clean technologies

MDPI

Article

Optimal Placement of Distributed Generation Based on Power Quality Improvement Using Self-Adaptive Lévy Flight Jaya Algorithm

Gubbala Venkata Naga Lakshmi [1,†], Askani Jaya Laxmi [2,†], Venkataramana Veeramsetty [3,†] and Surender Reddy Salkuti [4,*,†]

1 Department of Electrical Engineering, University College of Engineering, Osmania University, Hyderabad 500007, India
2 Department of Electrical and Electronics Engineering, JNTU Hyderabad, Hyderabad 500085, India
3 Center for AI and Deep Learning, Department of Electrical and Electronics Engineering, SR University, Warangal 506371, India
4 Department of Railroad and Electrical Engineering, Woosong University, Daejeon 34606, Republic of Korea
* Correspondence: surender@wsu.ac.kr
† These authors contributed equally to this work.

Abstract: The optimal placement of distributed generation (DG) is a critical task for distribution companies in order to keep the distribution network running smoothly. The optimal placement of DG units is an optimization problem. In this paper, minimization of the voltage deviation from flat voltage is considered as an objective function. The self-adaptive Lévy flight-based Jaya algorithm is used as an optimization technique to determine the best location and size of distributed generation units. In the MATLAB environment, the proposed algorithm was implemented on IEEE 15 and PG and E 69 bus distribution systems. According to the simulation results, distribution networks can supply more quality power to customers by minimizing the voltage deviation from the flat voltage profile if the DG units are properly placed and sized.

Keywords: distributed generation; optimal placement; self-adaptive Lévy flight Jaya algorithm; power quality; voltage deviation

check for updates

Citation: Naga Lakshmi, G.V.; Jaya Laxmi, A.; Veeramsetty, V.; Salkuti, R.S. Optimal Placement of Distributed Generation Based on Power Quality Improvement Using Self-Adaptive Lévy Flight Jaya Algorithm. *Clean Technol.* **2022**, *4*, 1242–1254. https://doi.org/10.3390/cleantechnol4040076

Academic Editor: Nick Papanikolaou

Received: 7 September 2022
Accepted: 27 October 2022
Published: 28 November 2022

Publisher's Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Copyright: © 2022 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

The incorporation of distributed generation (DG) into the distribution system has grown at a rapid pace due to its technical, economic, and environmental benefits [1,2], such as power quality improvement, loss reduction, emission reduction and increase in the financial growth margin for distribution companies (DISCOs), leading to an increase in the integration of DG units over the last decade [3]. This integration may have a positive or negative impact on the distribution system. The positive benefits built into the distribution network are achieved by optimal positioning and sizing of the DG units. Incorrect positioning of DG units has a negative impact on the distribution network.

The optimal placement and sizing of DG units is a common issue in radial distribution systems. Determining the optimal location and size of DG units to maximise the voltage profile, while maintaining the required high quality operating conditions, is critical. Power quality (PQ) refers to the ability to maintain the power distribution bus voltages near to the flat voltage profile. It is commonly used to express the voltage quality. However, voltage quality and power losses are the fundamental factors that influence other factors [4]. In this paper, the optimal placement of DG units in distribution system is determined based on power-quality improvement using a self-adaptive Lévy flight-based Jaya algorithm.

Many optimization algorithms and objective functions have been proposed to determine the ideal location and size of DG units so that distribution businesses can profit from DG unit integration. DG placement in IEEE 15 bus and PG and E 69 bus radial distribution systems based on loss reduction using the genetic algorithm, the firefly algorithm and the hybrid genetic dragonfly are discussed in [5–7]. DG placement in IEEE 15 bus and PG and E 69 bus radial distribution systems based on benefit to DISCOs using black widow optimization is discussed in [8]. DG placement in IEEE 33 bus and PG and E 69 bus radial distribution systems based on a voltage stability index using butterfly optimization is discussed in [9].

DG placement in IEEE 33 bus and PG and E 69 bus radial distribution systems based on minimization of active power losses using grasshopper optimization and the cuckoo search technique is discussed in [10]. DG placement in IEEE 33 bus and PG and E 69 bus radial distribution systems based on minimization of active power losses and voltage deviation using an enhanced genetic algorithm is discussed in [11]. DG placement in IEEE 33 bus and PG and E 69 bus radial distribution systems based on minimization of active power losses using heuristic algorithms is discussed in [12]. DG placement in IEEE 38 bus radial distribution systems based on economic and operational issues using a lightning search algorithm is discussed in [13]. Event-trigger-based distributed cooperative energy management for multi-energy systems is proposed in [14]. Automated distribution network reliability optimization in the presence of DG units considering the probability of customer interruption is discussed in [15]. The optimal placement and sizing of DG units using an improved non-dominated sorting genetic algorithm is proposed in [16].

DG placement in IEEE 14 bus and 30 bus radial distribution systems based on transmission costs using the MW-Mile method is discussed in [17]. DG placement in an IEEE 33 bus radial distribution system based on voltage profile enhancement using an equilibrium optimizer is discussed in [18]. DG placement in an IEEE 14 bus radial distribution system based on LMP and congestion using a GA-GSF algorithm is discussed in [19]. DG placement in an IEEE 6 bus radial distribution system based on minimization of active power losses using a fuzzy expert system is discussed in [20]. DG placement in an IEEE 33 bus radial distribution system based on minimization of active power losses using GA, PSO and BWO is discussed in [21]. DG placement in IEEE 33 and PG and E 69 bus radial distribution systems based on minimization of active power losses using the firefly algorithm is discussed in [22]. DG placement in IEEE 33 and PG and E 69 bus radial distribution systems based on node power mismatches using the soccer game optimization is discussed in [23].

