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Optimal Placement and Sizing of Distributed Generations for Power Losses Minimization Using PSO-Based Deep Learning Techniques

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Abstract

The integration of distributed generations (DGs) into distribution systems (DSs) is increasingly becoming a solution for compensating for isolated local energy systems (ILESs). Additionally, distributed generations are used for self-consumption with excess energy injected into centralized grids (CGs). However, the improper sizing of renewable energy systems (RESs) exposes the entire system to power losses. This work presents an optimization of a system consisting of distributed generations. Firstly, PSO algorithms evaluate the size of the entire system on the IEEE bus 14 test standard. Secondly, the size of the system is allocated using improved Particles Swarm Optimization (IPSO). The convergence speed of the objective function enables a conjecture to be made about the robustness of the proposed system. The power and voltage profile on the IEEE 14-bus standard displays a decrease in power losses and an appropriate response to energy demands (EDs), validating the proposed method.

Keywords

Distributed Generations, Deep Learning Techniques, Improved Particle Swarm Optimization, Power Losses, Power Losses Minimization, Optimal Placement

1. Introduction

For several decades, fossil fuels have been recognized as one of the main causes of global warming [1]. As a result, we are experiencing adverse effects such as climate change, which leads to flooding.

Furthermore, these resources are being progressively depleted in the industry and technology sectors [2]. This distributed generation comprises all renewable energies such as wind power, biomass, geothermal, solar, hydropower, hydrogen generators, etc. [3]…These sources have garnered significant attention in recent decades [4]. Current electrical systems integrate the development of new solutions and diverse technologies to meet the growing demand for electrical energy caused by demographic evolution, technological advancements, and the pursuit of decent life [5]. Among these distributed generators, distributed solar production is predominantly used to reinforce low voltage lines [6]. DGs offer significant advantages for electric systems located outside urban areas, particularly for networks with low voltage levels and repeated power outages. These sources are increasingly used for active power generation in distribution networks in isolated areas [7]. The installation of DGs is essential for lines with demand exceeding supply [8]. Given the rapid growth of renewable energy penetration in distribution networks, strategies regarding the appropriate location and size of these sources are increasingly significant. In [9], a solution for the fault management system and real-time control and operation system is proposed, along with the design and main function modules of DGs. In [10], an online voltage and power control-based management algorithm is suggested. To ensure safety and optimal operation, the management of energy flows in a distributed energy management system controlled by an event is described in [11]. Electric systems provide the possibility of having active power which is always supported by reactive power to meet the needs of users with non-linear loads [12]. The power transmission on the transport line increases as the energy demand at the load increases. Furthermore, nonlinear loads in electric networks are responsible for energy disturbance problems such as power factor disturbances, voltage fluctuations, odd harmonics, and high demand for reactive power. The majority of encountered issues stem from the demand for reactive power. To compensate for reactive power requirements, distribution systems may employ flexible techniques based on inverters connected to the grid [13]. One of these techniques is the use of flexible AC transmission systems (FACTS) [14], which play a crucial role in power compensation. These resources can increase the available transfer capacity of the transmission line and regulate reactive power flow in the electrical system which can create fluctuations and stability of the system voltage. One of the most commonly used FACTS devices in current electrical systems is the Static Synchronous Compensator (STATCOM), which is a parallel or shunt compensator. The STATCOM has various applications in the management and control of electrical systems. One of the most commonly used FACTS devices in current electrical systems is the Static Synchronous Compensator (STATCOM) [15], which is a parallel or shunt compensator. These methods all facilitate voltage regulation, improvement of power factor, mitigation of current and voltage harmonics [16], as well as compensation of reactive power. To enhance the daily energy quality, the shunt compensator maintains the capacitor voltage at the level of the continuous bus which is assumed to be stable. It automatically injects or absorbs both active and reactive power into the system, opposite in amplitude to the coupling point's common point. Furthermore, it balances power fluctuations in the system connected to the proposed network by performing charging and discharging operations on capacitors. Furthermore, in the event of proper allocation and sizing, it can enhance the reliability and quality of the system in question, while minimizing investment and operational costs while mitigating environmental risks associated with decentralized or centralized electricity production.

