed as follows:

$$P_{ik\_loss} = \frac{R_{ik}\left(P_k^{\ 2} + Q_k^{\ 2}\right)}{(V)^2} \tag{12}$$

Where R_{ik} is the line resistance between bus *i* and *k*, P_k and Q_k are the real and reactive power flow and *V* is the terminal voltage. The objective function is to minimize the voltage deviation is expressed as:

$$V_{ik\Delta} = \sum_{i=1}^{k}\left(V_{ref} - V_k\right) \quad (13)$$

Where $V_{ik\Delta}$ is the voltage deviation between bus *i* and *k*. V_{ref} is the reference voltage and V_k is the voltage at bus *k* at the receiving end. The constraints considered are the load balance constraint, voltage limits, renewable generation constraints, thermal and other limits. The power balance equations should be fulfilled as follows:

$$\left.\begin{aligned} P_{Gni} - P_{Dni} - V\sum_{j=1}^{N} V_{nj}Y_{nj}\cos\left(\delta_{ni} - \delta_{nj} - \theta_{nj}\right) = 0 \\ Q_{Gni} - Q_{Dni} - V\sum_{j=1}^{N} V_{nj}Y_{nj}\cos\left(\delta_{ni} - \delta_{nj} - \theta_{nj}\right) = 0 \end{aligned}\right\} \quad (14)$$

Where n_i = 1,2,…, n_n P_{Gni} and Q_{Gni} the real and reactive power injected at bus *i*, P_{Dni} and Q_{Dni} are real and reactive power demand at bus *i*

The generator voltage and the load/bus voltage maintain the same level and in connection with power flow along the line. The voltage rise is proportional to the power flow. Therefore, the increase in power flow significantly impacts voltage level because the resistive elements on the DN are higher than the transmission line. Hence, the voltage has to be maintained with the statutory limit at each bus:

$$V_{ni}^{\min} < V_{ni} < V_{ni}^{\max} \quad (15)$$

For the distribution network, the value adopted for this work ranges from 0.95 to 1.05. $V_{ni}^{\min}$ is the minimum voltage at bus *i*, and $V_{ni}^{\max}$ is the maximum voltage at bus *i*.

The DG size is inherently limited due to available energy resources in a given location. It is significant to maintain the capacity between the minimum and maximum values.

$$P_{Gni}^{\min} \le P_{Gni} \le P_{Gni}^{\max} \quad (16)$$

Where $P_{Gni}^{\min}$ and $P_{Gni}^{\max}$ are the minimum power and maximum power injected at bus *i*. (13)

The procedure for implementing the PSOWOA optimization grid connected DG system is shown in Algorithm 1.

Algorithm 1. PSOWOA implementation for DG at static load condition

1. **Read**: load data, line data of the system and read renewable metrological data
2. **Store:** the agent number, MaxCycle and set matric format for the final solution
   Agent population = 100, MaxCycle is the maximum cycle or iteration (500)
3. **Set:** the generator and system constraints
4. **Initialization:** population is randomly generated:
   The decision variables are the location and sizing of DG.
   $X_i = \left(\left(upperbound - lowerbound\right).*rand\left(1,dim\right) + lowerbound\right),$
   $X_i = \left(X_i^1,\ldots X_i^{dim},\ldots X_i^n\right)$, *for i* = 1,2…*N*
   Where $X_i^{\dim}$ denotes the position of *ith* agent in the *dimth* dimension, *n* is the dimension of space. *N* is the bus number.
5. **Set:** zero the counter
6. **Calculate:** power flow analysis for DG connected power network
7. **Evaluate:** objective functions for each search agent using Equation (12) and (13)
Update: fitness function to determine the best between the previous objective value and the present value to obtain the Pbest and Gbest
8. **Update:** velocity and position using Equation (1) and (2) from PSO
9. **Update:** position using Equation (8) and (9) from WOA
10. **Generate:** the updated population for the next iteration
11. **Cycle** = 1
12. **Repeat:** step 6 to 13
13. **Store:** the best solution so far
14. **Cycle** = Cycle + 1
15. Until, Cycle = MaxCycle

16. **Print:** Final solution

Different types of DGs are categorized as [32], however, for this study, only type I and type III are considered for analysis and performance evaluation. The DG types are as follows:

Type I: Only real power injecting DG, examples are photovoltaic and fuel cells

Type II: Only reactive power injecting DG, an example is a synchronous condenser

Type III: Both real and reactive power injecting DG, an example is synchronous machines

Type IV: Real power injection DG but consumes reactive power, an example is an induction generator in wind generation.