DG placement in a Park–Umngeni 11kV feeder radial distribution network based on active and reactive power losses using simulated annealing optimization is discussed in [24]. DG placement in a PG and E 69 bus radial distribution system based on minimization of active power losses using the honey badger optimization is discussed in [25]. DG placement in an IEEE 14 bus radial distribution system based on minimization of active power losses and voltage deviation using the battle royale optimization, accelerated PSO and the genetic algorithm is discussed in [26]. DG placement in IEEE 16 and 33 bus and PG and E 69 bus radial distribution systems based on minimization of active power losses using mixed-integer linear programming is discussed in [27]. DG placement in an IEEE 33 bus radial distribution system based on minimization of active power losses and enhancement of voltage profile using PSO is discussed in [28]. DG placement in IEEE 33 bus and PG and E 69 bus radial distribution systems based on minimization of active power losses using an iterative algorithm is discussed in [29].

DG placement in an IEEE 33 bus radial distribution system based on minimization of active power losses and operational cost using GA and PSO is discussed in [30]. DG placement in 15, 118 and 51 bus radial distribution systems based on emission, cost and voltage deviation using the manta ray foraging optimization is discussed in [31]. DG placement in an IEEE 33 bus radial distribution system based on voltage stability, loss and cost using PSO is discussed in [32]. DG placement in a PG and E 69 bus radial distribution system based on the voltage stability index and loss using an iterative procedure is discussed in [33]. DG placement in a 34 bus radial distribution system based on voltage profile and loss using GA, SA, HGA and VNS is discussed in [34]. DG placement in a 33 bus radial distribution system based on voltage stability and loss using Advanced-PSO is discussed in [35]. DG placement in 37 and 119 bus radial distribution systems based on voltage profile and loss using an exhaustive iterative method is discussed in [36]. DG sizing in IEEE 15 bus and PG and E 69 bus radial distribution systems based on losses, emission and reliability using game theory, the point estimation method and hybrid heuristic algorithms is discussed in [37–40].

The main contributions of this paper are as follows:

- Determination of optimal location and size for multiple DG units based on power quality in terms of voltage deviation from the flat voltage profile
- A self-adaptive Lévy flight Jaya algorithm (SALFJA) representing an improved version of the Jaya algorithm by the addition of Lévy flight for extensive search is used for optimal DG placement
- The performance of the proposed method is validated in a stochastic environment
- The power quality of the distribution system is mathematically modeled as a sum of squares of voltage deviation at each bus from the flat voltage profile

The remainder of the paper is organized asfollows: Section 2 discusses the formulation of the problem and describes the optimization algorithm. Section 3 provides an analysis of the simulation results. Section 4 presents the conclusions.

2. Methodology

2.1. Mathematical Modeling of DG Placement

DG placement in a radial distribution system is an optimization problem. In this paper, power quality enhancement is considered as an objective by keeping DG units in a proper location with appropriate size. Power quality in the network is measured in terms of the total voltage deviation from the flat voltage profile that is mathematically modeled as shown in Equation (1).

$$Min\ \ VoltageDeviation = \sum_{i=1}^{n} (1 - v(i))^2 \tag{1}$$

The DG placement problem as a constrained optimization problem, and the equality constraint as a power balance constraint, is represented in Equation (2). The inequality constraint as a thermal limit of the feeder is represented in Equation (3),

$$\sum_{i=1}^{n} P(i) = P_D + P_{loss} \tag{2}$$

$$S_l \leq S_{max} \tag{3}$$

In this optimization problem, the DG unit location and size are the decision variables; the boundaries are represented in Equations (4) and (5), respectively.

$$2 \leq DG_{loc} \leq n \tag{4}$$

$$0 \leq DG_{size} \leq 1MW \tag{5}$$

In this paper, two DG units were considered for study and both were considered to be PQ models.

2.2. Self-Adaptive Lévy Flight Jaya Algorithm (SALFJA)

Meta-heuristic algorithms are created because traditional optimization approaches are unsuitable for handling non-linear problems and are extremely sensitive to initial guesses [41]. The Jaya algorithm [42] was designed with the intention that the solution should move away from the worst solution and towards the best solution. In this study, Lévy flight is employed in conjunction with the Jaya algorithm to increase search capabilities—by avoiding the solution from becoming trapped in the local optimum, an effective search utilising Lévy flight may be obtained. The Lévy flight search improves the capacity to perform both global and local searches at the same time. The Lévy flight is modeled mathematically as shown in Equations (6) and (7).

$$Lvy = 0.01 \times \frac{r_1 \sigma}{|r_2|^{\frac{1}{\beta}}} \tag{6}$$

$$\sigma = \left(\frac{\Gamma(1+\beta) \times sin(\frac{\pi\beta}{2})}{\Gamma(\frac{1+\beta}{2}) \times \beta \times 2(\frac{\beta-1}{2}))} \right)^{\frac{1}{\beta}} \tag{7}$$

where r_1 and r_2 are random numbers in [0, 1] produced by a normal distribution. A complete flowchart representing SALFJA for optimal DG placement based on power quality enhancement is presented in Figure 1.

