symmetry

MDPI

Article

Optimal Location and Sizing of Photovoltaic-Based Distributed Generations to Improve the Efficiency and Symmetry of a Distribution Network by Handling Random Constraints of Particle Swarm Optimization Algorithm

Muhammad Abid Ali [1], Abdul Rauf Bhatti [1,*], Akhtar Rasool [2,*], Muhammad Farhan [1] and Ebenezer Esenogho [2]

1 Department of Electrical Engineering and Technology, Government College University Faisalabad, Faisalabad 38000, Pakistan; muhammadabidali@gcuf.edu.pk (M.A.A.); mfarhan@gcuf.edu.pk (M.F.)

2 Department of Electrical Engineering, University of Botswana, Gaborone UB0061, Botswana; esenoghoe@ub.ac.bw or drebenic4real@gmail.com

* Correspondence: bhatti_abdulrauf@gcuf.edu.pk (A.R.B.); akhtar@sabanciuniv.edu (A.R.)

Abstract: Distributed generators (DGs) are increasingly employed in radial distribution systems owing to their ability to reduce electrical energy losses, better voltage levels, and increased dependability of the power supply. This research paper deals with the utilization of a Particle Swarm Optimization algorithm by handling its random constraints to determine the most appropriate size and location of photovoltaic-based DG (PVDG) to keep the asymmetries of the phases minimal in the grid. It is thus expected that this algorithm will provide an efficient and consistent solution to improve the overall performance of the power system. The placement and sizing of the DG are done in a way that minimizes power losses, enhances the voltage profile, i.e., bringing symmetry in the voltage profile of the system, and provides maximum cost savings. The model has been tested on an IEEE 33-bus radial distribution system using MATLAB software, in both conditions, i.e., with and without PVDG. The simulation results were successful, indicating the viability of the proposed model. The proposed PSO-based PVDG model further reduced active power losses as compared to the models based on the teaching–learning artificial bee colony algorithm (TLABC), pathfinder algorithm (PFA), and ant lion optimization algorithm (ALOA). With the proposed model, active power losses have reduced to 17.50%, 17.48%, and 8.82% compared to the losses found in the case of TLABC, PFA, and ALOA, respectively. Similarly, the proposed solution lessens the reactive power losses compared to the losses found through existing TLABC, PFA, and ALOA techniques by an extent of 23.06%, 23%, and 23.08%, respectively. Moreover, this work shows cost saving of 15.21% and 6.70% more than TLABC and ALOA, respectively. Additionally, it improves the voltage profile by 3.48% of the power distribution system.

Keywords: distributed generator; PVDG; PSO algorithm; voltage profile improvement; cost savings; power losses; radial distribution network; constraints handling

check for updates

Citation: Ali, M.A.; Bhatti, A.R.; Rasool, A.; Farhan, M.; Esenogho, E. Optimal Location and Sizing of Photovoltaic-Based Distributed Generations to Improve the Efficiency and Symmetry of a Distribution Network by Handling Random Constraints of Particle Swarm Optimization Algorithm. *Symmetry* **2023**, *15*, 1752. https://doi.org/10.3390/sym15091752

Academic Editors: Yi Zhang and Ying Wang

Received: 7 July 2023
Revised: 1 August 2023
Accepted: 8 September 2023
Published: 13 September 2023

1. Introduction

Electrical energy demand is increasing because of the world's rising population and the usage of more electrical-based appliances in human life. It is required to generate more electrical power to fulfill these demands. Electrical power should be generated from sources that are neither depleting nor causing global warming. Thus, renewable-based electrical power generation (PV, wind turbines, microturbines, biomass, etc.) is one of the preferred choices. Among renewable-based electrical power generation, electrical power generation from solar power-based DGs is on a rising trend.

Currently, the integration of DGs has become an attractive choice for technical, economic, and environmental benefits in power distribution networks [1,2]. The distributed generator is used to generate electrical power on a small scale (1 kW to 50 MW) and is generally embedded in the electrical power distribution networks [3]. The DG unit assists in improving the efficiency of the electrical system by decreasing power losses, stabilizing system oscillation, and improving voltage profile, reliability, and security. This is accomplished by injecting active and reactive power into the load side, as reported in several research studies [4–6]. The advantages of integrating DGs at the distribution side are clear; they require less time and money to install than traditional centralized generators [7–9]. This research aims to use a biogeography-based optimization algorithm to join multiple power voltage distributed generators (PVDGs) in the power distribution system. It is expected to reduce power losses and total harmonics distortion while improving the efficiency of the system [10]. The integration of PVDG in RDS can yield a range of advantages, such as decreased power losses, improved voltage profile, and increased voltage stability index. This integration can also reduce global warming by decreasing the greenhouse effect. In [11], the FFA algorithm was used to identify the optimal position and size of DG in the RDS. In [12], the GA technique was used to determine the optimal location and size of solar-based DG in RDS for minimizing power losses. Similarly, [13] proposed a PSO technique for integrating PVDG at the optimal position and size to reduce actual power losses and improve the voltage profile. The Whale optimization algorithm for multi-objective optimization is proposed for inserting distributed generators in RDS [14]. The renewable-based DGs are in sub-transmission and distribution systems to compare their impacts on Voltage profile and power losses [14]. The enactment of renewable-based DGs into the distribution network has been incorporated by using multi-state modeling through probability density function [15]. A hybrid technique known as TLABC has been employed to determine the most suitable position and size of PV and wind DGs in RDS, to reduce power losses and reduce costs. This technique is based on active power loss reduction [16]. The paper introduces an intelligent augmented social network seeking power dispatch (ORPD) in energy networks. It outperforms the social network seek (ASNS) algorithm for the best reactive (SNS) algorithm with the aid of attaining as much as a 22% power loss discount and up to a 93% development in voltage profiles on tested IEEE fashionable grids [17]. This article offers an improved primarily Heap-based optimizer with a Deeper Exploitative development (HODEI) set of rules for power distribution feeder reconfiguration (PDFR) and allotted generator (DG) allocation; it outperforms conventional techniques in voltage profiles and health metrics [18]. The paper offers an advanced hybrid evolutionary algorithm (PODESCA) and a primarily sensitivity-based decision-making technique for the optimal planning of shunt capacitors in radial distribution structures, reaching higher effects than preceding techniques [19]. This paper introduces a unique mixed-evolutionary technique, the quasi-oppositional differential evolution Lévy flights method (QODELFM), for solving the ideal making plans of distribution generators in radial distribution networks, demonstrating its superiority over existing techniques phrases of robustness and efficiency [20]. This paper proposes an international framework for short-time collection modeling with a rolling mechanism, gray model, and meta-heuristic algorithms. It outperforms popular models and enhances the accuracy and speed of complex structure prediction. Dragonfly and whale optimization boost performance [21]. This paper introduces the Quasi-opposition-based studying and Q-learning-based Marine Predators set of rules (QQLMPA) to beautify the overall performance of the traditional Marine Predators algorithm (MPA) for solving optimization troubles. Q-learning enables better utilization of beyond iteration facts, at the same time as quasi-opposition-based studying improves populace diversity, decreasing convergence to neighbored optima [22]. This study introduces QLADIFA, a novel optimization algorithm combining Q-learning with the adaptive logarithmic spiral-Levy flight firefly algorithm. QLADIFA leverages fireflies' environmental awareness and memory, leading to improved performance compared to existing methods. Numerical experiments validate its effectiveness on benchmark functions and various engineering problems [23]. This paper examines a 150.7 kW grid-connected PV system at GCU Faisalabad. the use of PVSyst 7.4 and Metronome, it carried out an average yearly PR of 79.64%, with a peak of 85.4% in January. The PV array produced 218.12 MWh of DC electricity, injecting 211.70 MWh of AC power into the grid yearly [24].