2. Literature Review

In the literature [17], many works have focused on the implementation and sizing of DG in distribution networks, with the aim of improving the quality of low and high-voltage electric energy [18]. Numerous studies have suggested scenarios for load shedding or strengthening using primary sources. In addition to these methods, energy optimization and planning models employ mathematical approaches and strategies based on deep learning or artificial intelligence (AI) [19]. Some algorithms are used based on system complexity. Optimization models and mathematical approaches are used to find optimal and adequate solutions. In [20], evolutionary algorithms are proposed. However, some intelligent techniques take time and may sometimes provide only local optimal solutions instead of the appropriate global optimal solutions [21]. The same applies to certain algorithms that generate too many redundant steps, making the control and management system very slow. The most commonly used algorithms include artificial rabbit algorithms, genetic algorithms, non-dominated sorting genetic algorithms, particle swarm optimization, and hybrid algorithms based on genetic algorithms and particle swarm optimization. Technical term abbreviations will be explained upon first use.

Photovoltaic power generation is becoming increasingly successful in the field of emerging energy technologies. Maximum Power Point Tracking technology is an integral part of any solar power generation system. In the presence of local shading, the output power of the solar panel exhibits a phenomenon with multiple peaks [22]. The use of a method should be proven to keep an eye on peak performance, as well as in the state of local optimization. However, the adaptive approach of particle swarm optimization used by the intelligent algorithm suffers from tracking problems such as significant oscillations, low precision and a long optimization time [23]. This article presents a control strategy based on a greedy algorithm for an adaptive particle swarm optimization algorithm to solve this challenge. The limitations of traditional adaptive particle swarm optimization methods are overcome by combining global and local optimal particle differences with the proportional coefficient of particle motion speed.

The result is a reduction in the world's fossil fuel reserves. Furthermore, the primary source of environmental pollution and climate degradation is humanity's excessive dependence on fossil fuels for its energy. The focus of future energy development will be on producing and utilizing new energies, primarily based on solar power, to better safeguard the ecological environment of the planet through sustainable development. Improvements are not possible as the text already adheres to the given principles and lacks context. Maximizing Power Point Tracking (MPPT) is an integral aspect of photovoltaic energy production because, in a dynamic natural environment, maximum photovoltaic power is essential to improve electricity production efficiency. MPPT is an automated method that optimizes system parameters based on solar cell characteristics. Researchers are constantly improving the MPPT algorithm to combat the problem of low energy conversion rates in shady conditions.

In order to study the proposed system, this work seeks to evaluate the dynamic behavior in transient and steady state of the voltage and power fluctuation. To estimate the robustness of the system, an objective function is defined based on constraints due to the stochastic behavior of the non-linear loads. The speed of convergence of this objective function leads to a conjecture about the robustness of the system. Evaluating the overall size of the system gives an idea of the energy efficiency of the proposed system. Another method of assessing power quality in a distributed generation system is to evaluate the rate of harmonic distortion at a common point of coupling. However, it is difficult to know the robustness of the system without clearly defining the constraints. The proposed method defines the constraints required to achieve good voltage and power performance.

3. Methodology

3.1. Minimization of the Power Losses Using the Test of Standard IEEE 14 Bus

Although distributed generations are encouraged to integrate their energies into the electrical network, there are times when non-compliance with standards or poor management of energy flows creates disturbances during periods when the load does not require too much energy. The presence of DGs can disturb receivers or lines, which can damage equipment. This is why it is important to schedule power flows and regulate the integration rate of renewable energies in a non-proprietary source. **Figure 1** depicts the power flows between two buses [24].

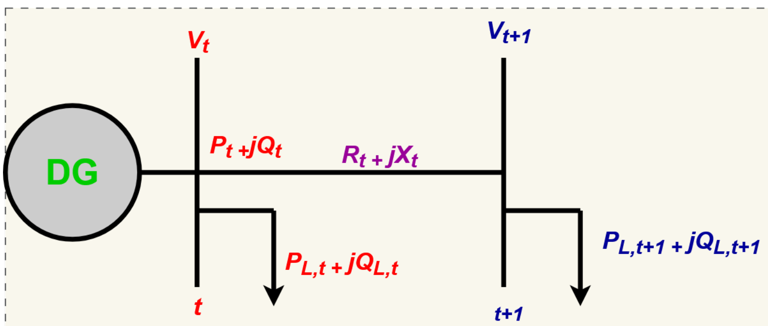

Figure 1. Line feeder for radial distribution system.