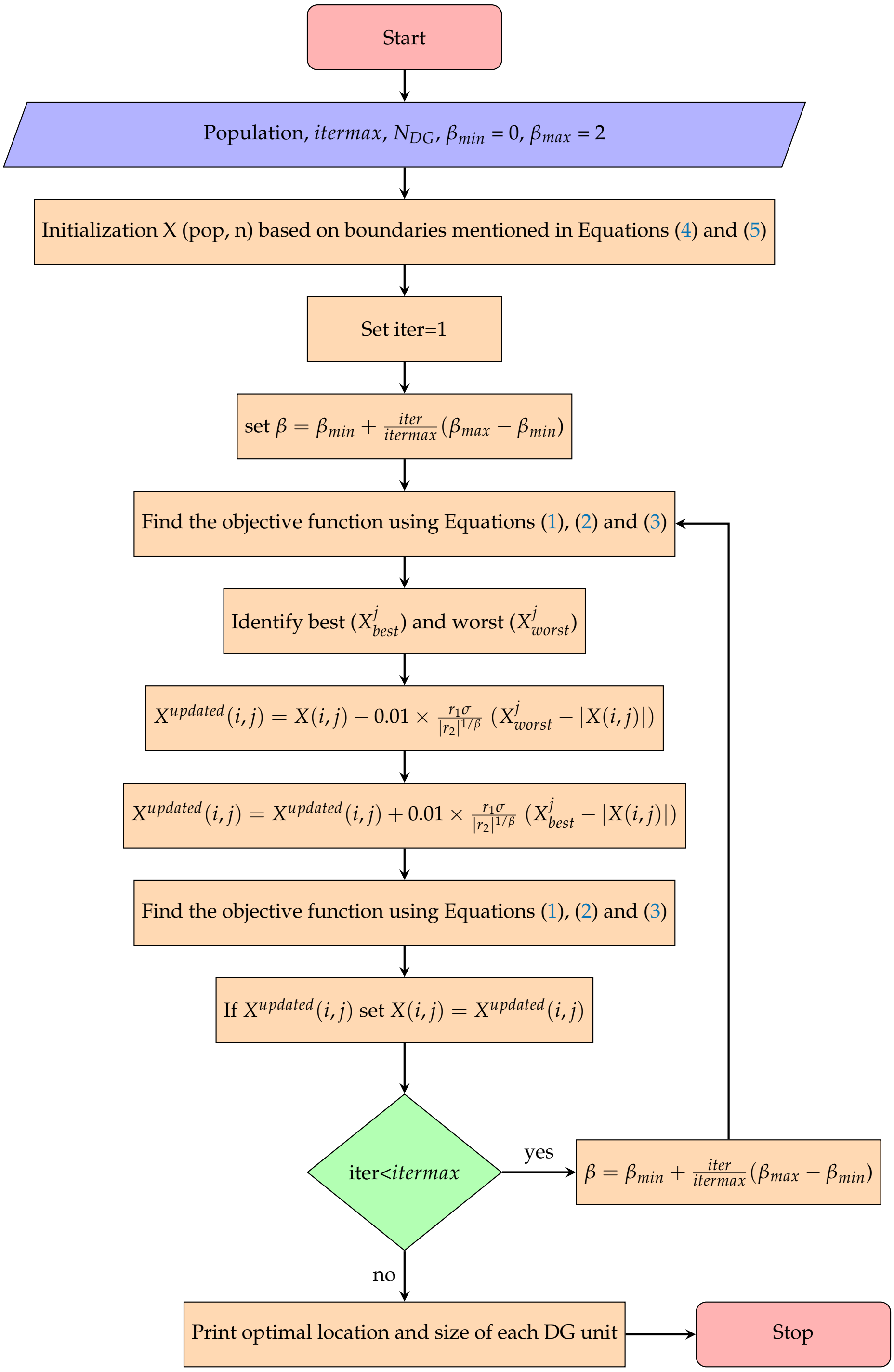

Figure 1. DG placement using SALFJA in radial distribution system.

3. Results Analysis

The SALFJA algorithm to address the proposed DG placement optimization problem was implemented on IEEE 15 bus and PG and E 69 bus distribution systems. The line and load data for the test systems were drawn from [43]. In this study, two PQ modeled DG units, each with a capacity of 1 MW and a 0.9 lagging power factor, were used and simulated in a MATLAB environment.

3.1. Case Study—01: IEEE 15 Bus Radial Distribution System

To identify the placement and generating capacity of the DG units, the proposed SALFJA algorithm was simulated ten times in MATLAB. The best of ten simulations, in terms of minimum total square voltage deviation in the test system, was used to determine the placement and generating capacity of the DG units. Table 1 shows the performance of the proposed method in a stochastic setting. The standard deviation was 0 since the suggested approach produced the same amount of total square voltage deviation (TSVD)) across all runs, i.e., 0.00018. A standard deviation of zero indicates that the suggested SALFJA algorithm produced a solution that was free of ambiguity.

Table 1. Stochastic behaviour of SALFJA on IEEE-15 bus test system.

Simulation	TSVD	Simulation	TSVD
1	0.00018	6	0.00018
2	0.00018	7	0.00018
3	0.00018	8	0.00018
4	0.00018	9	0.00018
5	0.00018	10	0.00018
Min	0.00018	Max	0.00018
Mean	0.00018	Std.	0

Figure 2 depicts the performance curves of the proposed SALFJA for optimal placement of DG units throughout ten simulations. According to Figure 2, the suggested method converged at an TSVD value of 0.00018 for all ten simulations.

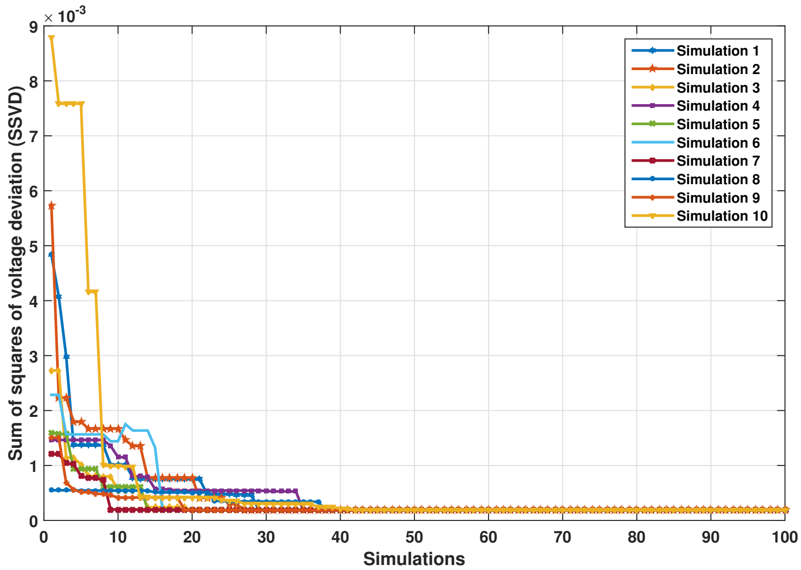

Figure 2. IEEE 15 bus system-Convergence characteristics.

Table 2 shows the ideal location and capacity for the two DG units in the IEEE 15 bus distribution network. According to Table 2, the distribution network will run with a TSVD value of 0.00018 if two DG units with generating capacities of 1MW each are linked at bus 2 and 3, respectively.

