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Optimal Sitting and Sizing of Distributed Generators using Pareto-Based Multi-Objective Particle Swarm Optimization for Improving Power System Operation

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Abstract: Utilization of distributed generation (DG) in the distribution network has become trending ever since it has been introduced with proven benefits. DG plays a significant role in improving the quality and quantity as well as the efficiency of the power transmission and distribution system. By allowing smaller generating units to operate in parallel with the main grid, a continuous reliable power supply with lower power loss and higher power output can be achieved. However, improper placement and inappropriate sizing of DG leads to a moderate level performance in terms of power loss and voltage profile. Limited studies have been conducted on mitigating these problems in order to maximize the benefits from DG's application. To solve this problem, a research is proposed which mainly aims in determining the location and size of DG as well as improving the voltage profile and efficiency of the distribution system significantly. A metaheuristic algorithm called Multi-Objective Particle Swarm Optimization (MOPSO) method is used to simultaneously determine the optimal size and location of DG. To assist the proposed method, Pareto analysis is incorporated to handle conflicting objectives. This method is then tested on the IEEE 14-bus and 33-bus distribution systems under two different conditions which is before and after optimization. The percentage of power loss reduction is calculated and the voltage profile is drawn to compare the output of both conditions. Evaluations from the tests have proven that by using the Pareto-Based MOPSO method, the most optimal size and location of DG in producing an improved voltage profile with lower power loss is identified.

Keywords: Distributed Generation, Multi-Objective Particle Swarm Optimization, Optimal sitting and sizing, Pareto analysis, Power system operation.

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1. INTRODUCTION

Long transmission line in the power system operation causes the power losses consisting of real and reactive powers to be as high as 20% from the total power transmitted. If considered separately, distribution system tends to have higher losses as compared to transmission system due to its R/X ratio, which is the ratio of the system reactance to the system resistance when short circuit is applied at any point in the power circuit. These losses derange the voltage profile of the distribution system, causing the bus voltages to run out of an acceptable level after being subjected to any disturbance.

Minimization of these losses is significant for the power utilities to provide a reliable and quality power supply. In order to reduce the power losses and improve the voltage profile of the distribution system, the concept of Distributed Generation (DG) is introduced in which smaller generating units are allowed to operate in parallel with the main grid to produce electricity. It also acts as a replacement for the conventional power plants such as the thermal and nuclear power plants that have large impacts on the environment and are responsible for the Green House Effect.

There are many advantages of implementing DG in the power distribution system. Some of them includes smaller size, lower operational and maintenance cost, better reliability and lesser environmental effects, especially if non-conventional generators are used. However, inappropriate sizing and improper placement of DG leads to a moderate level performance. One of the most effective and convenient way to improve the performance of DG is by placing it in an optimum size and location.

Therefore, this study utilizes a good optimization technique along with considering better multi-objective functions and effect of other constraints to improve the sizing and location optimization as well as providing a better performance of DG. Also, this research focuses on improving the voltage profile and reducing the power loss of the distribution system by determining the optimal size and location of DG using Pareto-Based Multi-Objective Particle Swarm Optimization (MOPSO) method.

The rest of this paper is organized as the following. A review based on previous researches related to the study is presented in Section 2. Section 3 explains the theoretical background whereas Section 4 produces the research methodology. This section covers the problem formulation, load flow technique and optimization method used in this research. Section 5 provides the simulation results obtained from the tests and discusses the outcome. Lastly, Section 6 proposes a conclusion to this effort.

2. LITERATURE REVIEW

Recently, researchers are experimenting on introducing DG into power system operation to reduce power losses, increase efficiency, reduce line current, enhance voltage profile, improve system stability and raise the load performance. Hence, a variety of algorithms and optimization strategies including heuristic and metaheuristic techniques are applied. In this section, some researches related to the performance improvement of DG are studied.