Given the objective function $F = \phi + \psi$, the line can be modelled taking into account the power P_{Losses}, the reactive losses $P_{(t,t+1)}^{losses}$, the nominal voltage V_ψ and the voltage V_t at node *t*. The parameter μ_t represents a state of connection or disconnection of a DG. The following equations correspond to the modelling of the line of a radial distribution system [25].

$$P_{Losses}(t,t+1) = R_t \frac{P_t^2 + Q_t^2}{|V_t|^2} \tag{1}$$

$$P_{T,Losses} = \sum\nolimits_{t=1}^{n} P_{Losses}(t,t+1) \tag{2}$$

$$V_\psi = \sum\nolimits_{t=1}^{n} \frac{|V_i - V_t|}{V_i}, \ t = 1,2,\cdots,n \tag{3}$$

$$\mu_t = \begin{cases} 1, \text{if DG is injected at bus } t \\ 0, \text{otherwise} \end{cases} \tag{4}$$

$$V^{\min} \le V_t \le V^{\max} \tag{5}$$

where $V^{\min}$ and $V^{\max}$ are minimal and maximal bus voltages.

$$V_t - V_{t+1} = P_{(t,t+1)} R_{(t,t+1)} + Q_{(t,t+1)} X_{(t,t+1)} \tag{6}$$

$$V_t - V_{t+1} = \left(P_{t+1}^{load} - P_{DG\,t+1}\right) R_{(t,t+1)} + \left(Q_{t+1}^{load} - Q_{DG\,t+1}\right) X_{(t,t+1)} \tag{7}$$

$$P_{(t,t+1)}^{losses} = \sum\nolimits_{t=1}^{n} \sum\nolimits_{t+1=1}^{n} \left(\alpha_{(t,t+1)}\left(P_t P_{t+1} + Q_t Q_{t+1}\right) + \beta_{(t,t+1)}\left(Q_t P_{t+1} - P_t Q_{t+1}\right)\right) \tag{8}$$

Considering (Equation (7)) we can have:

$$Q_{(t,t+1)}^{losses} = \sum\nolimits_{t=1}^{n} \sum\nolimits_{t+1=1}^{n} \left(\gamma_{(t,t+1)}\left(P_t P_{t+1} + Q_t Q_{t+1}\right) + \delta_{(t,t+1)}\left(Q_t P_{t+1} - P_t Q_{t+1}\right)\right) \tag{9}$$

$$S_{(t,t+1)}^{losses} = P_{(t,t+1)}^{losses} + jQ_{(t,t+1)}^{losses} \tag{10}$$

$$I_t \le I^{\max} \tag{11}$$

$I^{\max}$ is maximal current that can be injected at node t

$$\psi = \sum_{n}^{t} C_t^{DG} \mu_t + \sum_{n}^{t} \sum_{n}^{t+1} C_{(t,t+1)}^{losses} S_{(t,t+1)}^{losses} + \sum_{n}^{t} C_t^{Pl} V_t \tag{12}$$

where C_t^{Pl} and $C_{(t,t+1)}^{losses}$ are respectively cost for violation limit and its total cost in case of violation

$$C_t^{Pl} > C_{(t,t+1)}^{losses} \tag{13}$$

$$\phi = \sum\nolimits_{\varsigma=1}^{\mu} \left(1 - \min\left(\psi_\varsigma^\gamma\right)\right)^2 \quad \forall \varsigma \,\&\, \gamma = 1 \text{ to } 24 \tag{14}$$

$$\min = \phi + \psi \tag{15}$$

3.2. Voltage Enhancement

The importance of taking into account the parameters of a line lies in the fact that when the line is poorly modelled it can cause losses or even deterioration [26]. This is why, in Equation (1), the flow of energy along this section is controlled by shaping the signals between two distinct points known as nodes. The whole system is modelled in such a way that each circuit portion constitutes a sub-system as shown in **Figure 2**. The evaluation of the size of the DG at each node takes into account the availability of the transited energy at the different busbar connections where other sources can be injected [27].

4. Standard Particle Swarm Optimization

The particle swarm optimization (PSO) algorithm is a random search algorithm based on group cooperation developed by simulating the foraging behavior of a flock of birds [28]. The evolution process of the standard particle swarm optimization algorithm is as follows [29]:

$$X_i = \left(x_{i,1}, x_{i,2}, \cdots, x_{i,N}\right) \tag{16}$$

$$V_i = \left(v_{i,1}, v_{i,2}, \cdots, v_{i,N}\right) \tag{17}$$

$$X_i^{t+1} - X_i^t < \varepsilon \tag{18}$$

$$P_{besti} = \left(P_{besti,1}, P_{besti,2}, \cdots, P_{besti,N}\right) \tag{19}$$

$$G_{besti} = \left(g_{besti,1}, g_{besti,2}, \cdots, g_{besti,N}\right) \tag{20}$$

$$V_i^{t+1} = \omega_i V_i^t + c_1 r_1 \left(P_{besti} - X_i^t\right) + c_2 r_2 \left(g_{besti} - X_i^t\right) \tag{21}$$

$$X_i^{t+1} = X_i^t + \chi\left(v_i^{t+1}\right),\ t = 1, 2, \cdots, N \tag{22}$$

$$\omega_i = \omega_{\max} - \frac{\omega_{\max} - \omega_{\min}}{iter_{\max}} iter \tag{23}$$

w is the inertia weight, and the size of w determines the strength of the particle swarm's local and global search ability. c_1 is the individual learning factor, c_2 is the social learning factor, and proper selection of learning factors can prevent particles from falling into local optimums. r_1 and r_2 are random numbers of [0, 1] [30]. p_{best} is the individual optimal value; g_{best} is the group optimal value.