Table 2. Optimal location and size of DG units.

DG1		DG2			
Location	**Size**	**Location**	**Size**	**TSVD**	**Base Case TSVD**
2	1 MW	3	1 MW	0.00018	0.0283

The proposed SALFJA algorithm for optimal placement of DG units in the IEEE 15 bus distribution network was validated by comparing it to the genetic algorithm [44], the Jaya algorithm [42] and the particle swarm optimization [45]. Because all of these meta-heuristic algorithms are stochastic in nature, a comparison of all of them for the DG optimum placement issue was conducted in a stochastic setting. Each algorithm was simulated ten times on the IEEE 15 bus network and its performance was assessed using statistical characteristics, such as the mean and standard deviation, as shown in Table 3. The proposed SALFJA algorithm had a standard deviation of zero, as shown in Table 3. However, compared to SALFJA, the remaining meta-heuristic algorithms, i.e., GA and PSO, had higher standard deviation values, indicating that SALFJA exhibited more robust behaviour with respect to determining the optimal location and size for DG units. The performance of SLAFJA for optimal DG placement was confirmed statistically using the Wilcoxon rank sum test [46]; the resulting p-values are shown in Table 3. The p-value of less than 0.05 obtained for SALFJA indicated a higher level of statistical significance than for GA or PSO. However, on a small distribution system, the IEEE 15 bus system, both the Jaya algorithm and SALFJA performed similarly.

Table 3. Stochastic validation of proposed SALFJA algorithm for DG placement.

Simulation	SALFJA	Jaya	GA	PSO
1	0.00018	0.00018	0.00087	0.00090
2	0.00018	0.00018	0.00057	0.00093
3	0.00018	0.00018	0.00095	0.00054
4	0.00018	0.00018	0.00077	0.00095
5	0.00018	0.00018	0.00021	0.00079
6	0.00018	0.00018	0.00078	0.00232
7	0.00018	0.00018	0.00055	0.00074
8	0.00018	0.00018	0.00084	0.00106
9	0.00018	0.00018	0.00051	0.00056
10	0.00018	0.00018	0.00094	0.00091
Min	0.00018	0.00018	0.00021	0.00054
Max	0.00018	0.00018	0.00095	0.00232
Mean	0.00018	0.00018	0.000699	0.00097
Std	0	0	0.000235	0.000503
p-value	-	-	3.18×10^{-5}	0.000388

Figure 3 shows a comparison of the proposed SALFJA algorithm with different meta-heuristic algorithms in terms of convergence characteristics. In comparison to GA and PSO, the proposed SALFJA exhibited smoother convergence properties. SALFJA was faster than GA and PSO in reaching the optimal position, i.e., the least TSVD value.

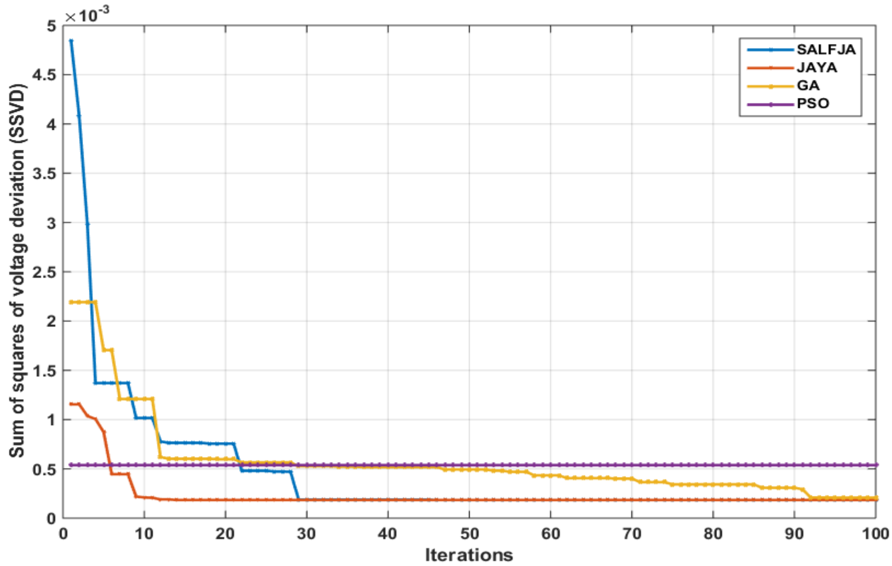

Figure 3. IEEE 15 bus system-Validation with convergence characteristics.

Figure 4 depicts the voltage at each bus in the IEEE 15 bus test system. The voltage at each bus was lower in the absence of DG units in the system than in the presence of DG units owing to reverse power flow, which reduced losses and improved the voltage profile. The voltage profile with SALFJA was superior to GA and PSO, being closer to unity. A voltage profile closer to unity indicates that optimizing the location and size of DG units leads to enhanced power quality operation of the distribution system.

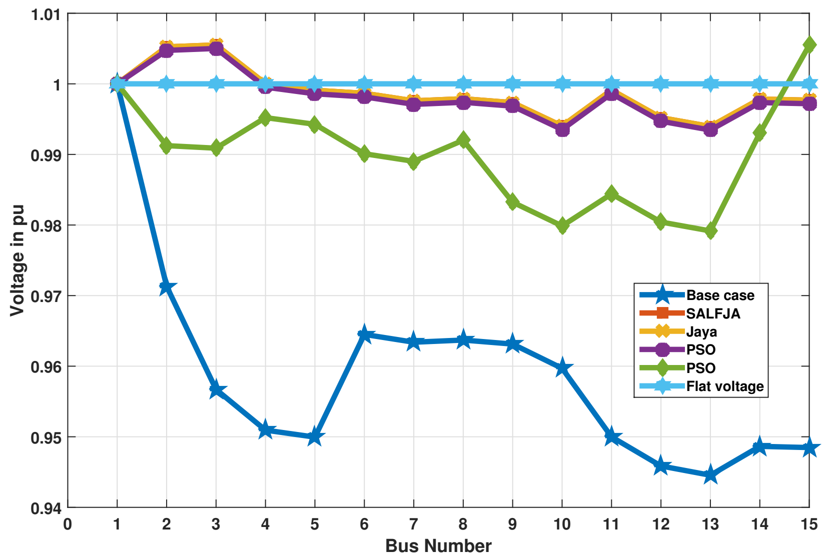

Figure 4. IEEE 15 bus system: Voltage profiles.

