Journal of Advanced Research in Science and Technology
ISSN: 2352-9989

Optimal Placement and Sizing of PVDGs in Radial Distribution System Using Hybrid PSO-GSA

Mohamed Zellagui [1*] and Heba Ahmed Hassan [2]
[1] Electrical Engineering Department, Faculty of Technology, University of Batna 2
Batna, Fesdis, Algeria
[2] Electrical Power and Machines Department, Faculty of Engineering, Cairo University
Giza, Egypt

Abstract. The objectives of this work are to minimize power losses and improve voltage profile in the radial distribution system by the optimal placement and sizing of Photovoltaic Distributed Generators (PVDGs). The hybrid Particle Swarm Optimization-Gravitational Search Algorithm (PSO-GSA) been employed to minimize a multi-objective function. Two scenarios have been studied in this work. In the first scenario, the constraint for PVDG unit size has not been considered and problem has been solved for different number of PVDGs (one, two and three). In the second scenario, the constraint for PVDG unit size has been considered and problem has been solved while using one PVDG. The studies have been carried out on IEEE 33-bus test system. The results show that PVDG penetration has decreased power loss and improved the voltage profile. Comparison of the results obtained by the proposed optimization PSO-GSA with those attained in other studies shows the effectiveness of the proposed method.

Keywords : PhotoVoltaic Distributed Generator (PVDG), Multi-objective Performance Index, Optimal Placement and Sizing of PVDG, Hybrid Particle Swarm Optimization-Gravitational Search Algorithm (PSO-GSA), Radial Distribution System.

1. Introduction

Among the renewable energy sources, the photovoltaic application has received a great attention in research because it appears to be one of the most efficient and effective solutions for the environment-related problems as well as the existing electric power systems [1-2].

Distributed Generators (DGs) are small scale (typically 1 kW–50 MW) electric power generators that produce electricity at a site close to the customer or that are tied to an electric distribution system. In the last few decades, the use of renewable and nonrenewable DGs is increasing worldwide, encouraged by national and international policies aiming to increase the share of renewable energy sources and highly efficient micro-combined heat and power units in order to reduce greenhouse gas emissions and alleviate global warming [3]. Next to environmental advantages, DGs contribute to the technical benefits and their inappropriate placement may increase system losses and network capital and operating costs.

* Corresponding author.
E-mail: m.zellagui@univ-batna2.dz (Zellagui, M.).
Address: University of Batna 2, Batna, Algeria

The optimal placement of DGs can improve network performance in terms of voltage profile, reduce flows and system losses, and improve power quality and reliability of supply. The DG placement problem has always attracted the interest of many researchers [3]. In order to maximize the benefits of using DGs in power systems, it is crucial to find the best placement and size of DGs simultaneously [4].

Many techniques and optimization algorithms have been addressed in literature to deal with the problem of optimal placement and sizing of DGs in distribution systems such as Linear Programming (LP) [5], Nonlinear Programming (NLP) [6], Mixed Integer Non Linear Programming (MINLP) [7], Analytical Approach (AA) [8], Dynamic Programming (DP) [9], Genetic Algorithm (GA) [10], Particle Swarm Optimization (PSO) [11], Artificial Bee Colony (ABC) [12], Modified Artificial Bee Colony (MABC) [13], Harmony Search Algorithm (HSA) [14], Group Search Optimizer (GSO) [15], Sensitivity Approaches (SA) [16], Invasive Weed Optimization (IWO) [17], Firefly Optimization Algorithm (FOA) [18], Grey Wolf Optimizer (GWO) [19] and Krill Herd Algorithm (KHA) [20].

The number of PVDGs installed in distribution systems has been increasing significantly and their technical, economic and environmental impacts on the power system are being analyzed. Presently, the technical impacts of interest are voltage profile, power loss, power quality, reliability, protection, power control and stability [21].

The objectives of this paper are to minimize power losses and improve voltage profile in the radial distribution system by the optimal placement and sizing of PVDGs using a hybrid PSO-GSA.