Incorrect siting and sizing of Distributed Generation (DG) can have a negative effect on the existing system's technical balance. To improve the radial distribution system performance, a single or hybrid technique for optimal siting and sizing of DG is essential. Recently, a combination of Real Power Loss Sensitivity Index (RPLSI) and Artificial Ecosystem-based Optimization (AEO) was proposed to identify the optimal placement of photovoltaic and wind-powered DG units in a radial distribution system, to improve the voltage profile and reduce power losses [25]. The accurate PV array-based DGs siting in RDS by using a differential evolution (DE) algorithm is presented in [26] to obtain the optimal reduction in actual power losses and voltage improvement. Recently, an innovative pathfinder algorithm (PFA) has been developed to identify the best possible locations for incorporating solar-based distributed energy resources (DERs) in a radial distribution system (RDS) [27]. This algorithm leverages a backtracking search optimization technique to reduce active power losses [28]. Moreover, an ALOA algorithm has been proposed to identify the most suitable size and position of photovoltaic (PV) and wind-based DERs, which would ultimately reduce power losses, enhance the voltage profile, and improve voltage stability, thus maximizing cost savings [29].

Previous research has highlighted the capacity for the reduction in power losses and improvement in the voltage profile, execution time, and cost savings. This provides an opportunity for further reduction in real power losses, execution time, cost savings, and DG size. To this end, the integration of solar-based DG using Particle Swarm Optimization (PSO) has not been addressed in detail. This study used the Backward Forward Sweep Method (BFSM) to compare the power losses and voltage profile in the IEEE 33-bus system with and without PVDG. Moreover, PSO was deployed to identify the most suitable location and size for photovoltaic-based distributed generators in a radial distribution network. Simulation of the proposed optimized algorithm in MATLAB has been used to generate the results.

The PSO algorithm was first introduced in 1995. Meanwhile, it has been used as a robust technique for solving optimization issues in a wide variety of applications. It is becoming very popular for its simplicity of implementation and also for its ability to quickly converge to a good solution. It requires no information about the gradient of the function to be optimized and uses only primitive mathematical operators. Compared to other optimization methods, it is faster, cheaper, and more efficient [30–32]. In addition, there are a few parameters to adjust in PSO. Thus, PSO is well suited to solving non-linear, non-convex, continuous, discrete, and integer variable problems. On the other hand, this algorithm does not always work well and there is still room for development. In comparison to other optimization techniques, along with Genetic Algorithms (GA), Differential Evolution (DE), or Simulated Annealing (SA), PSO frequently reveals faster convergence, superior international exploration capabilities, and ease of implementation. But the choice of optimization technique relies upon on the unique characteristics and complexity of the hassle, and in a few cases, other algorithms may additionally outperform PSO below positive situations. Consequently, it is far more crucial to remember the problem's nature and necessities earlier than deciding on the maximum appropriate optimization method for a given radial disbursed strength machine.

This research's main aims are to compute the optimal size and position of single and multiple PVDG units for reducing the real power losses, boosting the voltage profile, and maximizing cost savings by using the PSO algorithm. In this work, the PSO is utilized by handling the random constraints of the original PSO algorithm to improve the efficiency and symmetry of a distribution network. Moreover, Improvement in the voltage profile, Reduction in Active Power Loss (%), Reduction in Reactive Power Loss (%), Execution Time (Sec), and Maximum Cost Savings (USD) of the radial distribution system have been achieved through proposed work by handling the random constraints. On the other hand, no existing published work has achieved all five above-mentioned improvements simultaneously. The main contributions of this paper are listed below precisely.

i. Photovoltaic PV distributed generation, as well as constant load, is all factored into the RDG sizing and allocation problem.
ii. The stochastic characteristics are achieved by using appropriate probability density functions (PDFs).
iii. The Particle Swarm optimization algorithm (PSO), a metaheuristic algorithm, is used to determine the optimal solution with high exploitation potential and exploration aptitude.
iv. The FBSM load flow approach is used to calculate the number of power losses and voltage profiles or symmetry/asymmetry in the voltages.
v. PVDG is injected into the RDS at its optimal location and sizing to minimize the active power loss, reactive power loss, cost savings, and improve the voltage profile.
vi. To show the effectiveness and performance of the proposed model, an IEEE 33 RDS is considered.
vii. The simulation results of the proposed technique are compared with those of recently available algorithms in the literature.

This paper is structured in a way to cover the research work in its entirety. Section 2 talks about the problem and the relevant constraints for optimal PVDG placement. Section 3 explains the proposed optimization technique for the placement and sizing of the PVDG. Section 4 evaluates the simulation results obtained from the procedure. Finally, Section 5 sums up the article with the appropriate conclusion.

2. Methodology

Solar-based DGs at their optimal size and location in the radial distribution system are shown in Figure 1. This figure illustrates that all the data are provided to the control system, which decides the optimal location and size of DGs by using PSO. Additionally, it calculates the voltage profile, active and reactive power losses, and annual cost savings in radial distribution systems.

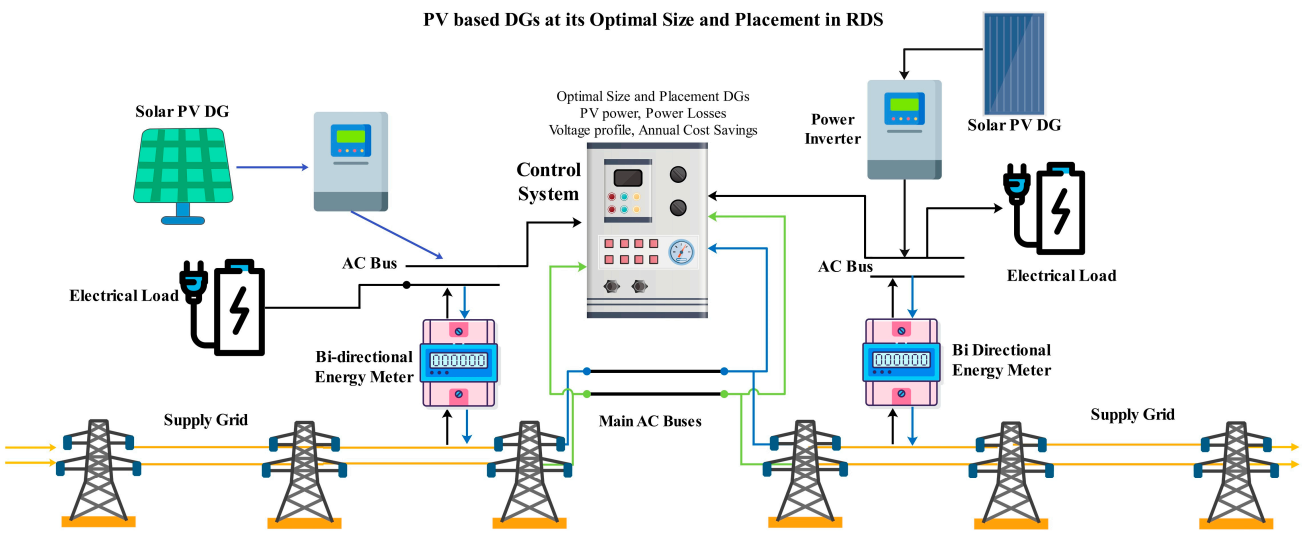

Figure 1. Electric power distribution system with PVDGS.

This proposed work is dedicated to inserting the DG at its optimal location and sizing in the radial distribution network and improving its technical and economic benefits.

The proposed system involves the layout and development of a model using the PSO approach in MATLAB software. Initially, the existing system is studied, and various technical and economic values can be calculated. Eventually, the particle swarm optimization approach could be applied to decide the optimal location and size of PVDG. Once the optimal places and sizes in its RDS are calculated. For making sure the accuracy and reliability of results obtained from MATLAB, a comparison among the numerous techniques has been accomplished, theory cross-checking the validity of the findings.