When the optimal simulation was used, the effectiveness of SALFJA for optimal DG allocation on an IEEE 15 bus distribution system was shown to be better than both GA and PSO in a stochastic setting, which is important because all algorithms are stochastic in nature.

3.2. Case Study—02: PG & E 69 Bus Radial Distribution System

To identify the placement and generating capacity of DG units, the proposed SALFJA algorithm was simulated ten times in MATLAB. The best of ten simulations in terms of minimum TSVD was used to determine the placement and generating capacity of the DG units. Table 4 shows the performance of SALFJA in a stochastic setting. The standard deviation was 0.000081 since the proposed approach produced the same TSVD value across all runs. A standard deviation close to zero indicates that the suggested SALFJA provided a solution that was free of ambiguity.

Table 4. Stochastic behaviour of SALFJA on PG and E 69 bus test system.

Simulation	TSVD	Simulation	TSVD
1	0.01161	6	0.01158
2	0.01142	7	0.01142
3	0.01139	8	0.01147
4	0.01138	9	0.01147
5	0.01155	10	0.01152
Min	0.01138	Max	0.01161
Mean	0.011481	Std.	0.000081

Figure 5 depicts the performance curves of the proposed SALFJA for optimal DG unit placement throughout ten simulations. According to Figure 5, the SALFJA algorithm converged close to the optimal TSVD value of 0.01138 for all ten simulations.

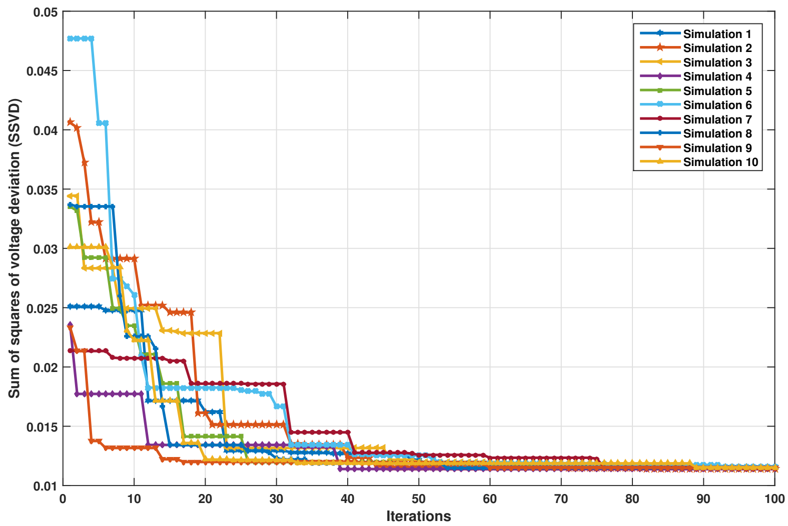

Figure 5. PG and E 69 bus system: Convergence characteristics.

Table 5 shows the best position and size for the two DG units in the PG and E 69 bus test system. According to Table 5, the distribution network will run with a lower TSVD value, i.e., 0.01138, if two DG units with 1000 kW and 824 kW generating capacity are linked at bus 61 and 15, respectively.

Table 5. PG and E 69 bus test system: Optimal placement of DG units.

DG1		DG2			
Location	Size	Location	Size	TSVD	Base Case TSVD
61	1 MW	15	0.82 MW	0.01138	0.0993

The proposed SALFJA algorithm for optimal placement of DG units in the PG and E 69 bus test system was validated by comparing it to the genetic algorithm [44], the Jaya algorithm [42] and the particle swarm optimization [45]. Because all of these meta-heuristic algorithms are stochastic in nature, a comparison of all of them for the DG optimum placement issue was performed in a stochastic setting. Each algorithm was simulated ten times on the PG and E 69 bus test system and its performance was assessed using statistical characteristics, such as the mean and standard deviation, as shown in Table 6. The proposed SALFJA algorithm had a standard deviation close to zero, as shown in Table 6. However, compared to SALFJA, the remaining meta-heuristic algorithms, i.e., GA, Jaya and PSO had higher standard deviation values, indicating that SALFJA exhibited more robust behaviour with respect to determining the optimal location and size for the DG units. The proposed SALFJA's performance for optimal DG placement was confirmed statistically using the Wilcoxon rank sum test [46]; the resulting *p*-values are shown in Table 3. The *p*-values for GA and PSO were less than 0.05 in comparison with SALFJA; the results obtained for SALFJA, were more statistically significant than for GA and PSO.

Table 6. PG and E 69 bus test system: Stochastic validation of proposed SALFJA algorithm for DG placement.

Simulation	SALFJA	Jaya	GA	PSO
1	0.01161	0.01580	0.05750	0.02131
2	0.01142	0.01155	0.02872	0.02424
3	0.01139	0.01187	0.01618	0.02001
4	0.01138	0.01187	0.05025	0.02135
5	0.01155	0.01667	0.02419	0.01241
6	0.01158	0.01986	0.03762	0.01301
7	0.01142	0.01187	0.04480	0.01187
8	0.01147	0.01187	0.04259	0.01187
9	0.01147	0.01489	0.04805	0.01727
10	0.01152	0.01187	0.01612	0.02989
min	0.01138	0.01155	0.01612	0.01187
max	0.01161	0.01986	0.05750	0.02989
mean	0.01148	0.01381	0.03660	0.01832
std	0.00008	0.00286	0.01457	0.00612
p-value	NA	0.013664	0.0002	0.00321

Figure 6 shows a comparison of the proposed SALFJA algorithm with different meta-heuristic algorithms in terms of convergence characteristics. In comparison to GA, Jaya and PSO, the proposed SALFJA exhibited smoother convergence properties in achieving results closer to the global optimum TSVD value, i.e., 0.01138.