2. Problem Formulation and Index

2.1. Objective Function Formulation

The objective of this study is to minimize the power losses and improve the voltage profile by including an optimal size PVDG in an optimal location. The PVDG placement and its corresponding size in the distribution feeders can be optimally determined using the following function:

$$\min\ f\left(P_{loss}, Q_{loss}, V_{level}\right) \tag{1}$$

In this work, several indices will be computed in order to describe the effect of PVDG in the power losses and voltage improvement. These indices are defined as follows:

Real Power Loss Index (ILP): This index is defined as follows:

$$ILP = \frac{P_{loss}^{withPVDG}}{P_{loss}^{withoutPVDG}} \tag{2}$$

Where, $P_{loss}^{withPVDG}$ is the total real power loss of the distribution system after the inclusion of PVDG, and $P_{loss}^{withoutPVDG}$ is the total real system loss without including PVDG in the distribution system.

Reactive Power Loss Index (ILQ): This index is defined as follows:

$$ILQ = \frac{Q_{loss}^{withPVDG}}{Q_{loss}^{withoutPVDG}} \tag{3}$$

Where, $Q_{loss}^{withPVDG}$ is the total reactive power loss of the distribution system after the inclusion of PVDG. And $Q_{loss}^{withoutPVDG}$ is the total reactive system loss without including PVDG in the distribution system.

Voltage Profile Index (IVD): One of the advantages of proper placement and size of the PVDG is the improvement in the voltage profile. This index penalizes a size–location pair which gives higher voltage deviations from the nominal value (V_{nom}). In this way, the closer the index is to zero the better is the network performance. This index is defined as follows:

$$IVD = {}_{i=2}^{n}\max\left[\frac{|V_{nom}| - |V_i|}{|V_{nom}|}\right] \tag{4}$$

Where, n is the number of buses.

The Multi-Objective Performance Index (IMO): This index is produced from gathering the previously mentioned indices by the weighting factor assigned to that impact.

$$IMO = w_1 * ILP + w_2 * ILQ + w_3 * IVD \tag{5}$$

The sum of the absolute values of the weights assigned to all indices should add up to one as shown in the following equation:

$$w_1 + w_2 + w_3 = 1 \tag{6}$$

This weighting factor is chosen by the planning engineer to reflect the relative importance of each parameter in the decision-making of PVDG placement and sizing. Table 1 shows the values for the weights used in this paper which are selected guided by the weights in [11-14]. However, these values may vary according to the concerns of the planning engineer.

Table 1. Weights of Indices

Indices	***Weights***
ILP	0.55
ILQ	0.25
IVD	0.2

2.2. Constraint Formulation

Voltage Limits: The voltage drop limits depend on the prescribed voltage regulation limits such that:

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

Line Thermal Limits: Power flow through any distribution feeder must comply with the thermal capacity of the line such that:

$$S_i \leq S_{i,\max} \tag{8}$$

PVDG Capacity: This constraint defines the boundaries of the power generation by PVDG:

$$P_{\min}^{PVDG} \leq P_i^{PVDG} \leq P_{\max}^{PVDG} \tag{9}$$

3. Application of PSO-GSA for Load Flow

3.1. Load Flow Method

Traditional load flow methods, which incorporate the Gauss–Seidel method, the Newton–Raphson method and fast decoupled techniques, were primarily developed for transmission system analysis. Additionally, a Backward Forward Sweep method for radial distribution systems using basic circuit theories and laws is another well-known method [22, 23].

Distribution systems usually fall into the category of ill-conditioned power systems having high R/X ratios, due to which the methods like Newton–Raphson and fast decoupled, may provide inaccurate results and may not converge.

Therefore, traditional load flow methods cannot be directly applied to distribution systems since the assumptions made for transmission systems are not valid for the unique characteristics of distribution systems [15-20]. On the other hand, Backward Forward Sweep methods are quite suitable for radial networks with high R/X ratio [23].

3.2. Standard PSO Algorithm [24]

PSO is a population based stochastic optimization technique developed in 1995, inspired by social behavior of bird flocking or fish schooling [24]. In a PSO system, particles fly around in a multi-dimensional search space.