Several researches have used the Genetic Algorithm (GA) which is a metaheuristic algorithm that depends on biologically inspired operators including mutation, crossover and selection to develop high-quality solutions for optimization and search problems. In [1], [2] and [4], GA is combined with different load flow techniques such as Power Flow (PF), Newton Raphson (NR) and topology-based load flow. As for [3] and [5], Neuro-Genetic algorithm and Micro-Genetic algorithm are used respectively.

Besides, researchers have also implemented nature-inspired algorithms such as Bat Algorithm (BA), Artificial Bee Colony Algorithm (ABC) and Particle Swarm Optimization (PSO) to find the best size and location of DG. In [6], [8] and [9], the multi-objective approach of Shuffled BA, Pareto Optimal BA and Fuzzy-based BA are used respectively whereas in [7], the Modified Discrete BA is implemented. Meanwhile, [10] and [11] have utilized ABC as the optimization method without any improvement followed by [12] and [13] with multi-objective ABC and modified ABC.

As for [14], PSO is combined with Voltage Stability Index (VSI) whereas in [17], weight-improved PSO is used. [15] has proposed the multi-objective PSO along with NR, which is then improved by [16] through modified multi-objective PSO with NR. Lastly, the Artificial Immune System (AIS) is used in [18] and [19] under different conditions. [18] combined the clonal selection principle with PSO for a novel approach whereas [19] combined the clonal selection principle with Optimal Power Flow (OPF) to optimize the performance of DG.

In summary, most of the methods addressed in the literature have only evaluated single objective optimization, namely the minimization of power losses or the enhancement of the voltage profile but not both. As for those researches that have used multi-objective approach, it is still in the initial stages and requires improved objective functions as well as considering the effects of additional constraints for better improvement.

As a result, a multi-objective function is applied in this study whereby it analyses not only the power losses but also the voltage profile of the system. Also, a strong optimization algorithm called PSO is chosen as it demonstrates great problem-solving capacity due to its better efficiency in locating global optima as well as its rapid convergence. Despite the fact that alternative approaches appear to be fairly competitive, they are not chosen due to their inadequacy for the proposed system. Hence, the logic of this work is to introduce the Pareto analysis to the MOPSO algorithm in order to enhance the system's performance.

3. THEORETICAL BACKGROUND

For maximum improvement in the performance of DG, it has to be incorporated in an optimal size and location. In order to develop this system, the fundamental knowledge of DG, Pareto-based multi-objective approach and PSO method is presented in this section.

3.1 Distributed Generation (DG)

DG is defined as a local generation of electricity that is usually situated near the end-users. They operate in parallel with the central grid and generate power from renewable or non-renewable resources at a near distant. Some common examples of systems that uses renewable resources are the wind turbines, hydropower and solar photovoltaic panels. As for the non-renewable resources, fuel cells fired by natural gas and reciprocating combustion engine fueled by oil are used in producing power supply for the end-users.

As the DG transmits power over a short distance, the amount of losses released due to the inefficiency of transmission line is reduced greatly. This allows an improvement in the efficiency of the distribution system as well as a reduction in the carbon pollution. Besides, by generating additional electricity, higher load demand can be fulfilled while curtailing the requirement for new transmission investments. DG also reduces the fossil fuel consumption, providing cleaner generation of electricity.

DG can be implemented in both residential and commercial or industrial sectors. In residential sectors, it usually serves as a single structure such as the solar panel installed on the rooftop of a house. In commercial or industrial sectors, it normally becomes a part of the microgrid, a small network attached with the central grid that uses local resources to generate electricity and is able to detach and function independently on certain circumstances. Such example of application is the backup generators situated in an industrial facility.

3.2 Pareto-Based Multi-Objective Approach

The multi-objective optimization is an approach that involves more than one objective function to be optimized. The final outcome or answer to the optimization will be the set of solutions that define the best trade-off between the competing objectives. In single objective optimization, a solution's superiority is easily determined by comparing its objective function values. However, in multi-objective approach, the goodness of a solution is determined by its dominance.