3. Problem Formulation

The objective of this study is to optimize the active power losses, reactive power losses, voltage profile improvement, and cost savings. Additionally, the minimum and maximum voltage magnitudes and power balance were used as constraints to ensure the desired outcome of the problem.

3.1. Objective Function

The statistics presented in [33] have shown that the distribution system contains about 13% of electrical power losses from the total power generation. The main purpose of the optimal position and size of PVDGs in a power distribution network is to achieve the maximum possible benefits by increasing the efficiency of the system in terms of reduction in power losses, improvement in the voltage profile, and cost savings. BFSM has been used to compute electrical power losses and voltage profiles [34]. The objectives of minimizing the active (P_L) and reactive (Q_L) power losses have been mathematically formulated as in Equations (1) and (2) [35].

$$\text{Minimize } P_L = \sum_{i=1}^{N} P_{loss} = \sum_{i=1}^{N} {I_{br,i}}^2 \times R_i \; for \; i = 1, 2 \ldots N \tag{1}$$

where $I_{br,i}$ and R_i is the ith branch current and the branch resistance, respectively.

$$\text{Minimize } Q_L = \sum_{i=1}^{N} Q_{loss} = \sum_{i=1}^{N} {I_{br,i}}^2 \times \; X_i \;\; for \; i = 1, \; 2 \ldots N \tag{2}$$

where $I_{br,i}$ and X_i is the ith branch current and the branch impedance, respectively.

The voltage profile problem of the distribution network is again related to power quality. This is normally less important than the power losses from the utility point of view. However, in the recent era, it looks like due to the penetration of highly intermittent natural renewable-based DGs in power distribution systems, the interest in voltage profiles at the distribution level is increasing. The voltage at different nodes may differ due to sudden changes in load and generation requirements.

$$V_{Profile} = \sum_{i=1}^{n_i} (V_{\,i} - V_{rated}) \; where \; i = 1, 2 \ldots n \tag{3}$$

V_i is the voltage at bus i and V_{rated} is a rated voltage of the distribution system and selected as 1 p.u. in this study.

where ΔV = total change in voltage profile

$$\Delta V = 1.05 p.u. \leq v \geq 0.95 p.u. \tag{4}$$

3.2. Constraints

There are two types of constraints: equality constraints, and inequality constraints.

3.2.1. Equality Constraints

The following operating conditions must be fulfilled during the optimization process.

$$P_{Grid} + P_{DG} = P_{Loss} + P_{Load} \tag{5}$$

$$Q_{Grid} + Q_{DG} = Q_{Loss} + Q_{Load} \tag{6}$$

where, P_{Grid} and Q_{Grid} are the total active and reactive power inserted by the grid into the system. P_{DG} and Q_{DG} are active and reactive power injected by the distributed generator. P_{Loss} and Q_{Loss} are active and reactive power losses. P_{Load} and Q_{Load} are active and reactive power consumed, respectively.

3.2.2. Inequality Constraints

- Voltage Limitation.
- For keeping a proper stable voltage magnitude or voltage symmetry of the whole IEEE 33-bus network, the absolute voltage value at all nodes of the distribution system should meet the defined constraints.

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

- Current Limitation.
- For keeping a proper current flow in all branches, it should not exceed the rated limit. The absolute value of the current at all nodes of the RDS should meet the defined constraints.

$$|I_{ij}| \leq |I_{ij}|^{max} \tag{8}$$

- Thermal line restriction:
- The thermal line restriction condition is mentioned in Equation (9).

$$|S_{li}| \leq |I_{li}|^{max} \tag{9}$$

3.3. Photovoltaic (PV)-Based DG Model

Solar-based DGs or PV modules convert sunlight directly into electrical power. The amount of power generation is directly dependent on the sunlight intensity. This power generation is in the form of DC and the demand side consumes power in the form of AC. An inverter is a device that is used to transform direct current (DC) power from a solar generator into alternating current (AC). The converter would provide compatible AC output power with the AC utility distribution system. According to a paper [36], the output power capacity (P_{cpv}) of the PVDG is as follows.

$$P_{cpv} \rightarrow f\left(A_{sp}, I_{solar}, \mu_{sp}\right) \tag{10}$$

where A_{sp} is the area of solar panels; I_{solar} is solar irradiance, which is the function of time; and μ_{sp} is solar cells' efficiency in the PVDG. The calculation of the $P_{cpv}(\Delta t)$ at a time instance using the equation is given below.

$$P_{cpv}(\Delta t) = A_{sp} \times I_{solar} \times \mu_{sp}(\Delta t) \tag{11}$$

Therefore, the power generated from solar photovoltaic panels can be considered power generated from a non-dispatchable source. Another important feature of this source is that it provides active and reactive power (either stable or unity power factor depending on the usage of the converter). If this source needs to provide power with a constant power factor, then a static electronic converter is used. The PVDG model is generally considered a constant power factor model. The maximum power evaluation of the PVDG (Pmax) has been computed using the equation given below.

$$P_{max} = \frac{1}{m \to n} \sum_{m=1}^{n=24} P_{cpv}(\Delta t)_{mn} \tag{12}$$

4. Particle Swarm Optimization (PSO) Algorithm

The Particle Swarm Optimization algorithm is a powerful tool for solving optimization problems in a stochastic manner. It mimics the behavior of animals that search for food in groups, such as a school of fish or a flock of birds. This technique is useful in finding the optimal solution in each search space. Many researchers have considered the use of this technique due to its substantiated strength, ease of implementation, and universal examination ability in many applications. This optimization technique was introduced by Kennedy and Ebert in 1995, in which a group of the swarm (named population) was randomly created. Every particle inside the search space had an individual momentum and speed in correlation with the object. This speed and direction would be adjusted based on the particle's history of the best experiences and the collective best experiences of its surroundings. Due to this, the particle has the tendency to move in a particular direction toward the desired goal in the search region [30–32]. Each particle moves in an N-dimensional search space with the position and velocity of a particle could be updated by using Equations (13) and (14) as given.

$$\mathrm{V_p^{k+1}} = \omega \mathrm{V_p^k} + \mathrm{c_1} * \mathrm{rand_1} * \left(\mathrm{p_{best}} - T_\mathrm{p}^\mathrm{k}\right) + \mathrm{c_2} * \mathrm{rand_2} * \left(\mathrm{g_{best}} - T_\mathrm{p}^\mathrm{k}\right) \tag{13}$$

$$T_p^{k+1} = T_p^k + \gamma * V_p^{k+1} \tag{14}$$

- T^k is the present search point and Tk+1 is the changed search point.
- $\mathrm{V^k}$ is the present velocity and Vk+1 is the changed velocity.
- c_1 and c_2 are weighing coefficients.
- $rand_1$ and $rand_2$ are random numbers [0, 1]; $\mathrm{c_1} = \mathrm{c_2} = 2$; inertia weight is $\omega = \omega_{max} - k(\omega_{max} - \omega_{min})/k_{max}$ and $\omega_{min} = 0.4, \omega_{max} = 0.9$ [37]. K and k_{max} are present and the maximum iteration number, respectively.

The proposed model is illustrated in Figure 2, which utilizes the Particle Swarm Optimization (PSO) technique to identify the best location and size of PVDG. This method enables the model to achieve an optimal solution. The algorithm begins by setting the input parameters and selecting the line and bus data of the IEEE 33-bus system. The FBSM is used to evaluate the number of power losses and voltage profiles (symmetric or asymmetric voltages) before the integration of the DG (Distributed Generation). The PSO (Particle Swarm Optimization) algorithm is then applied to identify the appropriate placement and size of the PVDG (Photovoltaic Distributed Generation). In each round, the FBSM is again used for computing the voltage profiles and power losses. The proposed model obtains the best position and size of PVDG, which lessens power losses, reduces cost, and improves the voltage profile for the target issues. The conforming DG fitness value represents the improvement for the mentioned problems.