III. Results and Discussion

The performance of the proposed hybrid PSOWOA optimization algorithm is tested on the standard IEEE 33 – bus distribution feeder being a commonly proposed feeder in the literature. Figure 3 shows the thirty-three bus system. It contains the main feeder, three laterals and thirty-two branches. The total loads are 3.72 MW and 2.3MVAr. The substation voltage is 12.66kV at the base power of 100MWA [33]. The system data are referenced as [34]. Table 1 shows the network performance indicators in terms of voltage and power loss due to Type I and Type III DG installation.

With one location of DG and hybrid of Type 1 & III on the IEEE 33 – bus feeder, the optimal capacity and location obtained using PSOWOA are calculated. The best site for the installation of the Type 1 DG is bus 6, and its capacity evaluated is 2551kW.

A decrement in power losses from 243.60kW to 123.96kW resulted in a 49.14% power loss reduction. The lowest voltage at bus 18 for the case without DG increased from 0.9131 p.u. to 0.9686 p.u at bus 7. A comparison of the proposed technique in terms of voltage improvement and power loss reduction with PSO and WOA simulated under the same condition is shown in Table 2. Moreover, Figure 4 shows the effects of one DG and hybrid PVSHP installation on the feeder.

The Type III DG operates at a 0.8 power factor to yield a better loss reduction due to reactive power generation However, Type I DG has the highest impact in voltage improvement. The combination of Type I & III in hybrid configuration results in a slight improvement in loss reduction.

The number of DG locations is increased to two and the effects on the network were investigated using the proposed PSOWOA technique. Figure 5 shows the voltage profile on the IEEE 33-bus distribution system with the installation of two DGs.

Results show that buses 12 and 30 are the optimal locations for the Type I DG, with 1000kW and 1044kW as the optimal capacity respectively. The power losses reduced to 92.10KW with 62.19 percentage reduction and 86.12 percent voltage improvement. With the integration of Type III DG, DG's sizes are 1057kVA and 1328kVA, which are installed on buses 9 and 30 respectively. The percentage loss reduction is 85.99, with 89.84 corresponding voltage improvement, as shown in Table 3.

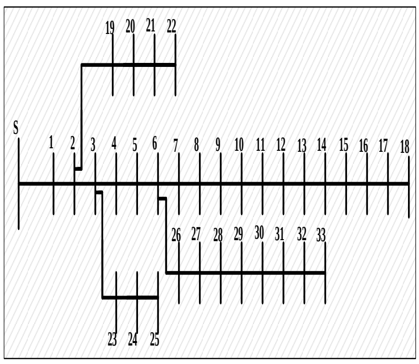

Figure 3: IEEE 33 bus test system based on hybrid power system

Table 1: Voltage Magnitude and Power Loss for IEEE 33 – Bus Distribution Feeder for One DG Location

Items	Without DG	With DG One DG Type I	With DG One DG Type III	Hybrid Type 1&III PVSHP
Total losses (kW)	243.60	123.96	78.94	76.53
Loss reduction (%)	…	49.11	67.59	68.58
Min. voltage	0.9131	0.9686	0.9720	0.9712
Max. voltage	0.9965	1.0110	1.0217	1.0341
Bus no		6	30	29
Power Factor		Unity	0.8	0.6
Size(kW)		2551		
Size(kVA)			1888	2046
Feeder voltage deviation (pu)	1.7009	0.1709	0.2526	0.2389
Voltage Improvement. (%)		89.95	85.15	85.95

Table 2: Comparison of the Proposed Method with Other Techniques

DG.	Method	DG installed Size (kVA/PF)	Bus	% Loss reduction	Minimum voltage	Maximum voltage	% Voltage improvement
Type I	PSO	2556/1	6	47.43	0.9622	0.9965	88.19
	WOA	2555/1	9	48.25	0.9635	1.0021	86.67
	Proposed	**2551/1**	**6**	**49.11**	**0.9686**	**1.0110**	**89.95**
Type III	PSO	1890/0.8	30	63.94	0.9675	1.0921	83.87
	WOA	1883/0.8	31	65.42	0.9646	1.0064	84.20
	Proposed	**1888/0.8**	**30**	**67.59**	**0.9720**	**1.0217**	**85.15**