For an instance, X1 dominates X2 if the solution of X1 is no worse than that of X2 in all objectives or if the solution of X1 is strictly better than that of X2 in at least one objective. The non-dominated solutions are optimal as no other solutions in the design space are better than them or can 'dominate' them when all the objectives are considered. These set of solutions are called Pareto optimal solutions whereby all the other solutions are 'dominated' by them. The set of Pareto optimal solutions is generated to ease the process of choosing the best solution out of the set of alternatives.

3.3 Particle Swarm Optimization (PSO)

As for PSO, it is a metaheuristic algorithm proposed by Kennedy and Eberhart, inspired by the collective intelligence of swarms of biological populations such as flock of birds, colonies of insects, schools of fish and herds of animals. This method is a population-based search method where by it moves from a set of points (particles' positions) to another set of points with likely improvement in one iteration (move) as explained by the following.

A swarm of birds flying over a place must find a point with maximum survival conditions to land (more food and less predators). To find the best point, each bird flies searching and assessing different points at the same time. Each member of the swarm balances its individual and swarm knowledge experience by sharing information among themselves. All the birds of a swarm will know the best point when it is found by one of the swarm's members. The movement of the flock happens once the best place to land is defined and all the flock lands at once.

4. PROPOSED SOLUTION

In this section, the problem formulation of the research is discussed followed by the load flow technique. Then, the step-by-step procedure of the optimization method is also included.

4.1 Problem Formulation

The proposed algorithm's aim is to minimize the objective functions of the system and find the best size and location for DG implementation. Two main elements involved in establishing the formula are power loss and voltage deviation. Mathematically, the objective functions are written as (1) and (2) subjected to the equality constraints (3) and (4) and inequality constraints (5), (6), (7) and (8).

$$\min\ f_1(x) = \min \sum_{(i,j)\in B} g_{ij}\left(V_i^2 + V_j^2 - 2V_iV_j\cos\theta_{ij}\right) \quad (1)$$

$$\min\ f_2(x) = \min \sum_{i=0}^{N} \left(\frac{V_i - V_i^{spec}}{V_i^{max} - V_i^{min}}\right)^2 \quad (2)$$

$$P_{DGi} - P_{di} = V_i \sum_{j=1}^{N} V_j\left(G_{ij}\cos\theta_{ij} + B_{ij}\sin\theta_{ij}\right) \quad (3)$$

$$Q_{DGi} - Q_{di} = V_i \sum_{j=1}^{N} V_j\left(G_{ij}\sin\theta_{ij} - B_{ij}\cos\theta_{ij}\right) \quad (4)$$

$$P_{DGi}^{min} \le P_{DGi} \le P_{DGi}^{max} \quad (5)$$

$$Q_{DGi}^{min} \le Q_{DGi} \le Q_{DGi}^{max} \quad (6)$$

$$V_i^{min} \le V_i \le V_i^{max} \quad (7)$$

$$S_{ij}^{min} \le S_{ij} \le S_{ij}^{max} \quad (8)$$

4.2 Newton-Raphson (NR) Load Flow

The NR load flow method is used in this study to perform the load flow analysis. This method is begined with the formation of a Y bus. Then, for i = 2, 3,.....n, the initial value of the bus voltages $|Vi|^0$ and phase angle δi^0 for PV buses are considered to be equal to the slack bus quantities, $|V_1| = 1.0$ and $\delta_1 = 0^{o}$.

After that, for each load bus, Pi, Qi, ΔPi and ΔQi are calculated. The exact value of Qi for PV buses is unknown, but its limitations are known. ΔPi is calculated only when the calculated value of Qi falls within the limit. If the computed value of Qi exceeds the limit, a suitable limit is set and ΔQi is determined by subtracting the calculated value of Qi from the suitable limit.

The bus under consideration is now classified as a load bus. The elements of the Jacobian matrix are calculated and the values of Δ|Vi| and Δδ are obtained. The voltage magnitude and phase angle at all load buses are modified using the values of Δδi and Δ|Vi| before commencing the next iteration cycle, which is repeated until all planned errors for all load buses are within a defined tolerance.