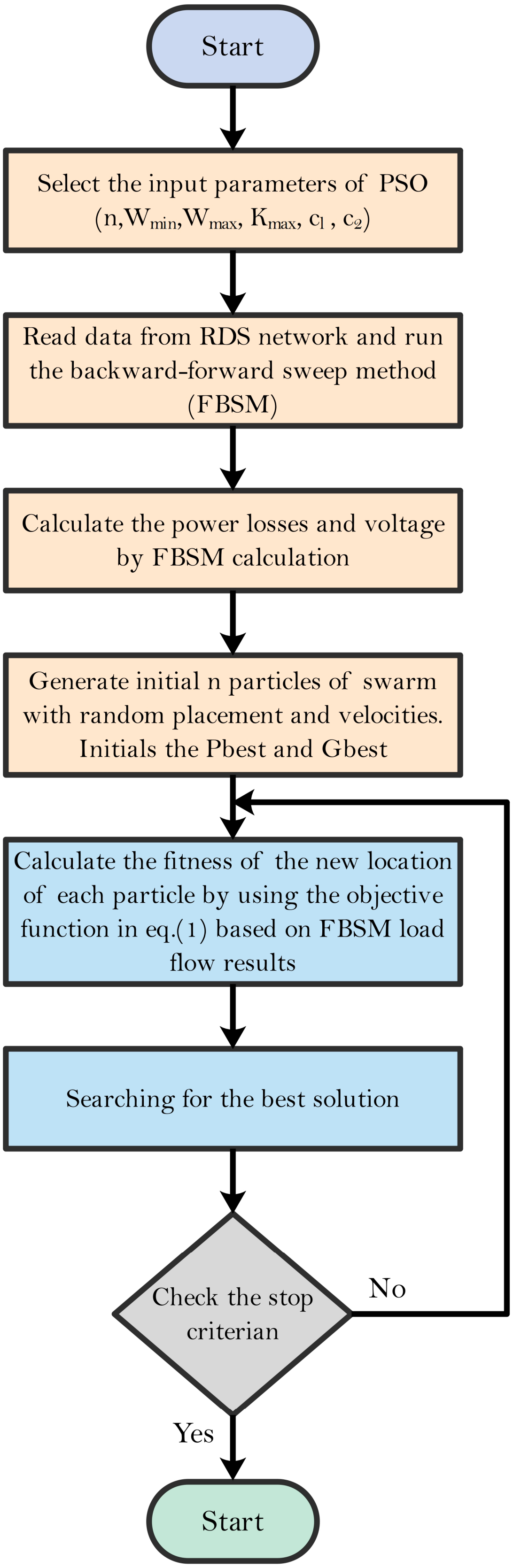

Figure 2. Flowchart of proposed PSO algorithm.

5. Results and Discussion

In the first stage, a base distribution system without DG was considered for analysis. Hereafter, a comparative study of the RDS with and without PVDG was considered. The proposed metaheuristic method was executed in MATLAB 2018a software. The simulation was been performed on a laptop with specifications of Intel® Core (TM) i7-3720 QM CPU@2.60 GHz and 4 GB RAM.

5.1. Performance Analysis of IEEE 33-Bus Power System without PVDG

The efficiency of the suggested approach was validated by using the IEEE 33-bus system, which is the benchmark for testing the performance of any system. The following performance parameters have been selected for comparison, i.e., active (Ploss), reactive (Qloss) power losses, and voltage profile (V). The 33 kV bus network was selected without PVDG and the input data of the proposed model was taken from the line and load data of the IEEE 33-bus system.

The IEEE 33-bus RDS, shown in Figure 3 [38], is composed of 33 buses and 32 lines. It is a standard type of network and is widely used in power sector research. The impedance of each line has different values, and this power distribution system is connected to a centralized power grid system. Different power sources like hydro, coal, nuclear, ocean, wind, PV, and geothermal power plants are connected to the grid as centralized power sources. The maximum and minimum voltage limits have been considered at ±5 for all buses of the network. The voltage level of all buses is 12.66 kV the load of the total active power is 3.715 MW, and the load of total reactive power is 2.3 MVAR.

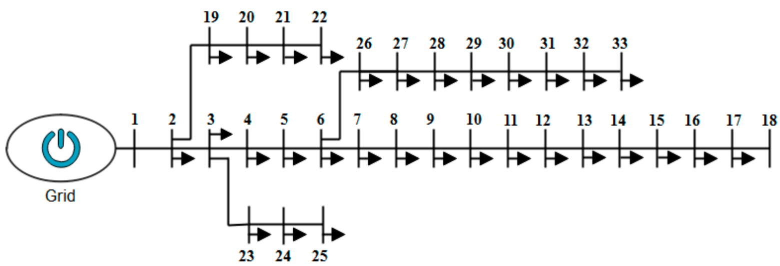

Figure 3. IEEE 33 radial distribution network.

The real power of the system with the load can be seen in Figure 4. It is noted that the initial active (Pi) and reactive (Qi) powers were zero at bus one and they changed from bus two to bus thirty-three. The total active power load was 3715 kW, and the total reactive power load was 2300 kVAR. The highest active power values were found at buses twenty-four and twenty-five, both having 420 kW, and the highest reactive power was at bus thirty with 600 kVAR. The minimum active and reactive powers were both zero at bus one.

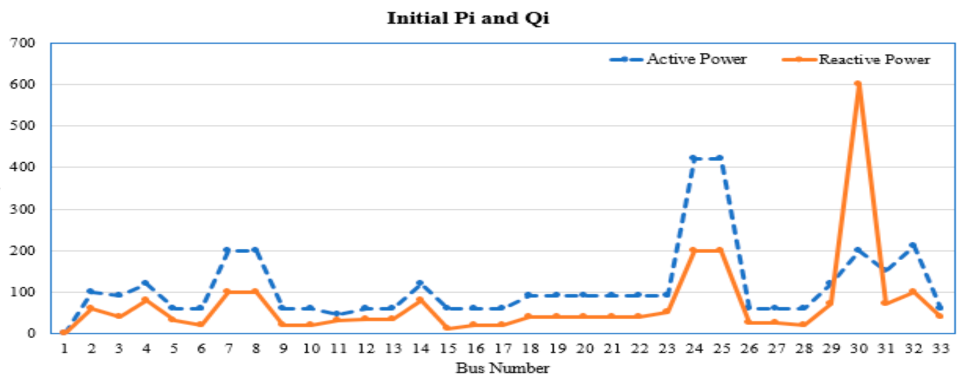

Figure 4. A load data plot (active and reactive power) for IEEE 33-bus system.

The impedance of the bus system is demonstrated in Figure 5, which was derived from the IEEE 33-bus network. This figure provides a graphical representation of the resistance and reactance of the line. The maximum resistance is observed at 1.542 ohms at line 19 and reactance is observed at 1.7210 ohms at line 16. The minimum resistance is 0.0922 ohms and a reactance of 0.0470 ohms has been observed at line one.

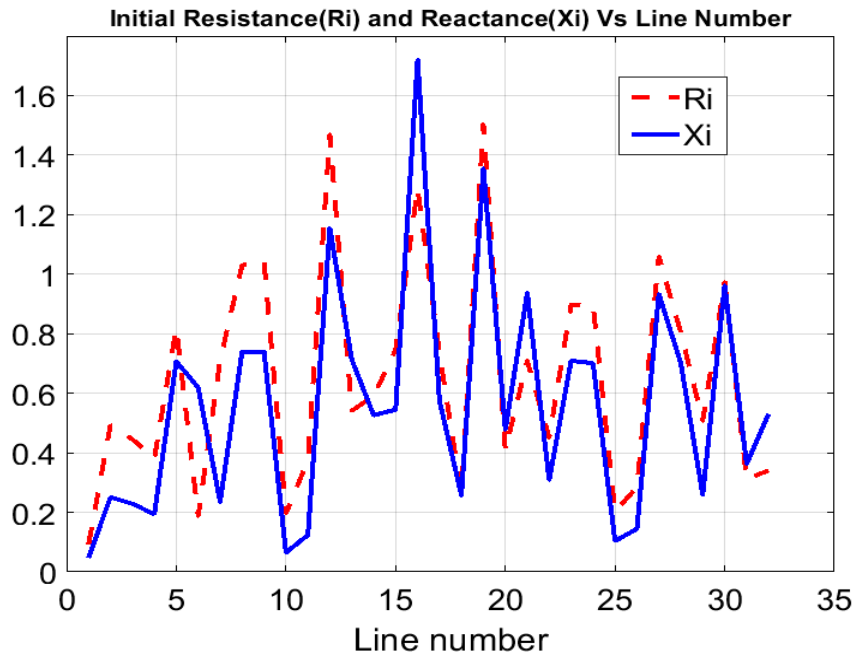

Figure 5. A plot of take-out load data (Resistance and reactance) for the IEEE 33-bus network.