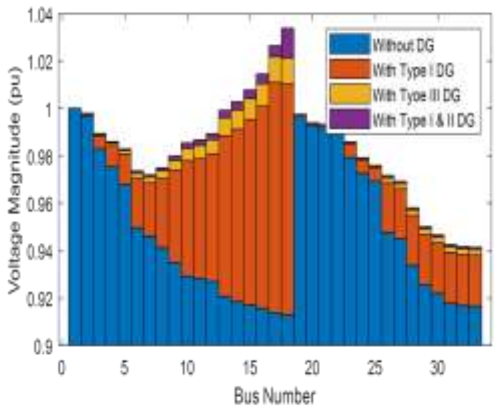

Figure 4: IEEE 33 – bus distribution system voltage magnitude with one DG

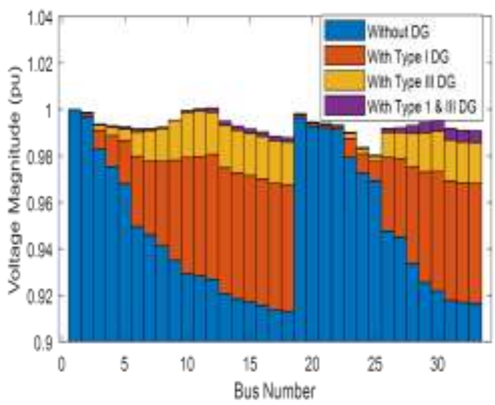

Figure 5: IEEE 33 – bus distribution system voltage magnitude with two DGs

A comparison of the proposed PSOWOA algorithm with other techniques shows the proficiency of the proposed algorithm in terms of voltage improvement and power loss reduction, as detailed in Table 4.

The multiple locations on IEEE 33 – bus distribution system considers DG of lesser capacities being a medium size network. The optimal size and location are obtained through PSOWOA and summarized in Table 5.

The convergence property of the hybrid technique is illustrated in Figure 6. The figure establishes the capability of the proposed hybrid algorithm in yielding efficient results with improved convergence compare to PSO and WOA. It is observed that the convergence in hybrid PSOWOA is achieved earlier than that of PSO and WOA in less than 50 iterations

.

Table 3: Voltage Magnitude and Power Loss for IEEE 33 - Bus Distribution Feeder for two DG Locations

Items	Without DG	With DG Two DG Type I	 Type III	With hybrid system Type I & III
Total losses (kW)	243.60	92.10	34.14	33.98
Loss reduction (%)	…	62.19	85.99	86.05
Min. voltage	0.9131	0.9672	0.9729	0.9835
Max. voltage	0.9965	0.9978	0.9982	0.9968
Bus no		12, 30	9, 30	12, 29
Power Factor		Unity	0.8	0.6
Size(kW)		1000, 1044		
Size(kVA)			1057, 1328	1046, 1409
Feeder voltage deviation (pu)	1.7009	0.2365	0.1728	0.1554
Voltage Improvement. (%)		86.12	89.84	90.86

Table 4:Comparison of the proposed method with other techniques

DG	Method	DG installed Size (kVA/PF)	Bus	% Loss reduction	Minimum voltage	Maximum voltage	% Voltage improvement
Type 1	PSO	1085/1 1302/1	10 29	60.19	0.9634	0.9830	85.19
	WOA	1053/1 1025/1	12 31	60.96	0.9689	0.9978	85.74
	Proposed	**1000/1** **1040/1**	**12** **30**	**62.19**	**0.8665**	**0.9897**	**86.12**
Type III	PSO	1093/0.8 1304/0.8	10 29	83.67	0.9745	0.9961	88.70
	WOA	1090/0.8 1078/0.8	10 30	83.99	0.9757	0.9979	89.10
	Proposed	**10570.8** **1328/0.8**	**9** **30**	**85.99**	**0.8665**	**0.9964**	**89.84**

Table 5: Voltage magnitude and power loss for IEEE 33 – bus distribution feeder for multiple locations of DG