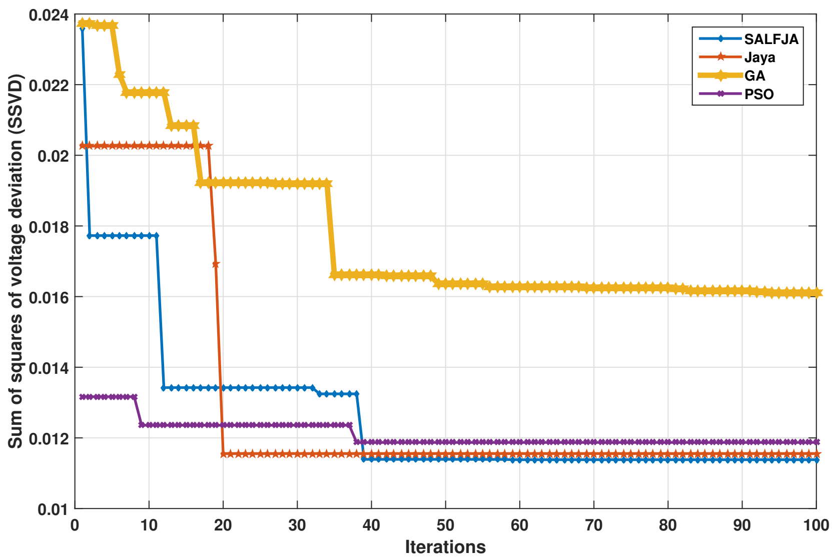

Figure 6. PG and E 69 bus test system: Validation with convergence characteristics.

Figure 7 depicts the voltage at each bus in the PG and E 69 bus test system. The voltage at each bus was lower in the absence of DG units in the system than in the presence of DG units owing to reverse power flow, which reduced losses and improved the voltage profile. The voltage profile with SALFJA was superior to GA. The Jaya and PSO results were close to unity. A voltage profile closer to unity shows that DG units having optimal location and size result in better power quality operation of the distribution system.

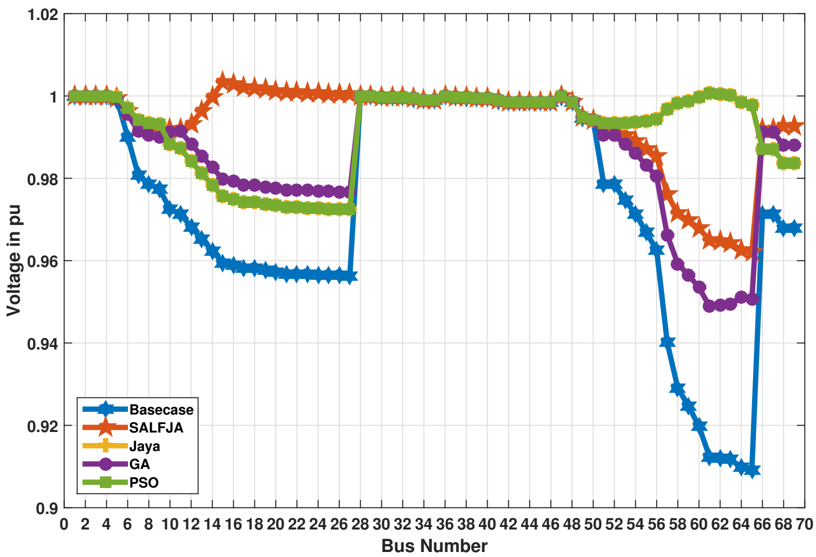

Figure 7. PG and E 69 bus system: Voltage profiles.

When the optimal simulation was used, the effectiveness of SALFJA for optimal DG allocation on a PG and E 69 bus system was better than GA, Jaya and PSO in a stochastic setting, which is important because all algorithms are stochastic in nature. However, for a small test system, the IEEE 15 bus, both SALFJA and Jaya performed identically.

4. Conclusions

A modified Jaya algorithm, denoted SALFJA, was created by adding Lévy flight to the Jaya algorithm to improve the search capability for finding the optimal location and size of DG units. The SALFJA algorithm was implemented to address the DG placement optimization issue by dealing with the appropriate objective function, i.e., minimization of the total square voltage deviation, and by considering the maximum line loading capacity as a constraint.

With regard to the simulation findings, the proposed method performed well, producing a solution that was closer to the global optimum point and which also worked well statistically with a standard deviation close to zero. The proposed algorithm was validated statistically by comparing it with well-known meta-heuristic algorithms, including GA, Jaya and PSO in both large test systems, such as the PG and E 69 bus system, and smaller systems, such as the IEEE 15 bus system.

The DG placement problem may be extended to include emissions and reliability as objectives, as well as the influence of load modeling, and by taking into account load and renewable energy uncertainty.

Author Contributions: Conceptualization, G.V.N.L. and A.J.L.; methodology, G.V.N.L. and A.J.L.; software, G.V.N.L.; validation, G.V.N.L. and A.J.L.; formal analysis, G.V.N.L. and A.J.L.; investigation, G.V.N.L.; resources, G.V.N.L.; data curation, G.V.N.L.; writing—original draft preparation, G.V.N.L. and V.V.; writing—review and editing, A.J.L. and S.R.S.; visualization, G.V.N.L.; supervision, A.J.L.; project administration, A.J.L.; funding acquisition, S.R.S. All authors have read and agreed to the published version of the manuscript.