The computation of the base impedance (Z_b) has been performed by assuming the kV and MVA of the IEEE 33-bus network. Base impedance is calculated using Equation (15).

$$Z_b = \frac{V^2}{MVA} \tag{15}$$

Furthermore, the per-unit value (p.u.) of resistance "$(R)_{p.u}$" and reactance "$(X)_{p.u}$" of each line is calculated as given in Equations (16) and (17).

$$(R)_{p.u} = \frac{R_i}{Z_b} \tag{16}$$

where R_i represents the preliminary value of resistance obtained from the line database of the network.

$$(X)_{p.u} = \frac{X_i}{Z_b} \tag{17}$$

where X_i represents the preliminary value of reactance also obtained from the line database of the network.

Figure 6 shows a graph of the obtained value of resistance $\left(R_{p.u}\right)$ and reactance $(X)_{p.u}$ against thirty-two lines of the 33-bus system. It is observed in the plot that the highest resistance is 0.93850849 shown in line number 19 and the highest value of reactance is 1.073775 shown in line 16. In line number 1, the lowest resistance of 0.057525912 along with the reactance value of 0.029324 is observed.

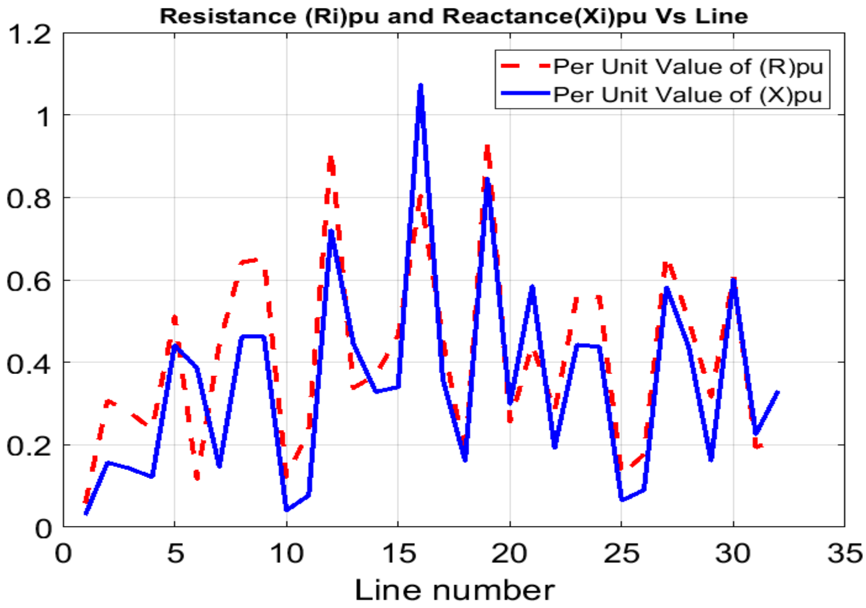

Figure 6. IEEE 33-bus network (per unit value of resistance and reactance for each line).

Figure 7 demonstrates the graph for the analysis of active and reactive power loss without a solar-based DG unit. It is indicated that bus 33 has peak active power losses of 206.95 kW and reactive power losses of 137.46 kVAR.

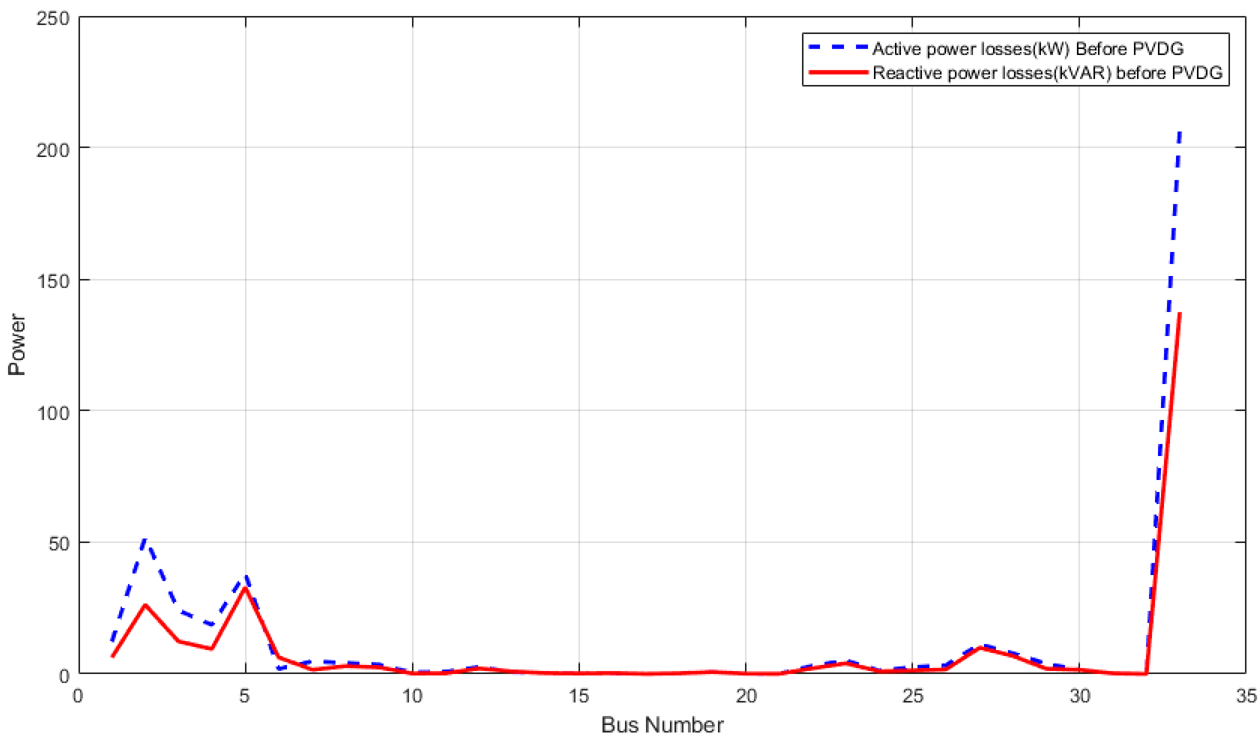

Figure 7. Active and reactive power losses without PVDG.

5.2. Performance Analysis of IEEE 33-Bus Power System with PVDG

This section investigates the effect of the optimum placement and size of PVDG in a radial distribution system. All the bus bars of the network are taken into consideration as possible candidates for the integration of PVDG, apart from bus number 1 which is regarded as a slack bus to relate to an external grid utility.

Figure 8 illustrates the optimal location and size of a solar-based distributed generator in a 33-bus system. The RDS system is connected to a centralized power utility with conventional and renewable power sources. When the proposed model is executed, it is noticed that minimum electrical power losses and improved voltage levels are observed at the optimal placement (node number 9) and size (2440 kW) of PVDG.