Items	Without DG	With DG Multiple DG Type I	 Type III	With hybrid system Type I & III
Total losses (kW)	243.60	83.04	31.38	20.95
Loss reduction (%)	…	65.91	87.12	91.40
Min. voltage	0.9131	0.9739	0.9931	0.9686
Max. voltage	0.9965	0.9986	1.0000	1.0250
Bus no		6, 16, 12, 24, 25, 27, 32	23, 24, 30, 6, 16, 7, 31	30, 7, 24, 18, 27, 13, 32
Power Factor		Unity	0.8	0.6
Size(kVA)		418, 530, 582, 415, 481, 569, 495	460, 424, 531, 551, 591, 596, 537	550, 466, 557, 408, 585, 434, 598
Feeder voltage deviation (p.u)	5.361	0.680	0.350	0.190
Voltage Improvement. (%)		87.32	93.47	96.46

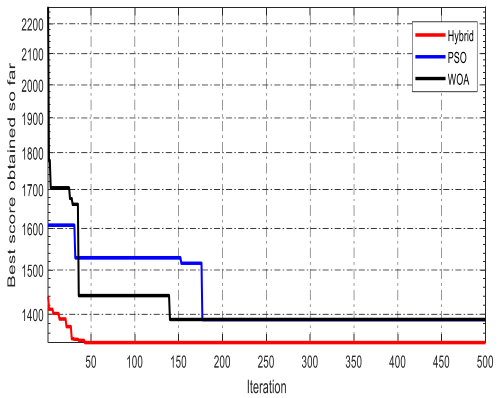

Figure 6: IEEE 33 – bus distribution system comparison of convergence property

IV. Conclusion

The grid-connected single and multiple distributed generation performance is formulated as an optimization problem considering both the equality and inequality network constraints of the connected systems. The proposed hybrid PSOWOA for performance optimization is tested on IEEE 33 - bus systems to confirm its proficient performance. The results conspicuously demonstrate the hybrid PSOWOA algorithm's capability to yield a better voltage improvement and power loss reduction compared to standalone techniques. The percentage improvement in voltage deviation for Type I and Type III single DG injection is 89.95 and 85.15 respectively, while 86.12 and 89.84 for the two DG injections. Also, the convergence in hybrid PSOWOA is achieved in less than 50 iterations compared to standalone approaches that converge in more than 100 iterations. Hence the proposed hybrid PSOWOA proffers an effective solution and shorter convergence time.

References

[1] El-Khattam, W. and. Salama, M.M.A. “Distributed Generation Technologies, Definitions and Benefits”, *Electr. Power Syst. Res.*, vol. 71, no. 2, 2004, pp. 119–128, doi: 10.1016/j.epsr.2004.01.006.

[2] Muttaqi, K.M., Le, A.D.T., Negnevitsky, M. and Ledwich, G. “An Algebraic Approach for Determination of DG Parameters to Support Voltage Profiles in Radial Distribution Networks”, *IEEE Trans. Smart Grid*, vol. 5, no. 3, 2014, pp. 1351–1360, doi: 10.1109/TSG.2014.2303194

[3] Elmubarak, E.S. and Ali, A.M. “Distributed Generation: Definitions, Benefits, Technologies & Challenges”, *Int. J. Sci. Res.*, vol. 5, no. 7, 2016, pp. 1941–1948, doi: 10.21275/v5i7.art2016445.

[4] Atwa, Y.M., El-Saadany, E.F., Salama, M.M.A. and Seethapathy, R. “Optimal Renewable Resources Mix for Distribution System Energy Loss Minimization”, *IEEE Trans. Power Syst.*, vol. 25, no. 1, 2010, pp. 360–370, doi: 10.1109/TPWRS.2009.2030276.

[5] Georgilakis, P.S. and Hatziargyriou, N.D. “Optimal Distributed Generation Placement in Power Distribution Networks: Models, Methods, and Future Research”, *IEEE Trans. Power Syst.*, vol. 28, no. 3, 2013, pp. 3420–3428, doi: 10.1109/TPWRS.2012.2237043.

[6] Soudi, S. “Distribution System Planning With Distributed Generations Considering Benefits and Costs”, *Int. J. Mod. Educ. Comput. Sci.*, vol. 5, no. 10, 2013, pp. 45–52, doi: 10.5815/ijmecs.2013.09.07.