During flight, each particle adjusts its position according to its own experience (this value is called P_{best}), and according to the experience of a neighboring particle (this value is called G_{best}), made use of the best position encountered by itself and its neighbor. The velocity of each particle in the swarm is defined as follows [22]:

$$v_i^{k+1} = \omega.v_i^k + C_1 rand_1 \times \left(Pbest_i - x_i^k\right) + C_2 rand_2 \times \left(Gbest - x_i^k\right) \tag{10}$$

Where, c_1 and c_2 are the weighting factors, $rand_1$ and $rand_2$ are two uniform random numbers between 1 and 2. The displacement of each particle in the research space is based on its position and its velocity:

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{11}$$

Where, x_i^{k+1} and x_i^k are the position of particle i in the iteration k +1 and k, respectively. The weighting function (ω) is defined as follows:

$$\omega = \omega_{\max} - \frac{\omega_{\max} - \omega_{\min}}{iter_{\max}} \times iter \tag{12}$$

3.3 Standard GSA [25]

GSA is a novel heuristic optimization method which was proposed in 2009 [23]. GSA can be considered as a collection of agents (candidate solutions), whose masses are proportional to their value of fitness function. During generations, all masses attract each other by the gravity forces between them. A heavier mass has the bigger attraction force. Therefore, the heavier masses which are probably close to the global optimum attract the other masses proportional to their distances. For a system with N agents, the algorithm starts with randomly placing all agents in search space. During all epochs, the gravitational force is defined as follows [25]:

$$F_{ij}^d(k) = G(k)\frac{M_{pi}(k).M_{aj}(k)}{R_{ij}(k)+\varepsilon}\left[x_j^d(k) - x_i^d(k)\right] \tag{13}$$

Where,

$$G(k) = G_0 e^{\left(-\alpha \frac{Iter}{Iter_{\max}}\right)} \tag{14}$$

In a problem space with the dimension d, the total force that acts on agent i is calculated as follows:

$$F_i^d(k) = \sum_{j=1, j\neq i}^{N} rand F_{ij}^d(k) \tag{15}$$

According to the law of motion, the acceleration of an agent is proportional to the result force and inverse of its mass, so the acceleration of all agents is calculated as follows:

$$ac_i^d(k) = \frac{F_i^d(k)}{M_i(k)}, \tag{16}$$

The velocity and position of agents are calculated as follows.

$$v_i^d(k+1) = rand v_i^d(k) + ac_i^d(k) \tag{17}$$

$$x_i^d(k+1) = v_i^d(k+1) + x_i^d(k) \tag{18}$$

3.4. Hybrid PSO-GSA

The PSO-GSA is a novel hybrid population-based algorithm proposed in 2010 and 2013, respectively [26-27]. The basic idea of the hybrid PSO-GSA is to combine the ability of social thinking (G_{best}) in PSO with the local search capability of GSA. In order to combine these algorithms, an equation is proposed as follows:

$$v_i(k+1) = \omega.v_i(k) + C_1' rand_1 \times ac_i(k) + C_2' rand_2 \times \left(Gbest - x_i(k)\right) \tag{19}$$

In each iteration, the position of particles is updated as follows:

$$x_i\left(k+1\right)=v_i\left(k+1\right)+x_i\left(k\right) \tag{20}$$

In the hybrid PSO-GSA, the quality of solutions is considered in the updated procedure. The agents near good solutions try to attract the other agents which are exploring the search space.

When all agents are near a good solution, they move very slowly. In this case, the G_{best} helps them to exploit the global best. The hybrid PSO-GSA uses a memory (G_{best}) to save the best solution found so far, so it is accessible anytime.

Each agent can observe the best solution so far and tend toward it. With adjusting C_1' and C_2', the abilities of global search and local search can be balanced. The use of the hybrid PSO-GSA for optimal coordination problem required the determination of several steps as follows [27]:

Initialize Population: The hybrid PSO-GSA must be provided with population number and the initial range of population at the start. The user can specify a range of values as the initial population.

Fitness Evaluation: Each particle in the initial population is evaluated using the fitness function which is the driving force behind the PSO-GSA.

Calculation of Parameters: Gravitational force, gravitational constant and resultant forces among agents are calculated using (13), (14) and (15), respectively. After that, the accelerations of particles are defined as (16).