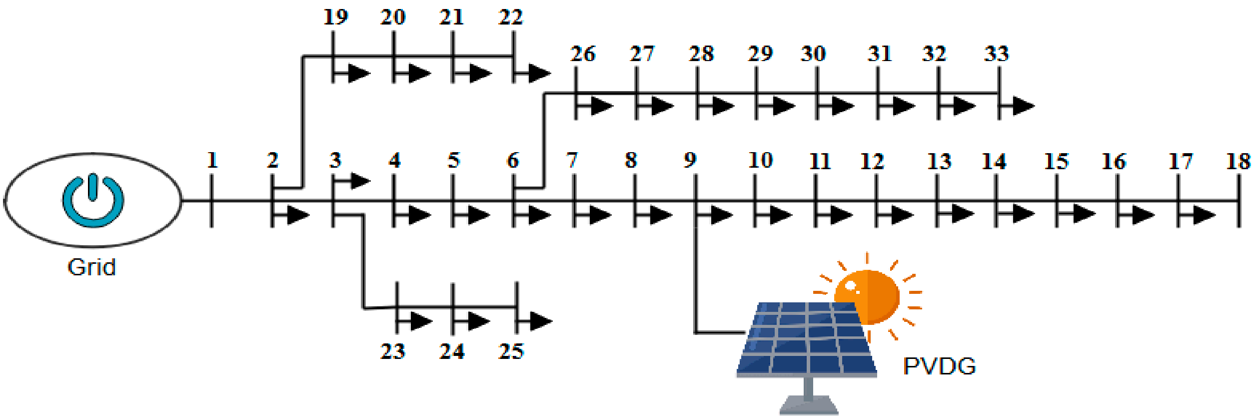

Figure 8. IEEE 33 radial distribution system with PVDG.

The optimized location and size of the PVDG have enabled a significant decrease in active and reactive power losses. The active power loss decreased from 206.95 kW to 91.75 kW, and the reactive power loss decreased from 137.46 kVAR to 64.79 kVAR, as demonstrated in Figure 9.

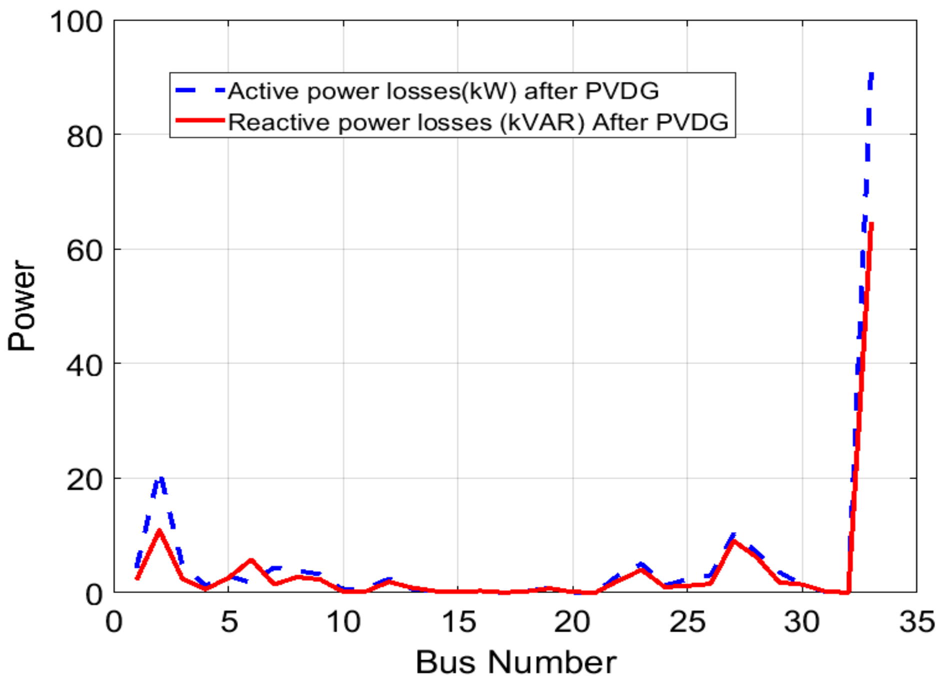

Figure 9. Active and reactive power losses with PVDG.

The effect of the PVDG unit on the voltage profile of a system is shown in Figure 10. The comparison between the system voltage profile with and without the PVDG system is visible. It is observed that the voltage profile improved when solar-based DG is integrated into the 33-bus system. At node 18, the voltage was observed to be 0.9116 per unit, which was improved to 0.9575 per unit when the PVDG system was incorporated. The highest voltage was observed at node one, which was 1 per unit. Incorporating the PVDG system, the overall voltage profile of the system was improved by 3.48%, providing better performance.

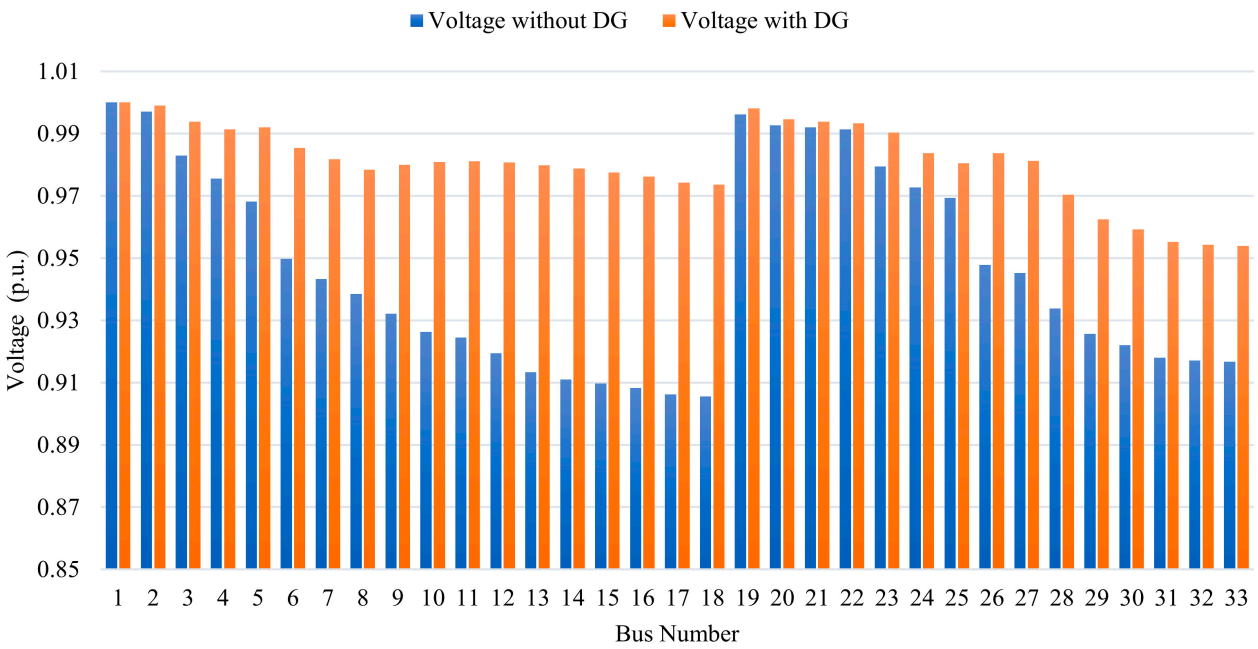

Figure 10. Voltage profile without PVDG and with PVDG.

The total electrical power losses in the RDS before the integration of the solar-based distributed generators were 206.95 kW of active power and 137.46 kVAR of reactive power. Table 1 provides the results of the model, which point out that total active and reactive power losses decreased by 55.66% and 52.85%, respectively after the integration of a 2440 kW PVDG unit. Additionally, the voltage level increased from 0.9116 p.u. to 0.9575 p.u., providing better overall performance. The execution time is just 3.254238 s.

Table 1. Main results found by the proposed model (IEEE 33-bus system).