[7] Rau, N.S. and. Wan, Y.H “Optimum Location of Resources in Distributed Planning”, *IEEE Trans. Power Syst.*, vol. 9, no. 4, 1994, pp. 2014–2020, doi: 10.1109/59.331463.

[8] Ochoa, L.F. and Harrison, G.P. “Minimizing Energy Losses : Optimal Accommodation and Smart Operation of Renewable Distributed Generation”, *IEEE Trans. power Syst.*, vol. 26, no. 1, 2011, pp. 198–205.

[9] Wang, C., Member, V., Nehrir, M.H. and Member, S. “Analytical Approaches for Optimal Placement of Distributed Generation Sources in Power Systems”, *IEEE Trans. power Syst.*, vol. 19, no. 4, 2004, pp. 2068–2076.

[10] Acharya, N., Mahat, P. and Mithulananthan, N. “An Analytical Approach for DG Allocation in Primary Distribution Network”, *Int. J. Electr. Power Energy Syst.*, vol. 28, no. 10,

2006, pp. 669–678, doi: 10.1016/j.ijepes.2006.02.013.

[11] Gözel, T. and. Hocaoglu, M.H. "An Analytical Method for the Sizing and Siting of Distributed Generators in Radial Systems", *Electr. Power Syst. Res.*, vol. 79, no. 6, 2009, pp. 912–918, doi: 10.1016/j.epsr.2008.12.007.

[12] Hung, D.Q., Mithulananthan, V., Bansal, R.C. and Member, S. "Analytical Expressions for DG Allocation in Primary Distribution Networks", *IEEE Trans. Energy Convers.*, vol. 25, no. 3, 2010, pp. 814–820.

[13] Hung, D.Q., Mithulananthan, N. and Bansal, R.C. "Analytical Strategies for Renewable Distributed Generation Integration Considering Energy Loss Minimization", *Appl. Energy*, vol. 105, 2013, pp. 75–85, doi: 10.1016/j.apenergy.2012.12.023.

[14] Hung, V., Mithulananthan, N. and Lee, K.Y. "Optimal Placement of Dispatchable and Nondispatchable Renewable DG Units in Distribution Networks for Minimizing Energy Loss", *Int. J. Electr. Power Energy Syst.*, vol. 55, 2014, pp. 179–186, doi: 10.1016/j.ijepes.2013.09.007.

[15] Bahmanifirouzi, B., Farjah, E., Niknam, T. and Farsani, E.A. "A New Hybrid Hbmo-sfla Algorithm for Multi-objective Distribution Feeder Reconfiguration Problem Considering Distributed Generator Units", *Iran. J. Sci. Technol. - Trans. Electr. Eng.*, vol. 36, no. E1, 2012, pp. 51–66, doi: 10.1002/etep

[16] Vinothkumar, K. and Selvan, M.P. "Fuzzy Embedded Genetic Algorithm Method for Distributed Generation Planning", *Electr. Power Components Syst.*, vol. 39, no. 4, 2011, pp. 346–366, doi: 10.1080/15325008.2010.528533.

[17] Vinothkumar, K. and Selvan, M.P. "Distributed Generation Planning: A New Approach Based on Goal Programming", *Electr. Power Components Syst.*, vol. 40, no. 5, 2012, pp. 497–512, doi: 10.1080/15325008.2011.647238.

[18] Afzalan, M. and Taghikhani, M.A. "DG Placement and Sizing in Radial Distribution Network Using PSO&HBMO Algorithms", *Energy and Power*, vol. 2, no. 4, 2012, pp. 61–66, doi: 10.5923/j.ep.20120204.04.

[19] Viral, R. and Khatod, D.K. "An Analytical Approach for Sizing and Siting of DGs in Balanced Radial Distribution Networks for Loss Minimization", *Int. J. Electr. Power Energy Syst.*, vol. 67, 2015, pp. 191–201, doi: 10.1016/j.ijepes.2014.11.017.

[20] Abdmouleh, Z., Gastli, V., Ben-Brahim, L., Haouari, M. and Al-Emadi, N.A. "Review of Optimization Techniques Applied for the Integration of Distributed Generation from Renewable Energy Sources", *Renew. Energy*, vol. 113, 2017, pp. 266–280, doi: 10.1016/j.renene.2017.05.087.