Update Velocities and Positions: The velocities of all agents can be calculated using (19). Finally, the positions of agents are defined as (20). Both velocities and positions are updated with the new values.

Termination: Iteration will be stopped if the stopping criterion is satisfied. In this algorithm, a maximum generation of 200 and tolerance of 10^{-6} is used as stopping criterion.

Results: Print out the optimal solution to the target problem. The best solution includes the optimal placement and sizes of PVDGs and the corresponding fitness value representing the minimum total real power loss.

4. Case Study, Results and Discussions

The studies have been carried out on an IEEE 33-bus test system. The load has been modelled as constant reactive power. Two load scenarios are studied which are Scenario I and Scenario II.

In Scenario I, the constraint for PVDG unit size has not been considered and the problem has been solved for different number of PVDGs (one, two and three).

In Scenario II, the constraint for PVDG unit size has been considered and the problem has been solved for one PVDG. The total active power penetration of the distribution system represents the constraint for PVDG unit size in this scenario.

The substation voltage in both scenarios was considered as 1.0 p.u. PVDGs can be connected to any bus except the first bus which is considered to be the slack bus.

The proposed PSO-GSA was applied to the IEEE 33-bus test system to determine the optimal size and placement of PVDG units such that the multi-objective function given in equation (5) is minimized. For this test system, three PVDG units were optimally sized and placed.

The IEEE 33-bus test system shown in Fig. 1 operates at 12.66 kV. The network data can be found in [13], [17-18]. This test network has loads connected to all buses except bus 1. The total demand of the network is 3.715 MW and 2.3 MVar.

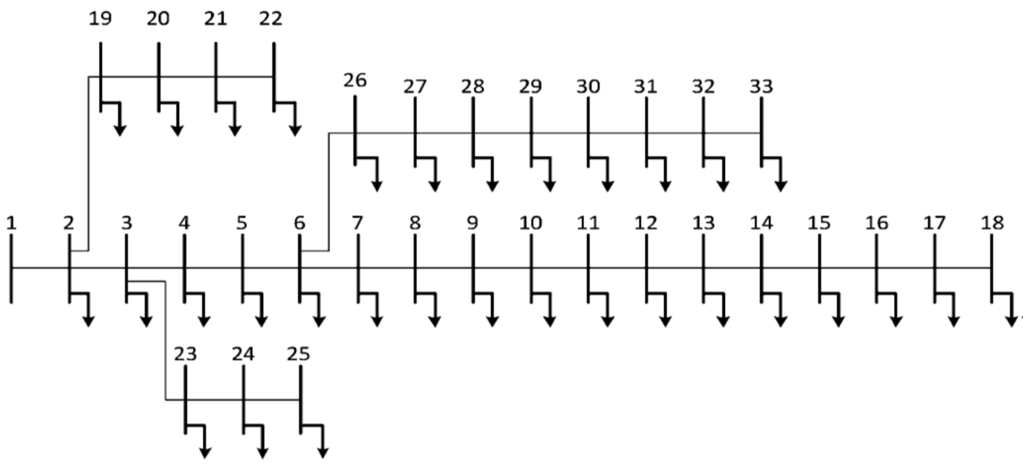

Fig. 1. Single line diagram of the IEEE 33-bus test system.

The power losses of the IEEE 33-bus test system for the base case (without using PVDG) are 201.7897 kW and 74.1422 kVar.

4.1. Scenario I

As earlier mentioned, the PVDG size constraint is not considered in this scenario. The proposed PSO-GSA results were obtained after carrying out 10 independent runs. In other words, the initial population was randomly generated in each run.

Table 2 shows the best results as well as the voltage and power losses of the IEEE 33-bus test system for Scenario I. Fig. 2 and Fig. 3 illustrate the voltage profiles and PSO-GSA convergence for PVDG placement, respectively.

Table 2. Results for Scenario I.