Funding: Woosong University Academic Research Funding 2022.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

DG	Distributed generation
TSVD	Total system voltage deviation
PQ	Power quality
DISCOs	Distribution companies
P(i)	Generation from *ith* DG unit
P_D	Power demand
P_{loss}	Active power loss
S_l	Apparent power in feeder 'i'
S_{max}	Thermal limit for feeder 'i'
V(i)	Voltage at *ith* bus
DG_{loc}	Location for DG
DG_{size}	Size for DG

References

1. Raut, U.; Mishra, S. A new Pareto multi-objective sine cosine algorithm for performance enhancement of radial distribution network by optimal allocation of distributed generators. *Evol. Intell.* **2020**, *14*, 1635–1656. [CrossRef]
2. Kawambwa, S.; Hamisi, N.; Mafole, P.; Kundaeli, H. A cloud model based symbiotic organism search algorithm for DG allocation in radial distribution network. *Evol. Intell.* **2021**, *15*, 545–562. [CrossRef]
3. Awad, A.; Abdel-Mawgoud, H.; Kamel, S.; Ibrahim, A.A.; Jurado, F. Developing a Hybrid Optimization Algorithm for Optimal Allocation of Renewable DGs in Distribution Network. *Clean Technol.* **2021**, *3*, 409–423. [CrossRef]
4. Chattopadhyay, S.; Mitra, M.; Sengupta, S. *Electric Power Quality*; Springer: Berlin/Heidelberg, Germany, 2011; pp. 5–12.
5. Veeramsetty, V.; Lakshmi, G.N.; Jayalaxmi, A. Optimal allocation and contingency analysis of embedded generation deployment in distribution network using genetic algorithm. In Proceedings of the 2012 International Conference on Computing, Electronics and Electrical Technologies (ICCEET), Nagercoil, India, 21–22 March 2012; pp. 86–91.
6. Lakshmi, G.N.; Jayalaxmi, A.; Veeramsetty, V. Optimal placement of distributed generation using firefly algorithm. In Proceedings of the IOP Conference Series: Materials Science and Engineering, Ulaanbaatar, Mongolia, 10–13 September 2020; Volume 981, p. 042060.
7. Lakshmi, G.N.; Jayalaxmi, A.; Veeramsetty, V. Optimal Placement of Distribution Generation in Radial Distribution System Using Hybrid Genetic Dragonfly Algorithm. *Technol. Econ. Smart Grids Sustain. Energy* **2021**, *6*, 1–13. [CrossRef]
8. Venkata, N.L.G.; Askani, J.L.; Veeramsetty, V. Optimal placement of distributed generation based on DISCO's additional benefit using self adaptive Lévy flight based black widow optimization. *Int. J. Emerg. Electr. Power Syst.* **2021**, *22*, 401–410. [CrossRef]
9. Mohanty, P.K.; Lal, D.K. Voltage stability index and butterfly optimization algorithm-based DG placement and sizing in electrical power distribution system. In *Green Technology for Smart City and Society*; Springer: Berlin/Heidelberg, Germany, 2021; pp. 311–326.
10. Suresh, M.; Edward, J.B. A hybrid algorithm based optimal placement of DG units for loss reduction in the distribution system. *Appl. Soft Comput.* **2020**, *91*, 106191. [CrossRef]
11. Almabsout, E.A.; El-Sehiemy, R.A.; An, O.N.U.; Bayat, O. A hybrid local search-genetic algorithm for simultaneous placement of DG units and shunt capacitors in radial distribution systems. *IEEE Access* **2020**, *8*, 54465–54481. [CrossRef]
12. Pal, A.; Chakraborty, A.K.; Bhowmik, A.R. Optimal placement and sizing of DG considering power and energy loss minimization in distribution system. *Int. J. Electr. Eng. Inform.* **2020**, *12*, 624–653. [CrossRef]
13. Manna, D.; Goswami, S.K. Optimum placement of distributed generation considering economics as well as operational issues. *Int. Trans. Electr. Energy Syst.* **2020**, *30*, e12246. [CrossRef]
14. Li, Y.; Zhang, H.; Liang, X.; Huang, B. Event-triggered-based distributed cooperative energy management for multienergy systems. *IEEE Trans. Ind. Inform.* **2018**, *15*, 2008–2022. [CrossRef]
15. Karimi, H.; Niknam, T.; Dehghani, M.; Ghiasi, M.; Ghasemigarpachi, M.; Padmanaban, S.; Tatabaee, S.; Aliev, H. Automated distribution networks reliability optimization in the presence of DG units considering probability customer interruption: A practical case study. *IEEE Access* **2021**, *9*, 98490–98505. [CrossRef]