4.3 Pareto-Based MOPSO

The optimization process is started by reading the network data consisting of the line and load data. Then, the position and velocity of the population is initialized based on the control parameters specified such as the inertia weighting (w) and acceleration constant (C1 and C2). This step is then followed by applying the objective functions, namely the active power loss minimization and voltage deviation reduction before proceeding to the process of each particle.

In this sub-process, the fitness value of each particle is calculated by running the Newton-Raphson load flow analysis. Then, the penalty function is called to apply equality and inequality constraints before generating the augmented function. Based on the fitness value of the augmented function, the MOPSO algorithm is run and the velocity, Pbest and Gbest for each particle is determined. Then, the best fitness value, Pbest is compared with the best fitness value achieved so far by any particle in the population, Gbest. If Pbest is found to be higher than Gbest, Gbest is then updated to the new value.

This process is repeated until the termination criteria is met which is when the maximum iteration is reached. Until the termination criteria is met, this sub-process is repeated by increasing the iteration count and updating the swarm position. Finally, the results display the location and size of DG that contributes to the lowest power loss and improved voltage profile. Figure 1 explains the overall operational flowchart of the proposed system.

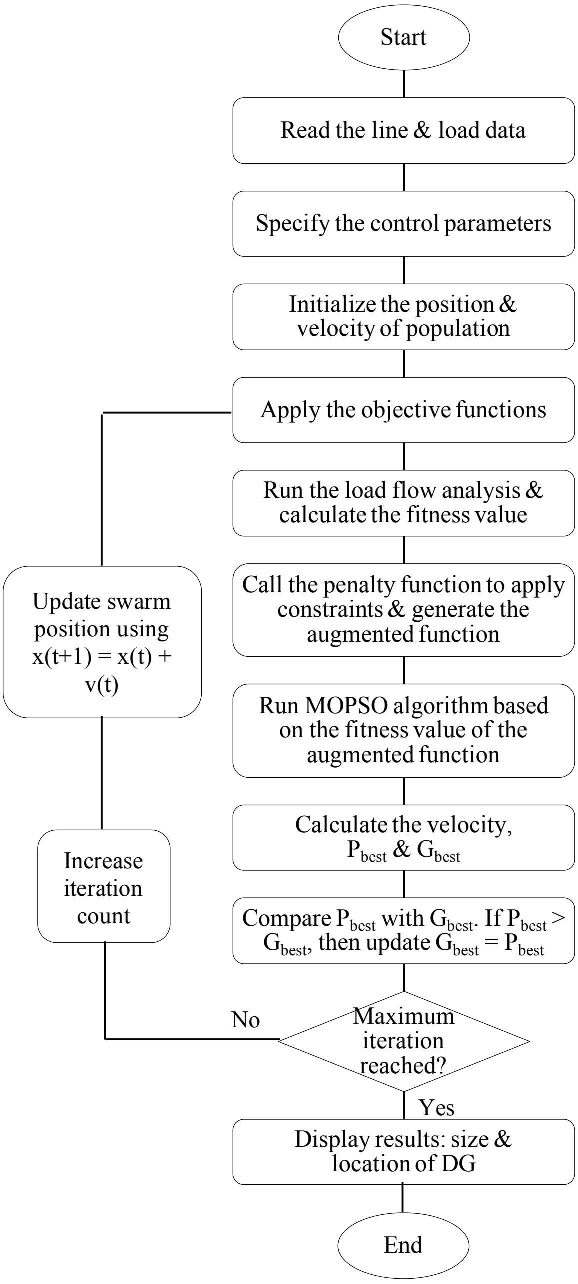

Figure 1. Operational flowchart of the proposed system

5. RESULTS AND DISCUSSION

In order to simulate the proposed solution, Matlab R2020a programming software is used on a 4 GB, 64-bit I5 Asus Laptop. To verify the effectiveness of the proposed work, it is tested on the IEEE 14-bus and 33-bus distribution systems under two different conditions, namely without and with DG implementation using Pareto-Based MOPSO. The results obtained are presented in this section.