Subject	without PVDG	with PVDG
Total Active Power loss (kW)	206.95	91.75
Total Reactive Power loss (kVAR)	137.46	64.79
Loss decrement in Pi	-	55.66%
Loss decrement in Qi	-	52.85%
Minimum Voltage V (p.u.)	0.9116@bus 18	0.9575@bus 18
Maximum Voltage V (p.u.)	0.9970@bus 2	0.9985@bus 2
Cost of losses ($)	108,772.92	48,223.4
Saving ($/year)	-	60,549.12
Total DG (Size@Location)	-	2440 kW@bus 9
Execution time (s)	-	3.254238

The proposed system energy cost savings results are shown in Figure 11, which shows that power losses annual saving cost has been increased. If the cost of electric power energy is taken at $0.06, the annual energy saving cost is $60,527.12, which is higher than the annual cost savings presented in [12,16,38].

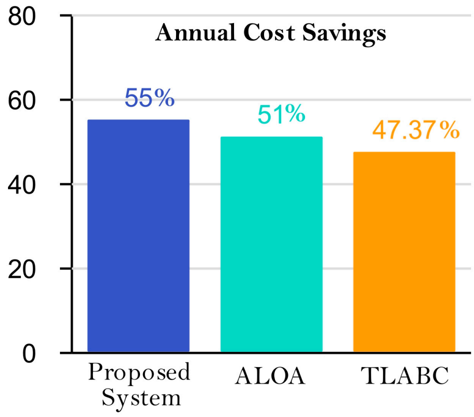

Figure 11. Comparison of annual saving cost of power losses.

The proposed metaheuristic algorithm improves convergence features using less computation time in addition the execution period for the proposed model system is 8.62 s to complete and get optimized results This study has established that the PVDG unit is most effective when placed at the 9th bus in the system with a capacity of 2.44 MW. This significant decrease in power losses has been noted, with a drop of 55.66% in active power losses and 52.78% in reactive power losses. This is an impressive achievement. The proposed results have less active power losses in RDS as compared with the firefly technique presented in [11] as shown above in Table 2. The results comparison has also been carried out with the GA technique [12], in which DG's size is 2.89 MW with a power loss reduction of 46.65%. The proposed model provides better results for active and reactive power when compared with [16,25–27,38] as given in Table 2. To evaluate the proposed research, a comparison was made with a PSO-based optimization technique [13]. This technique only considered the optimal sizing and location in terms of reduced active power loss and improved voltage profile. On the other hand, the proposed model considers additional parameters as listed in Section 2.

Table 2. Comparison of the proposed technique with existing control algorithms.

Author	Year	Control Algorithm	Min. Voltage Improved@Bus	Reduction in Active Power Loss (%)	Reduction in Reactive Power Loss (%)	Execution Time (s)	Maximum Cost Savings (USD)
Remha et al. [11]	2017	FFA	0.9412@18	47.39%	-	-	-
T. Matlokosti [12]	2017	GA	0.9175@18	46.65%	-	-	-
E.S. Ali [38]	2017	ALOA	0.9503@18	51.15%	42.88%	-	$56,726.5
M. Khasanov [16]	2019	TLABC	0.94237@18	47.37%	42.891%	-	$52,536.3
M. Khasanov [25]	2020	AEO	0.94237@18	47.37%	-	-	-
V Janamala [27]	2020	PFA	0.9424@18	47.38%	42.89%	25.342	-
J. Urinby [26]	2021	DE	0.95836@18	47.38%	-	-	-
Rekha C. M. [13]	2022	PSO	0.9180@17	49.28%	32.38%	-	-
Proposed System	2023	PSO	0.9575@18	55.66%	52.78%	3.254238	$60,527.12

6. Conclusions

Particle Swarm Optimization (PSO) is employed to effectively position and adjust the size of a solar-based Distributed Generator (DG) to minimize power losses and improve the voltage profile. To assess the performance of this model, the IEEE 33-bus system was used. The results show that power losses were minimized, the voltage profile improved, and cost savings were maximized when using PVDG units. The results show that the PVDG PSO-based model offers less active power losses as compared to the non-PVDG one. The proposed solution has proved to be superior to other techniques, as it can accurately pinpoint the optimal location and size of the PVDG. This makes it an invaluable tool for the purpose. Furthermore, the insertion of the solar PVDG into a 33-bus system can lessen energy (active and reactive power) losses to 55.66% and 52.78% when compared with the base case. So, it can be concluded that solar-based DGs with PSO algorithm can be a better choice for decreasing electrical power loss, improving in voltage profile, and increasing cost savings in the power RDS system. Additionally, the overall efficiency of the RDS network has been improved. The proposed model can ease the dependency of the utility system during the load demand. PVDG units can be installed in the area where sunlight intensity is adequate.

Future research could focus on the effects of combining PV and wind turbines in RDS along with the addition of energy storing systems. Additionally, the development of a wind-based DG model and the comparison of solar and wind DG results could be explored. Finally, future efforts should be devoted to addressing the uncertainty in load requirements.

Author Contributions: Conceptualization, A.R.B. and M.A.A.; methodology, M.A.A.; software, M.A.A.; validation, A.R.B., A.R., M.F. and E.E.; formal analysis, M.A.A.; investigation, M.A.A.; resources, A.R.B., A.R. and E.E.; data curation, A.R.B.; writing—original draft preparation, M.A.A. and M.F.; writing—review and editing, A.R.B. and A.R.; visualization, A.R.B.; supervision, A.R.B.; project administration, A.R.B. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: IEEE 33-bus data was utilized in this study and is publicly available on the IEEE website.

Acknowledgments: The authors acknowledge the support of IEEE for the provision of the 33 bus data publicly utilized for research purposes.

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

References

1. Chiradeja, P.; Ramakumar, R. An approach to quantify the technical benefits of distribution system. *IEEE Trans. Energy Convers.* **2004**, *19*, 764–773.
2. Pepermans, G.; Driesen, J.; Haeseldonckx, D.; D'haeseleer, W.; Belmans, R. Distribution generation: Definition, benefits and issues. *Energy Policy* **2005**, *33*, 787–798.
3. Mohammedi, R.D.; Hellal, A.; Arif, S.; Mosbah, M. Optimal DG Placement and Sizing in Radial Distribution Systems Using NSGA-II for Power Loss Minimization and Voltage Stability Enhancement. *Int. Rev. Electr. Eng.* **2013**, *8*, 6.
4. Sun, K.; Yao, W.; Fang, J.; Ai, X.; Wen, J.; Cheng, S. Impedance modeling and stability analysis of grid-connected DFIG-based wind farm with a VSC-HVDC. *IEEE J. Emerg. Sel. Top. Power Electron.* **2019**, *8*, 1375–1390.
5. Layadi, T.M.; Champenois, G.; Mostefai, M. Economic and ecological optimization of multi-source systems under the variability in the cost of fuel. *Energy Convers. Manag.* **2018**, *177*, 161–175.
6. Zhang, X.; Tan, T.; Zhou, B.; Yu, T.; Yang, B.; Huang, X. Adaptive distributed auction-based algorithm for optimal mileage based AGC dispatch with high participation of renewable energy. *Int. J. Electr. Power Energy Syst.* **2020**, *124*, 106371.
7. Wang, Q.; Yao, W.; Fang, J.; Ai, X.; Wen, J.; Yang, X.; Xie, H.; Huang, X. Dynamic modeling and small signal stability analysis of distributed photovoltaic grid-connected system with large scale of panel level DC optimizers. *Appl. Energy* **2019**, *259*, 114132.
8. Barik, S.; Das, D. A novel Q-PQV bus pair method of biomass DGs placement in distribution networks to maintain the voltage of remotely located buses. *Energy* **2020**, *194*, 116880.
9. Zhang, X.S.; Yang, B.; Yu, T.; Jiang, L. Dynamic Surrogate Model Based Optimization for MPPT of Centralized Thermoelectric Generation Systems Under Heterogeneous Temperature Difference. *IEEE Trans. Energy Convers.* **2020**, *35*, 966–976.
10. Duong, M.Q.; Pham, T.D.; Nguyen, T.T.; Doan, A.T.; Van Tran, H. Determination of Optimal Location and Sizing of Solar Photovoltaic Distribution Generation Units in Radial Distribution Systems. *Energies* **2019**, *12*, 174. [CrossRef]
11. Remha, S.; Chettih, S.; Arif, S. Optimal DG location and sizing for minimum active power loss in radial distribution system using firefly algorithm. *Int. J. Energetica* **2017**, *4*, 6–10.
12. Matlokotsi, T.; Chowdhury, S. Optimal Placement and Sizing of Renewable Distributed Generation in Electricity Networks Considering Different Load Models. *IEEE Conf.* **2017**, *1*, 1–6. [CrossRef]
13. Rekha, C.M.; Shankaralingappa, C.B. Optimal placement of PSO based Photovotaic (PV) distributed generator (DG) in a distribution system. *J. Tianjin Univ. Sci. Technol.* **2022**, *55*, 493–2137.
14. Prakash, D.; Lakshminarayana, C. Multiple DG placements in radial distribution system for multi objectives using Whale Optimization Algorithm. *Alex. Eng. J.* **2018**, *57*, 2797–2806. [CrossRef]