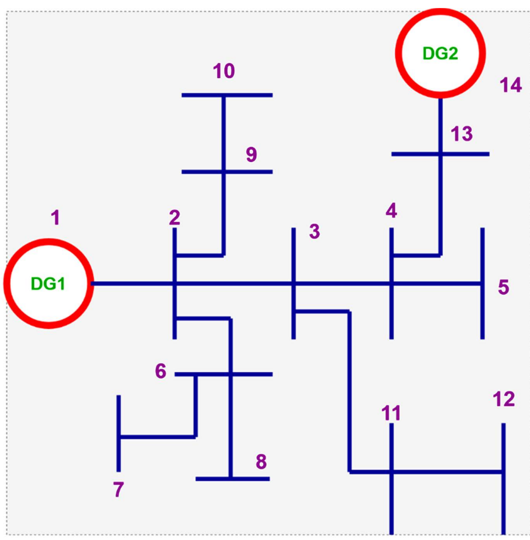

Figure 2. IEEE 14 bus configuration in radial distribution system.

5. Improved Particle Swarm Optimization (IPSO)

Fixed inertia weights and learning factors limit the evolutionary process of the standard particle swarm optimization algorithm. In the complex changing environment, MPPT control of standard particle swarm optimization is easy to fall into the local optimum. In order to make the algorithm more effective in tracking the maximum power of the PV array under local shading conditions, scholars proposed an adaptive particle swarm optimization algorithm. w gradually decreases from strong global tracking ability to strong local tracking ability. At the same time, c_1 keeps decreasing and c_2 keeps increasing, which avoids falling into the local optimum and improves the tracking speed. The updated formulas of w, c_1, and c_2 are as follows:

$$w = w_{\min} - \left(w_{\max} - w_{\min}\right) \times \frac{f(i) - f_{\min}}{f_{avg} - f_{\min}} \tag{24}$$

$$c_1 = c_{1\min} + c_{1\max} \times \cos\left(\frac{iter \times \pi}{2 \times iter_{\max}}\right) \tag{25}$$

$$c_2 = c_{2\min} + c_{2\max} \times \sin\left(\frac{iter \times \pi}{2 \times iter_{\max}}\right) \tag{26}$$

In the above formulas, $w_{\min} = 0.3$, $w_{\max} = 0.6$; $c_{1\min} = 0.6$, $c_{1\max} = 2$; $c_{2\min} = 0.4$, $c_{2\max} = 1.6$; $iter$ is the current iteration number, and $iter_{\max} = 15$; $f(i)$ is the fitness value of the current particle.

6. Results and Discussion

6.1. Load Profile

Figure 3 shows the active power profile demanded by the load at a common coupling point. This power demand is evaluated over a period of one day. Thanks to this power profile subscribed to at the PCC, it is possible to reduce active power losses thanks to the configuration on the IEEE 14 bus standard test. The proposed system is configured in a radial architecture. This radial system provides a global view of the allocation of the size of power that can be subscribed from the various buses via a voltage or current transformer.

After assessing the size of the system as a whole, Figure 4 shows the profile of the active power subscribed by the load and that of the available power produced by the grid and PV system as a whole. It can be seen that for one day, the energy produced is more than sufficient to meet demand. There is a peak in the power produced at periods such as 1 pm, 2 pm, 6 pm and 7 pm, which correspond to the hours of full power. During this time the user does not need energy storage because the reference load margin is much lower than the power transit level at the common point of coupling. Most systems of the size shown in Figure 4 are found in urban areas, where the surplus energy produced by decentralized distributors is fed into the low-voltage distribution network.