5.1 IEEE 14-Bus Distribution System

Table 1 is the power flow results without DG and when DG is implemented using Pareto-Based MOPSO. The total active power losses for the first case is 13.3933 MW, which is then reduced by 63% to 4.9599 MW when DGs are placed at bus 7, 13 and 9 with a size of 59.888, 60.0892 and 36.6429 MW respectively. Meanwhile, the voltage deviation for this test system is reduced by 5% from 0.9754 before optimization to 0.9244 after optimization.

Table 1. Power flow result for 14-bus system before and after optimization

	Without optimization	**With optimization using Pareto-Based MOPSO**
Voltage deviation	0.9754	0.9244
Power losses	13.3933	4.9599

Figure 2 portrays the distribution of Pareto optimal solution in (f1, f2) plane for the IEEE 14-bus distribution system. Referring to Figure 3, the plot clearly shows an obvious improvement in the voltage profile of the test system when DG is implemented using the Pareto-Based MOPSO.

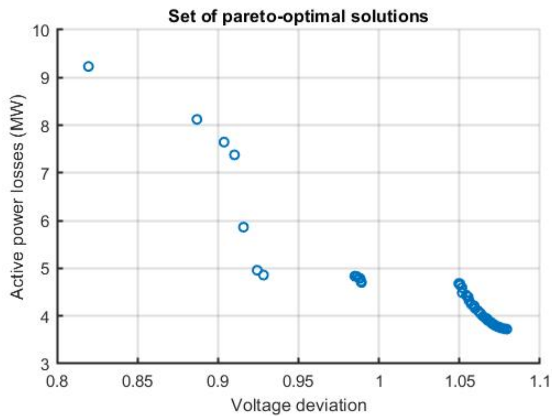

Figure 2. Pareto optimal solutions for 14-bus system

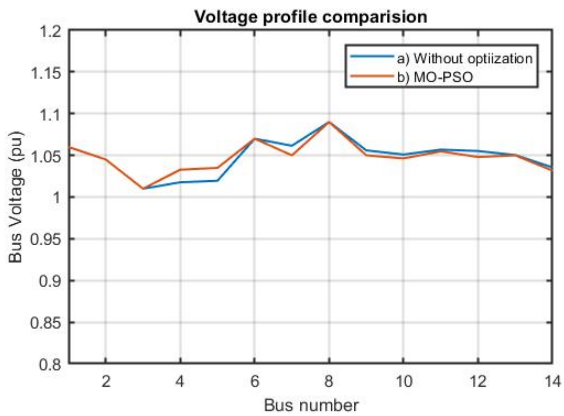

Figure 3. Voltage profile comparison for 14-bus system

5.2 IEEE 33-Bus Distribution System

For this test system, the power flow results without and with DG implementation is as shown in Table 2. The total active power losses for the non-optimized case is 0.2027 MW, which is then decreased by 80% to 0.0414 MW when DGs with sizes of 0.48, 1.4959 and 1.5003 MW are installed at bus 13, 30 and 24 respectively. In the meantime, the voltage deviation for this test system is lowered by 99%, from 2.9274 prior to optimization to 0.0151 after optimization.

Table 2. Power flow result for 33-bus system before and after optimization

	Without optimization	With optimization using Pareto-Based MOPSO
Voltage deviation	2.9274	0.0151
Power losses	0.2027	0.0414

The distribution of the Pareto optimum solutions on the (f1, f2) plane for the IEEE 33-bus distribution system is shown in Figure 4. When DG is applied using the Pareto-Based MOPSO, the voltage profile of the test system dramatically improves as depicted in Figure 5.