	Impact Index		**PVDG Placement**	**PVDG Size (kW)**	P_{loss} **(kW)**	Q_{loss} **(kVar)**
One PVDG	*ILP*	0.50913	6	2594.8287	102.7901	74.1464
	ILQ	0.55064				
	IVD	0.04757				
	IMO	0.42720				
Two PVDGs	*ILP*	0.41062	13	853.70764	82.9005	56.8199
	ILQ	0.42196				
	IVD	0.02657	30	1196.6774		
	IMO	0.33664				
Three PVDGs	*ILP*	0.34372	14	759.09867	69.3939	48.0883
	ILQ	0.35712	24	1059.4371		
	IVD	0.02650	30	1118.1396		
	IMO	0.28362				

Table 3. Voltage and power loss for Scenario I.

Case	**Power Loss as % of Total Active Load**	**Power Loss Reduction%**	**Minimum Voltage (p.u.)**
No PVDG	5.430	-	0.91340
One PVDG	2.766	49.06	0.95241
Two PVDGs	2.231	58.91	0.97343
Three PVDGs	1.867	65.61	0.97351

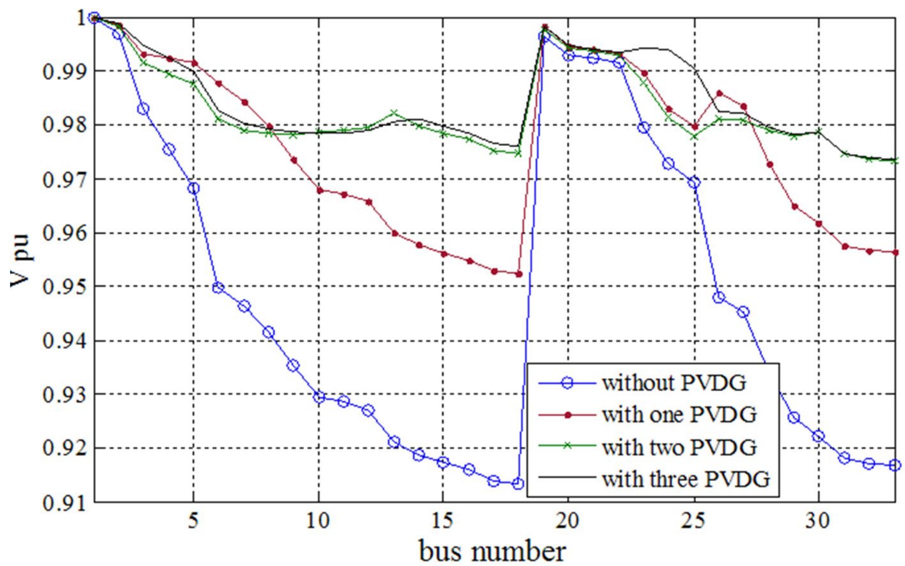

Fig. 2. Voltage profiles for Scenario I.

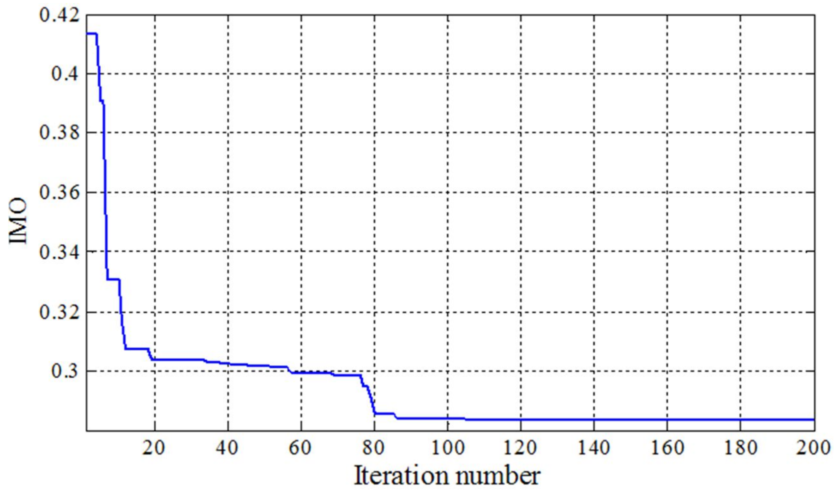

Fig. 3. The convergence of the PSO-GSA.