16. Sheng, W.; Liu, K.Y.; Liu, Y.; Meng, X.; Li, Y. Optimal Placement and Sizing of Distributed Generation via an Improved Nondominated Sorting Genetic Algorithm II. *IEEE Trans. Power Deliv.* **2015**, *30*, 569–578. [CrossRef]
17. Avar, A.; Sheikh-El-Eslami, M.K. Optimal DG placement in power markets from DG Owners' perspective considering the impact of transmission costs. *Electr. Power Syst. Res.* **2021**, *196*, 107218. [CrossRef]
18. Shaik, M.A.; Mareddy, P.L.; Visali, N. Enhancement of Voltage Profile in the Distribution system by Reconfiguring with DG placement using Equilibrium Optimizer. *Alex. Eng. J.* **2021**, *61*, 4081–4093. [CrossRef]
19. Dashtdar, M.; Najafi, M.; Esmaeilbeig, M. Reducing LMP and resolving the congestion of the lines based on placement and optimal size of DG in the power network using the GA-GSF algorithm. *Electr. Eng.* **2021**, *103*, 1279–1306. [CrossRef]
20. Manas, M.; Saikia, B.J.; Baruah, D.C. Optimal distributed generator sizing and placement by analytical method and fuzzy expert system: A case study in Tezpur University, India. *Technol. Econ. Smart Grids Sustain. Energy* **2018**, *3*, 1–12. [CrossRef]
21. Vempalle, R.; Dhal, P. Loss minimization by reconfiguration along with distributed generator placement at radial distribution system with hybrid optimization techniques. *Technol. Econ. Smart Grids Sustain. Energy* **2020**, *5*, 1–12. [CrossRef]
22. Jalili, A.; Taheri, B. Optimal sizing and sitting of distributed generations in power distribution networks using firefly algorithm. *Technol. Econ. Smart Grids Sustain. Energy* **2020**, *5*, 1–14. [CrossRef]
23. Venkatesan, Y.; Srilakshmi, K.; Palanivelu, A. Modified soccer game optimization and its application on power flow and distribution generation placement problems of distribution systems. *Evol. Intell.* **2021**, 1 –14. [CrossRef]
24. Lekhuleni, T.; Twala, B. Distributed Optimal Placement Generators in a Medium Voltage Redial Feeder. *Symmetry* **2022**, *14*, 1729. [CrossRef]
25. Elseify, M.A.; Kamel, S.; Abdel-Mawgoud, H.; Elattar, E.E. A Novel Approach Based on Honey Badger Algorithm for Optimal Allocation of Multiple DG and Capacitor in Radial Distribution Networks Considering Power Loss Sensitivity. *Mathematics* **2022**, *10*, 2081. [CrossRef]
26. Abbas, A.; Qaisar, S.M.; Waqar, A.; Ullah, N.; Al Ahmadi, A.A. Min-Max Regret-Based Approach for Sizing and Placement of DGs in Distribution System under a 24 h Load Horizon. *Energies* **2022**, *15*, 3701. [CrossRef]
27. Gallego Pareja, L.A.; López-Lezama, J.M.; Gómez Carmona, O. A Mixed-Integer Linear Programming Model for the Simultaneous Optimal Distribution Network Reconfiguration and Optimal Placement of Distributed Generation. *Energies* **2022**, *15*, 3063. [CrossRef]
28. Adeagbo, A.P.; Ariyo, F.K.; Makinde, K.A.; Salimon, S.A.; Adewuyi, O.B.; Akinde, O.K. Integration of Solar Photovoltaic Distributed Generators in Distribution Networks Based on Site's Condition. *Solar* **2022**, *2*, 52–63. [CrossRef]
29. Prakash, P.; Meena, D.C.; Malik, H.; Alotaibi, M.A.; Khan, I.A. A Novel Analytical Approach for Optimal Integration of Renewable Energy Sources in Distribution Systems. *Energies* **2022**, *15*, 1341. [CrossRef]
30. Prakash, P.; Meena, D.C.; Malik, H.; Alotaibi, M.A.; Khan, I.A. A Novel Hybrid Approach for Optimal Placement of Non-Dispatchable Distributed Generations in Radial Distribution System. *Mathematics* **2021**, *9*, 3171. [CrossRef]
31. Ramadan, A.; Ebeed, M.; Kamel, S.; Mosaad, M.I.; Abu-Siada, A. Technoeconomic and Environmental Study of Multi-Objective Integration of PV/Wind-Based DGs Considering Uncertainty of System. *Electronics* **2021**, *10*, 3035. [CrossRef]
32. Adewuyi, O.B.; Adeagbo, A.P.; Adebayo, I.G.; Howlader, H.O.R.; Sun, Y. Modified analytical approach for PV-DGs integration into a radial distribution network considering loss sensitivity and voltage stability. *Energies* **2021**, *14*, 7775. [CrossRef]
33. Kazmi, S.A.A.; Shin, D.R. DG placement in loop distribution network with new voltage stability index and loss minimization condition based planning approach under load growth. *Energies* **2017**, *10*, 1203. [CrossRef]
34. Ali, A.; Padmanaban, S.; Twala, B.; Marwala, T. Electric power grids distribution generation system for optimal location and sizing—A case study investigation by various optimization algorithms. *Energies* **2017**, *10*, 960. [CrossRef]
35. Mahesh, K.; Nallagownden, P.; Elamvazuthi, I. Advanced Pareto front non-dominated sorting multi-objective particle swarm optimization for optimal placement and sizing of distributed generation. *Energies* **2016**, *9*, 982. [CrossRef]
36. Shahzad, M.; Ahmad, I.; Gawlik, W.; Palensky, P. Load concentration factor based analytical method for optimal placement of multiple distribution generators for loss minimization and voltage profile improvement. *Energies* **2016**, *9*, 287. [CrossRef]
37. Veeramsetty, V.; Chintham, V.; DM, V.K. LMP computation at DG buses in radial distribution system. *Int. J. Energy Sect. Manag.* **2018**, *12*, 364–385. [CrossRef]
38. Veeramsetty, V.; Chintham, V.; Vinod Kumar, D. Proportional nucleolus game theory–based locational marginal price computation for loss and emission reduction in a radial distribution system. *Int. Trans. Electr. Energy Syst.* **2018**, *28*, e2573. [CrossRef]
39. Veeramsetty, V.; Chintham, V.; Vinod Kumar, D.M. Probabilistic locational marginal price computation in radial distribution system based on active power loss reduction. *IET Gener. Transm. Distrib.* **2020**, *14*, 2292–2302. [CrossRef]
40. Veeramsetty, V.; Chintham, V.; DM, V.K. Locational marginal price computation in radial distribution system using Self Adaptive Lévy Flight based Jaya Algorithm and game theory. *Int. J. Emerg. Electr. Power Syst.* **2021**, *22*, 215–231. [CrossRef]
41. Basetti, V.; Chandel, A.K.; Subramanyam, K. Power system static state estimation using JADE-adaptive differential evolution technique. *Soft Comput.* **2018**, *22*, 7157–7176. [CrossRef]
42. Rao, R. Jaya: A simple and new optimization algorithm for solving constrained and unconstrained optimization problems. *Int. J. Ind. Eng. Comput.* **2016**, *7*, 19–34.
43. Veeramsetty, V.; Venkaiah, C.; Kumar, D.V. Hybrid genetic dragonfly algorithm based optimal power flow for computing LMP at DG buses for reliability improvement. *Energy Syst.* **2018**, *9*, 709–757. [CrossRef]
44. Goldberg, D.E.; Holland, J.H. Genetic Algorithms and Machine Learning. *Mach. Learn.* **1988**, *3*, 95–99. [CrossRef]

45. Eberhart, R.; Kennedy, J. A new optimizer using particle swarm theory. In Proceedings of the MHS'95, Sixth International Symposium on Micro Machine and Human Science, Nagoya, Japan, 4–6 October 1995; pp. 39–43.
46. Ryan, T.P. *Statistical Methods for Quality Improvement*; John Wiley & Sons: Hoboken, NJ, USA, 2011.