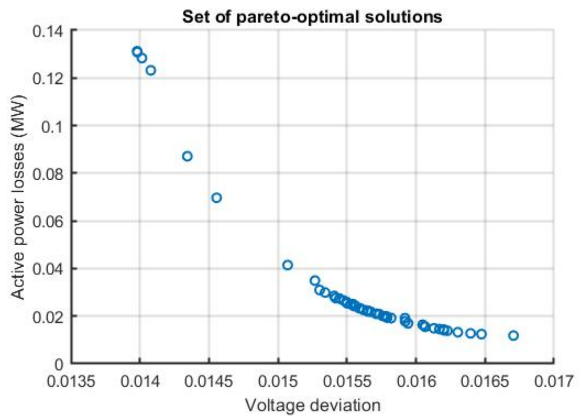

Figure 4. Pareto optimal solutions for 33-bus system

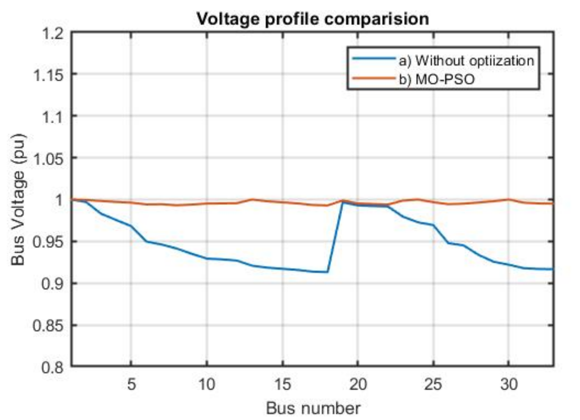

Figure 5. Voltage profile comparison for 33-bus system

6. CONCLUSION

In this paper, an alternative method for the improvement of power system operation by determining the sitting and sizing of DG using Pareto-based MOPSO is implemented. It estimates the size and location of DG for better performance by using improved objective functions and considering effect of other constraints. When tested using the IEEE 14-bus and 33-bus distribution systems, the DG works at its best when it is placed at the optimized size and location. The study also proves an obvious improvement in the voltage profile and the power loss which is reduced by 5% and 63% for IEEE 14-bus distribution system as well as 99% and 80% for IEEE 33-bus distribution system when DG is implemented using the Pareto-based MOPSO.

REFERENCES

[1] A. Alhamali, M. E. Farrag, G. Bevan, and D. M. Hepburn, “Determination of optimal site and capacity of DG systems in distribution network based on genetic algorithm,” *2017 52nd Int. Univ. Power Eng. Conf. UPEC 2017*, vol. 2017-January, pp. 1–6, 2017, doi: 10.1109/UPEC.2017.8231996.

[2] M. M. Gidd, S. L. Mhetre, and I. M. Korachagaon, “Optimum Position and Optimum Size of the Distributed Generators for Different Bus Network Using Genetic Algorithm,” *Proc. - 2018 4th Int. Conf. Comput. Commun. Control Autom. ICCUBEA 2018*, pp. 0–5, 2018, doi: 10.1109/ICCUBEA.2018.8697595.

[3] B. Kazeem and M. Alor, “distribution systems using Neuro-genetic Algorithm,” pp. 898–904, 2017.

[4] V. Reddy and G. Manjula, “The Optimal Size of Multiple DG Units in Distribution Network with Change of Load,” *2019 Glob. Conf. Adv. Technol. GCAT 2019*, no. 1, pp. 14–19, 2019, doi: 10.1109/GCAT47503.2019.8978350.

[5] C. Nayanatara, J. Baskaran, and D. P. Kothari, “Optimal location of Distributed Generation using micro-genetic algorithm,” *2014 Int. Conf. Comput. Power, Energy, Inf. Commun. ICCPEIC 2014*, pp. 525–530, 2014, doi: 10.1109/ICCPEIC.2014.6915419.

[6] C. Yammani, S. Maheswarapu, and S. K. Matam, “Optimal placement and sizing of distributed generations using shuffled bat algorithm with future load enhancement,” *Int. Trans. Electr. Energy Syst.*, vol. 26, no. 2, pp. 274–292, 2016, doi: 10.1002/etep.2076.

[7] M. Shivaie, M. Mokhayeri, M. Kiani-Moghaddam, and A. Ashouri-Zadeh, “A reliability-constrained cost-effective model for optimal sizing of an autonomous hybrid solar/wind/diesel/battery energy system by a modified discrete bat search algorithm,” *Sol. Energy*, vol. 189, no. July, pp. 344–356, 2019, doi: 10.1016/j.solener.2019.07.075.