Table 3 and Fig. 2 show how PVDG cases power loss reduction and voltage improvement on IEEE 33-bus test system for the first scenario. In the case of using three PVDGs, the power loss reduction is 52.39 % and the minimum voltage is improved from 0.91340 p.u. to 0.97351 p.u.

4.2. Scenario II

The PVDG size constraint is considered in this scenario. Table 4 shows the best results as well as the voltage and power losses of the IEEE 33-bus test system for Scenario II. Table 5 and Fig. 4 illustrate the power losses and voltage profiles.

Table 4. Results for Scenario II.

Power Generation of PVDG	Impact Index		PVDG Placement	PVDG Size (kW)	P_{loss} (kW)	Q_{loss} (kVar)
370 kW (10 %)	*ILP*	0.79504	16	370	160.5123	106.115
	ILQ	0.78805				
	IVD	0.07711				
	IMO	0.6497				
555 kW (15 %)	*ILP*	0.72712	15	555	146.8012	97.0985
	ILQ	0.72109				
	IVD	0.07415				
	IMO	0.59502				
930 kW (25 %)	*ILP*	0.62978	30	930	127.149	86.4207
	ILQ	0.64179				
	IVD	0.071684				
	IMO	0.52116				

Table 5. Voltage and power loss for Scenario II.

Case	Power Loss as % of Total Active Load	Power Loss Reduction %	Minimum Voltage (p.u.)
No PVDG	5.4300	-	0.9134
370 kW (10%)	4.3206	20.43	0.92281
555 kW (15%)	3.9515	27.22	0.92587
930 kW (25%)	3.4221	36.97	0.92832

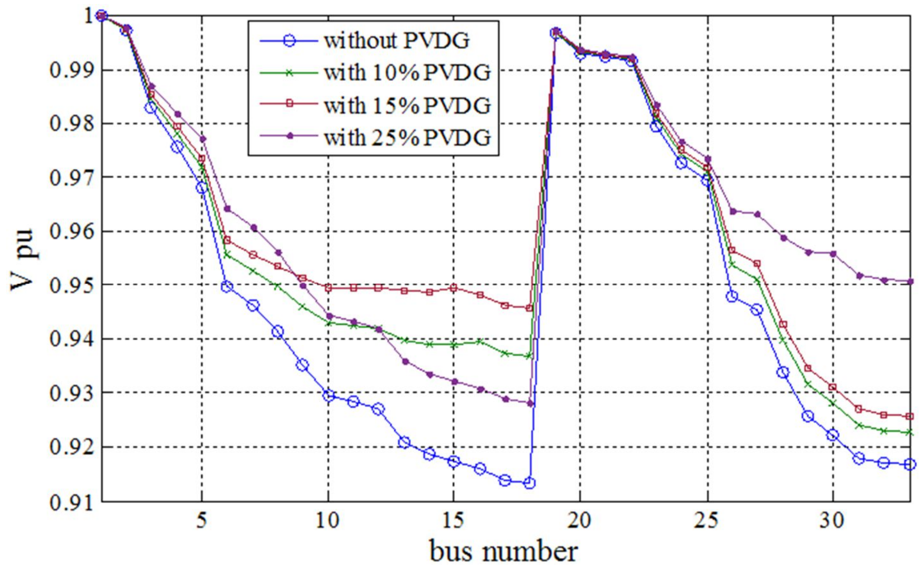

Fig. 4. Voltage profiles of Scenario II.

Results of the IEEE 33-bus test system for the second scenario revealed that in the case of having a PVDG size of 25 % of the total active load, the power loss is reduced by 36.97 % and the minimum voltage is improved to 0.92832 p.u.

4.3. Comparative Study

The comparative study has been done for validity of the results. As shown in Table 6, the results of the hybrid PSO-GSA for IEEE 33-bus test system were compared with the solutions obtained using the following algorithms: the Analytical Approach (AA) [8], Genetic Algorithm (GA) [10], Artificial Bee Colony (ABC) [12] and Modified Artificial Bee Colony (MABC) [13].

Table 6. Comparative study for Scenario I.