[21] Keane, A. and Malley, M.O. "Optimal Allocation of Embedded Generation on Distribution Networks", *IEEE Trans. Power Syst.*, vol. 20, no. 3, 2005, pp. 1640–1646, doi: 10.1109/TPWRS.2005.852115.

[22] Rezaee Jordehi, A. "Allocation of Distributed Generation Units in Electric Power Systems: A Review", *Renew. Sustain. Energy Rev.*, vol. 56, 2016, pp. 893–905, doi: 10.1016/j.rser.2015.11.086.

[23] Rugthaicharoencheep, N., Lantharthong, T., Ratreepruk, A. and Ratchatha, J. "Application of Tabu Search for Optimal Placement and Sizing of Distributed Generation for Loss Reduction", *Adv. Mater. Res.*, vol. 433–440, 2012, pp. 7190–7194, doi: 10.4028/www.scientific.net/amr.433-440.7190.

[24] Baghel, M., Agrawal, S. and Silakari, S. "Survey of Metaheuristic Algorithms for Combinatorial Optimization", *Int. J. Comput. Appl.*, vol. 58, no. 19, 2012, pp. 21–31, doi: 10.5120/9391-3813.

[25] Singh, N. and Singh, S.B. "Hybrid Algorithm of Particle Swarm Optimization and Grey Wolf Optimizer for Improving Convergence Performance", *J. Appl. Math.*, vol. 2017, 2017, doi: 10.1155/2017/2030489.

[26] Tolba, M., Rezk, H., Tulsky, V., Diab, A., Abdelaziz, A. and Vanin, A. "Impact of Optimum Allocation of Renewable Distributed Generations on Distribution Networks Based on Different Optimization Algorithms", *Energies*, vol. 11, no. 2, 2018, pp. 245, doi: 10.3390/en11010245.

[27] Ghanem, W.A.H.M. and Jantan, A. "Hybridizing Artificial Bee Colony with Monarch Butterfly Optimization for Numerical Optimization Problems", *Neural Comput. Appl.*, vol. 30, no. 1, 2016, pp. 1–19, doi: 10.1007/s00521-016-2665-1.

[28] Farjah, E., Bornapour, M., Niknam, T. and Bahmanifirouzi, B. "Placement of Combined Heat, Power and Hydrogen Production Fuel Cell Power Plants in a Distribution Network", *Energies*, vol. 5, no. 3, 2012, pp. 790–814, doi: 10.3390/en5030790.

[29] Tawfeek, T.S., Ahmed, A.H. and Hasan, S. "Analytical and Particle Swarm Optimization Algorithms for Optimal Allocation of Four Different Distributed Generation Types in Radial Distribution Networks", *Energy Procedia*, vol. 153, 2018, pp. 86–94, doi: 10.1016/j.egypro.2018.10.030.

[30] Yan, Z., Sha, J., Liu, B., Tian, W. and Lu, J. "An Ameliorative Whale Optimization Algorithm for Multi-objective Optimal Allocation of Water Resources in Handan, China", *Water (Switzerland)*, vol. 10, no. 1, 2018, doi: 10.3390/w10010087.

[31] Mirjalili, S. and Lewis, A. "The Whale Optimization Algorithm", *Adv. Eng. Softw.*, vol. 95, pp. 51–67, 2016, doi: 10.1016/j.advengsoft.2016.01.008.

[32] Kansal, S., Kumar, V. and Tyagi, B. "Optimal Placement of Different Type of DG Sources in Distribution Networks", *Int. J. Electr. Power Energy Syst.*, vol. 53, no. 1, 2013, pp. 752–760, doi: 10.1016/j.ijepes.2013.05.040.

[33] Wang, X. "Optimal Voltage Regulation for Distribution Networks with Multi-microgrids", *Appl. Energy*, vol. 210, no. 2017, 2018, pp. 1027–1036, doi: 10.1016/j.apenergy.2017.08.113

[34] Das, D., Kothari, D.P. and Kalam, A. "Simple and Efficient Method for Load Flow Solution of Radial Distribution Networks", *Int. J. Electr. Power Energy Syst.*, vol. 17, no. 5, pp. 335–346, 1995, doi: 10.1016/0142-0615(95)00050-