[8] R. Prakash, B. Lokeshgupta, and S. Sivasubramani, “Multi-Objective Bat Algorithm for Optimal Placement and Sizing of DG,” *2018 20th Natl. Power Syst. Conf. NPSC 2018*, 2018, doi: 10.1109/NPSC.2018.8771440.

[9] S. Remha, S. Chettih, and S. Arif, “A novel multi-objective bat algorithm for optimal placement and sizing of distributed generation in radial distributed systems,” *Adv. Electr. Electron. Eng.*, vol. 15, no. 5, pp. 736–746, 2017, doi: 10.15598/aeee.v15i5.2417.

[10] R. Deshmukh and A. Kalage, “Optimal Placement and Sizing of Distributed Generator in Distribution System Using Artificial Bee Colony Algorithm,”

Proc. - 2018 IEEE Glob. Conf. Wirel. Comput. Networking, GCWCN 2018, pp. 178–181, 2019, doi: 10.1109/GCWCN.2018.8668633.

[11] F. S. Abu-Mouti and M. E. El-Hawary, "Optimal distributed generation allocation and sizing in distribution systems via artificial bee colony algorithm," *IEEE Trans. Power Deliv.*, vol. 26, no. 4, pp. 2090–2101, 2011, doi: 10.1109/TPWRD.2011.2158246.

[12] A. A. Seker and M. H. Hocaoglu, "Artificial Bee Colony algorithm for optimal placement and sizing of distributed generation," *ELECO 2013 - 8th Int. Conf. Electr. Electron. Eng.*, no. January 2014, pp. 127–131, 2013, doi: 10.1109/ eleco.2013.6713817.

[13] E. A. Al-Ammar *et al.*, "ABC algorithm based optimal sizing and placement of DGs in distribution networks considering multiple objectives," *Ain Shams Eng. J.*, vol. 12, no. 1, pp. 697–708, 2021, doi: 10.1016/j.asej.2020.05.002.

[14] S. Bhuyan, M. Das, and K. C. Bhuyan, "Particle swarm optimizations based DG allocation in local PV distribution networks for voltage profile improvement," *2017 Int. Conf. Comput. Electr. Commun. Eng. ICCECE 2017*, pp. 12–15, 2018, doi: 10.1109/ICCECE.2017.8526201.

[15] W. Haider, S. J. Ul Hassan, A. Mehdi, A. Hussain, G. O. M. Adjayeng, and C. H. Kim, "Voltage profile enhancement and loss minimization using optimal placement and sizing of distributed generation in reconfigured network," *Machines*, vol. 9, no. 1, pp. 1–16, 2021, doi: 10.3390/machines9010020.

[16] S. Mahajan and S. Vadhera, "Optimal sizing and deploying of distributed generation unit using a modified multiobjective Particle Swarm Optimization," *2016 IEEE 6th Int. Conf. Power Syst. ICPS 2016*, no. 4, 2016, doi: 10.1109/ICPES.2016.7584092.

[17] R. Arulraj, N. Kumarappan, and T. Vigneysh, "Optimal location and sizing of DG and capacitor in distribution network using Weight-Improved Particle Swarm Optimization algorithm (WIPSO)," *Proc. - 2013 IEEE Int. Multi Conf. Autom. Comput. Control. Commun. Compress. Sensing, iMac4s 2013*, pp. 759–764, 2013, doi: 10.1109/iMac4s.2013.6526508.

[18] V. S. Bhadoria, N. S. Pal, and V. Shrivastava, "Artificial immune system based approach for size and location optimization of distributed generation in distribution system," *Int. J. Syst. Assur. Eng. Manag.*, vol. 10, no. 3, pp. 339–349, 2019, doi: 10.1007/s13198-019-00779-9.

[19] P. S. Meera and S. Hemamalini, "Optimal siting of distributed generators in a distribution network using artificial immune system," *Int. J. Electr. Comput. Eng.*, vol. 7, no. 2, pp. 641–649, 2017, doi: 10.11591/ijece.v7i2.pp641-649.