Case		AA [8]	GA [10]	ABC [12]	MABC [13]	Proposed PSO-GSA
One PVDGs	Placement, Size (kW)	6, 2490	6, 2380	6, 2400	6, 2590	6, 2594
	Power Loss Reduction %	47.33	44.83	48.19	46.92	49.06
Two PVDGs	Placement, Size (kW)	-	-	-	6, 1958.9 14, 606.3	13, 853 30, 1196
	Power Loss Reduction %	-	-	-	56.22	58.91
Three PVDGs	Placement, Size (kW)	-	-	-	6, 1189.1 14, 646.9 31, 686.3	14, 759 24, 1059 30, 1118
	Power Loss Reduction %	-	-	-	65.01	65.61

The comparison shows that the proposed PSO-GSA methodology is more effective in determining the optimal placement and size of PVDGs for minimizing power losses.

5. Conclusions

In this paper, applied hybrid PSO-GSA for optimal PVDGs placement and size in radial distribution system. The goal of this optimization was minimizing the power losses and improving the voltage profile by using PVDG.

The simulation results demonstrate that the optimal placement and sizing of PVDGs can reduce the power losses and improve the voltage profile. The results obtained for the test system were compared by those obtained while using other existing algorithms, where the proposed hybrid PSO-GSA showed superiority in minimizing the power losses.

6. References

[1] A. McEvoy, T. Markvart and L. Castaner, *"Practical Handbook of Photovoltaic's - Fundamentals and Applications"*, Elsevier, UK, 2012.

[2] D. Singh, D. Singh and K. S. Verma, *"Electrical Impact of Photovoltaic Planting Distributed Network"*, IEEE Transactions on Industry Applications, Vol. 45, No. 1, pp. 427-436, 2009.

[3] P. S. Georgilakis and N. D. Hatziargyriou, *"Optimal Distributed Generation Placement in Power Distribution Networks: Models, Methods, and Future Research"*, *IEEE Transactions* on *Power Systems*, Vol. 28, No. 3, pp. 3420-3428, 2013.

[4] A. Ameli, S. Bahrami, F. khazaeli and M. R. Haghifam, *"Optimum Location of Resources in Distributed Planning"*, IEEE Transactions on Power Delivery, Vol. 29, No. 4, pp. 1831-1840, 2014.

[5] G. Harrison, and A. Wallace, *"Optimal Power Flow Evaluation of Distribution Network Capacity for the Connection of Distributed Generation"*, IEE Generation, Transmission & Distribution, Vol. 152, No. 1, pp. 115-122, 2005.

[6] W. El-Khattam, Y. Hegazi, and M. M. Salama, *"An Integrated Distributed Generation Optimization Model for Distribution System Planning"*, IEEE Transactions on Power Systems, Vol. 20, No. 2, pp. 1158-1165, 2005.

[7] S. Porkar, P. Poure, A. Abbaspour-Tehrani-Fard, and S. Saadate, *"Optimal Allocation of Distributed Generation Using a Two-Stage Multi-Objective Mixed-Integer-Nonlinear Programming"*, European Transactions on Electrical Power, Vol. 21, No. 1, pp. 1072-1087, 2011.

[8] N. Acharya, P. Mahat, and N. Mithulananthan, *"An Analytical Approach for DG Allocation in Primary Distribution Network"*, Electric Power Systems Research, Vol. 28, No. 10, pp. 669-678, 2006.

[9] N. Khalesi, N. Rezaei, and M. R. Haghifam, *"DG Allocation with Application of Dynamic Programming for Loss Reduction and Reliability Improvement"*, *International Journal of Electrical Power & Energy Systems*, Vol. 33, No. 2, pp. 288-295, 2011.

[10] T. N. Shukla, S. P. Singh, V. Srinivasarao, and K. B. Naik, *"Optimal Sizing of Distributed Generation Placed on Radial Distribution Systems"* , *Electric Power Components* and *Systems*, Vol. 38, No. 3, pp. 260-274, 2010.

[11] M. Gomez-Gonzalez, A. López, and F. Jurado, *"Optimization of Distributed Generation Systems Using a New Discrete PSO and OPF"*, Electric Power Systems Research, Vol. 84, No. 1, pp. 174-180, 2012.