15. Kumar, M.; Nallagownden, P.; Elamvazuthi, I. Optimal Placement and Sizing of Renewable Distributed Generations and Capacitor Banks into Radial Distribution Systems. *Energies* **2017**, *10*, 811. [CrossRef]
16. Khasanov, M.; Kamel, S.; Xie, K.; Zhou, P.; Li, B. Allocation of Distributed Generation in Radial Distribution Networks Using an Efficient Hybrid Optimization Algorithm. In Proceedings of the 2019 IEEE Innovative Smart Grid Technologies-Asia (ISGT Asia), Chengdu, China, 21–24 May 2019; pp. 1300–1305.
17. Sarhan, S.; Shaheen, A.; El-Sehiemy, R.; Gafar, M. An Augmented Social Network Search Algorithm for Optimal Reactive Power Dispatch Problem. *Mathematics* **2023**, *11*, 1236.
18. Shaheen, A.M.; Elsayed, A.M.; Ginidi, A.R.; El-Sehiemy, R.A.; Elattar, E. A heap-based algorithm with deeper exploitative feature for optimal allocations of distributed generations with feeder reconfiguration in power distribution networks. *Knowl. -Based Syst.* **2022**, *241*, 108269.
19. Mahfoud, R.J.; Alkayem, N.F.; Sun, Y.; Haes Alhelou, H.; Siano, P.; Parente, M. Improved Hybridization of Evolutionary Algorithms with a Sensitivity-Based Decision-Making Technique for the Optimal Planning of Shunt Capacitors in Radial Distribution Systems. *Appl. Sci.* **2020**, *10*, 1384.
20. Jamil Mahfoud, R.; Sun, Y.; Faisal Alkayem, N.; Haes Alhelou, H.; Siano, P.; Shafie-Khah, M. A Novel Combined Evolutionary Algorithm for Optimal Planning of Distributed Generators in Radial Distribution Systems section. *Appl. Sci.* **2019**, *9*, 3394.
21. Cui, Z.; Wu, J.; Ding, Z.; Duan, Q.; Lian, W.; Yang, Y.; Cao, T. A hybrid rolling grey framework for short time series modelling. *Neural Comput. Appl.* **2021**, *33*, 11339–11353.
22. Zhao, S.; Wu, Y.; Tan, S.; Wu, J.; Cui, Z.; Wang, Y.G. QQLMPA: A quasi-opposition learning, and Q-learning based marine predators' algorithm. *Expert Syst. Appl.* **2023**, *213*, 119246.
23. Tan, S.; Zhao, S.; Wu, J. QL-ADIFA: Hybrid optimization using Q-learning and an adaptive logarithmic spiral-levy firefly algorithm. *Math. Biosci. Eng.* **2023**, *20*, 13542–13561.
24. Tamoor, M.; Bhatti, A.R.; Farhan, M.; Zaka, M.A.; ZakaUllah, P. Solar Energy Capacity Assessment and Performance Evaluation of Designed Grid-Connected Photovoltaic Systems. *Appl. Sci.* **2023**, *37*, 39. [CrossRef]
25. Khasanov, M.; Kamel, S.; Tostado-Véliz, M.; Jurado, F. Allocation of Photovoltaic and Wind Turbine Based DG Units Using Artificial Ecosystem-based Optimization. In Proceedings of the 2020 IEEE International Conference on Environment and Electrical Engineering and 2020 IEEE Industrial and Commercial Power Systems Europe, Madrid, Spain, 9–12 June 2020; pp. 1–5.
26. Urinboy, J.; Hasanov, M. Improvement Performance of Radial Distribution System by Optimal Placement of Photovoltaic Array. *Int. J. Eng. Inf. Syst.* **2021**, *5*, 157–159.
27. Janamala, V. A new meta-heuristic pathfinder algorithm for solving optimal allocation of solar photovoltaic system in multi-lateral distribution system for improving resilience. *SN Appl. Sci.* **2021**, *3*, 118.
28. El-Fergany, A. Optimal allocation of multi-type distributed generators using backtracking search optimization algorithm. *Int. J. Electr. Power Energy Syst.* **2015**, *64*, 1197–1205.
29. Ali, E.S.; Abd Elazim, S.M.; Abdelaziz, A.Y. Ant Lion optimization algorithm for optimal location and sizing of renewable distrib-uted generations. *Renew Energy* **2017**, *101*, 1311–1324.
30. Atwa, Y.M.; El-Saadany, E.F.; Salama, M.M.A.; Seethapathy, R. Optimal Renewable Resources Mix for Distribution System Energy Loss Minimization. *IEEE Trans. Power Syst.* **2009**, *25*, 360–370.
31. Kennedy, J.; Eberhart, R. Particle Swarm Optimization. In Proceedings of the ICNN'95—International Conference on Neural Networks, Perth, Australia, 27 November–1 December 1995; Volume 4, pp. 1942–1948. [CrossRef]
32. Eberhart, R.; Kennedy, J. A new optimizer using particle swarm theory. In Proceedings of the Sixth International Symposium on Micro Machine and Human Science, Nagoya, Japan, 4–6 October 1995; pp. 39–43. [CrossRef]
33. Bohre, A.K.; Agnihotri, G.; Dubey, M. Hybrid butterfly-based particle swarm optimization for optimization problems. In Proceedings of the First International Conference on Networks and Soft Computing (ICNSC), Guntur, India, 19–20 August 2014; pp. 172–177. [CrossRef]
34. Zeinalzadeh, A.; Mohammadi, Y.; Moradi, M.H. Optimal multi objective placement and sizing of multiple DGs and shunt capacitor banks simultaneously considering load uncertainty via MOPSO approach. *Int. J. Electr. Power Energy Syst.* **2015**, *67*, 336–349.
35. Haque, M. Efficient load flow method for distribution systems with radial or mesh configuration. *IEE Proc. Gener. Transm. Distrib.* **1996**, *143*, 33–38.
36. Salkuti, S.R.; Battu, N.R. An effective network reconfiguration approach of radial distribution system for loss minimization and voltage profile improvement. *Bull. Electr. Eng. Informatics* **2021**, *10*, 1819–1827. [CrossRef]
37. Eberhart, R.C.; Shi, Y. Comparing inertial weights and constriction factor in particle swarm optimization. In Proceedings of the International Congress on Evaluating Computation, La Jolla, CA, USA, 16–19 July 2000; pp. 84–89.
38. Vita, V. Development of a Decision-Making Algorithm for the Optimum Size and Placement of Distributed Generation Units in Distribution Networks. *Energies* **2017**, *10*, 1433. [CrossRef]