[20] K. Bhumkittipich and W. Phuangpornpitak, "Optimal placement and sizing of distributed generation for power loss reduction using particle swarm optimization," *Energy Procedia*, vol. 34, pp. 307–317, 2013, doi: 10.1016/j.egypro.2013.06.759.

APPENDIX

Table 3. Line data of IEEE 14-bus distribution system

Line no	From bus	To bus	Line Impedance (p.u)	
			Resistance	Reactance
1	1	2	0.01938	0.05917
2	1	5	0.05403	0.22304
3	2	3	0.04699	0.19797
4	2	4	0.05811	0.17632
5	2	5	0.05695	0.17388
6	3	4	0.06701	0.17103
7	4	5	0.01335	0.04211
8	4	7	0	0.20912
9	4	9	0	0.55618
10	5	6	0	0.25202
11	6	11	0.09498	0.19890
12	6	12	0.12291	0.25581
13	6	13	0.06615	0.13027
14	7	8	0	0.17615
15	7	9	0	0.11001
16	9	10	0.03181	0.08450
17	9	14	0.12711	0.27038
18	10	11	0.08205	0.19207
19	12	13	0.22092	0.19988
20	13	14	0.17093	0.34802

Table 4. Load data of IEEE 14-bus distribution system

Bus no	Load	
	Real power (MW)	Reactive power (MVAR)
1	0	0
2	21.7	12.7
3	94.2	19.1
4	47.8	-3.9
5	7.6	1.6
6	11.2	7.5
7	0	0
8	0	0
9	29.5	16.6
10	9.0	5.8
11	3.5	1.8
12	6.1	1.6
13	13.8	5.8
14	14.9	5.0

Table 5. Line data of IEEE 33-bus distribution system

Line no	From bus	To bus	Line Impedance (p.u)	
			Resistance	Reactance
1	1	2	0.0922	0.0470
2	2	3	0.4930	0.2511
3	3	4	0.3660	0.1864
4	4	5	0.3811	0.1941
5	5	6	0.8190	0.7070
6	6	7	0.1872	0.6188
7	7	8	1.7114	1.2351
8	8	9	1.0300	0.7400
9	9	10	1.0440	0.7400
10	10	11	0.1966	0.0650
11	11	12	0.3744	0.1238
12	12	13	1.4680	1.1550
13	13	14	0.5416	0.7129
14	14	15	0.5910	0.5260
15	15	16	0.7463	0.5450
16	16	17	1.2890	1.7210
17	17	18	0.7320	0.5740
18	2	19	0.1640	0.1565
19	19	20	1.5042	1.3554
20	20	21	0.4095	0.4784
21	21	22	0.7089	0.9373
22	3	23	0.4512	0.3083
23	23	24	0.8980	0.7091
24	24	25	0.8960	0.7011
25	6	26	0.2030	0.1034
26	26	27	0.2842	0.1447
27	27	28	1.0590	0.9337
28	28	29	0.8042	0.7006
29	29	30	0.5075	0.2585
30	30	31	0.9744	0.9630
31	31	32	0.3105	0.3619
32	32	33	0.3410	0.5302

Table 6. Load data of IEEE 33-bus distribution system

Bus no	Load	
	Real power (MW)	Reactive power (MVAR)
1	0	0
2	0.100	0.060
3	0.090	0.040
4	0.120	0.080
5	0.060	0.030
6	0.060	0.020
7	0.200	0.100
8	0.200	0.100
9	0.060	0.020
10	0.060	0.020
11	0.045	0.030
12	0.060	0.035
13	0.060	0.035
14	0.120	0.080
15	0.060	0.010
16	0.060	0.020
17	0.060	0.020
18	0.090	0.040
19	0.090	0.040
20	0.090	0.040
21	0.090	0.040
22	0.090	0.040
23	0.090	0.050
24	0.420	0.200
25	0.420	0.200
26	0.060	0.025
27	0.060	0.025
28	0.060	0.020
29	0.120	0.070
30	0.200	0.600
31	0.150	0.070
32	0.210	0.100
33	0.060	0.040