[12] F. S. Abu-Mouti and M. E. El-Hawary, *"Optimal Distributed Generation Allocation and Sizing in Distribution Systems via Artificial Bee Colony Algorithm"*, EEE Transactions on Power Delivery, Vol. 26, No. 4, pp. 2090-2101, 2011.

[13] I. Hussain, and A. K. Roy, *"Optimal Distributed Generation Allocation in Distribution Systems Employing Modified Artificial Bee Colony Algorithm to Reduce Losses and Improve Voltage Profile"*, IEEE International Conference 6n Advances In Engineering, Science and Management, Tamil Nadu, India, 30-31 March *2012*.

[14] K. Nekooei, M. M. Farsangi, H. N. Pour, and K. Y. Lee*, "An Improved Multi-Objective Harmony Search for Optimal Placement of DGs in Distribution Systems"*, IEEE Transaction on Smart Grid, Vol. 4, No. 1, pp. 557- 567, 2013.

[15] Q. Kang, M. C. Zhou, J. An, and Q. Wu, *"Swarm Intelligence Approaches to Optimal Power Flow Problem with Distributed Generator Failures in Power Networks"*, IEEE Transactions on Automation Science and Engineering, Vol. 10, No. 2, pp. 343-353, 2013.

[16] V. V. S. N. Murthy, and A. Kumar, *"Comparison of Optimal DG Allocation Methods in Radial Distribution Systems based on Sensitivity Approaches"*, International Journal of Electrical Power and Energy Systems, Vol. 53, pp. 450-467, 2013.

[17] D. R. Prabha , and T. Jayabarathi, *"Optimal Placement and Sizing of Multiple Distributed Generating Units in Distribution Networks by Invasive Weed Optimization Algorithm"*, Ain Shams Engineering Journal, Volume 7, Issue 2, pp. 683-694, 2016.

[18] M. M. Othman, W. El-Khattam, Y. G. Hegazy, and A. Y. Abdelaziz, *"Optimal Placement and Sizing of Voltage Controlled Distributed Generators in Unbalanced Distribution Networks Using Supervised Firefly Algorithm"*, International Journal of Electrical Power & Energy Systems, Vol. 82, pp. 105-113, 2016.

[19] U. Sultana, Azhar B. Khairuddin, A. S. Mokhtar, N. Zareen, and B. Sultana, *"Grey Wolf Optimizer based Placement and Sizing of Multiple Distributed Generation in the Distribution System"*, Energy, Vol. 111, pp. 525-536, 2016.

[20] S. Sultana, and P. K. Roy, *"Krill Herd Algorithm for Optimal Location of Distributed Generator in Radial Distribution System"*, Applied Soft Computing, Vol. 40, pp. 391-404, 2016.

[21] H. L. Willis, and W. G. Scott, *"Distributed Power Generation: Planning and Evaluation"*, Marcel Dekker, New York, USA, 2000.

[22] L. Powell, *"Power System Load Flow Analysis"*, McGraw-Hill Education Publishing, USA, 2004.

[23] J.D. Glover, T. Overbye, and M.S. Sarma, *"Power System Analysis and Design"*, 6th Edition, Cengage Learning, USA, 2016.

[24] R. Eberhart, and J. Kennedy, *"A New Optimizer Using Particle Swarm Theory"*, 6th International Symposium on Micro Machine and Human Science (MHS), Nagoya - Japan, 4-6 October 1995.

[25] E. Rashedi, H. Nezamabadi-Pour, and S. Saryazdi, *"GSA: A Gravitational Search Algorithm"*, Information Sciences, Vol. 179, No. 13, pp. 2232-2248, 2009.

[26] S. Mirjalili, and S. Z. M. Hashim, *"A New Hybrid PSOGSA Algorithm for Function Optimization"*, International Conference on Computer and Information Application (ICCIA), Tianjin, China, 3-5 December 2010.

[27] W. S. Tan, M. Y. Hassan, H. Abdul Rahman, M. P. Abdullah, and F. Hussin, "*Multi-Distributed Generation Planning Using Hybrid Particle Swarm Optimization - Gravitational Search Algorithm Including Voltage Rise Issue"*, IET Generation, Transmission & Distribution, Vol. 7, No. 9, pp. 929-942, 2013.