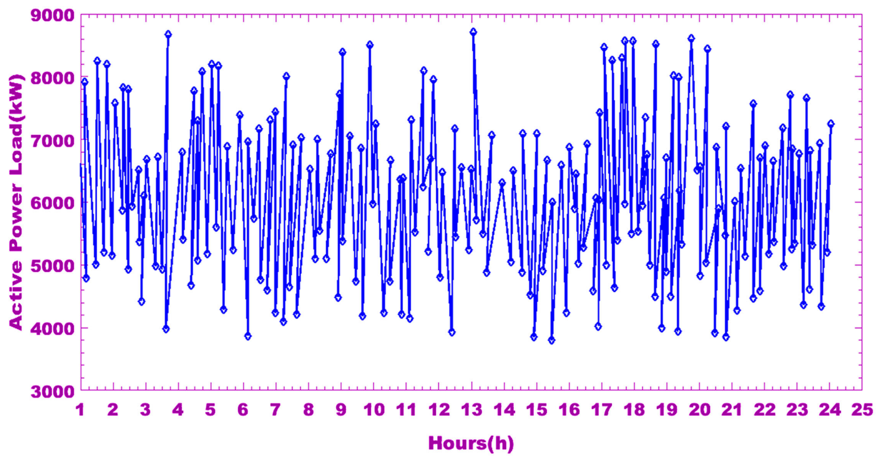

Figure 3. Load power profile during a day.

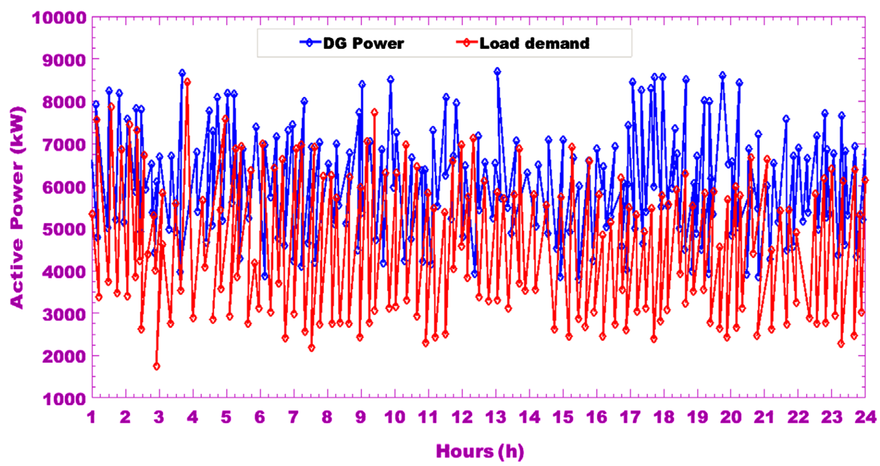

Figure 4. Load demand at the point of common coupling during a day.

6.2. Voltage Profile

In Figure 5 we can observe the voltage profile of different configurations, namely the network with battery and PV, the network without PV and the network with PV. This figure shows a considerable voltage drop at buses 2 and 4 over long periods. It can be seen that the voltage level stabilises when the grid and PV are combined with a battery bank. And as the number of DGs increases, the voltage level becomes stable. Furthermore, in the absence of 2DGs, it can be seen that at nodes 7, 8 and 9, the current and voltage levels are stable. These nodes can be used to connect loads, which implies that receivers can be connected to this bus. But in the absence of DGs, it is almost impossible to install receivers throughout the system, as this could create a general blackout, due to fluctuations in the frequency of the electrical grids.

6.3. Power Profile

Figure 6 illustrates the power profiles of the different configurations that can be obtained using the model proposed for standard IEEE 14 bus test. There is a

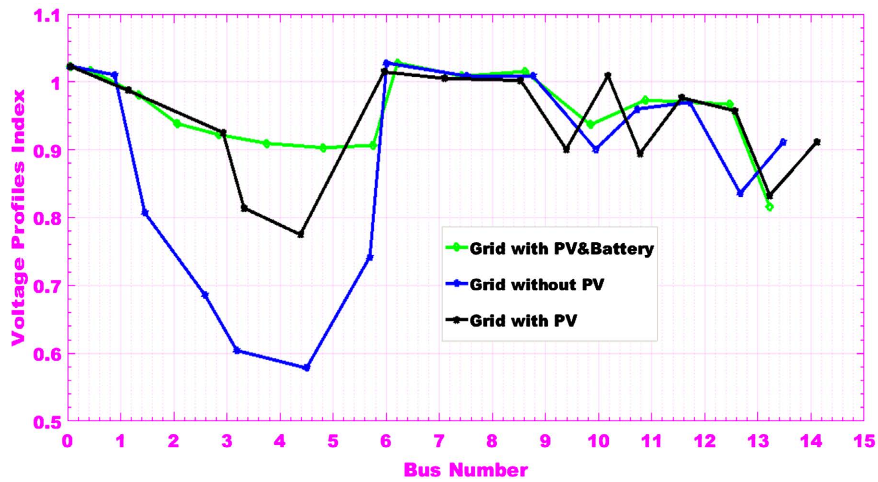

Figure 5. Voltage profiles for different configurations of DGs.

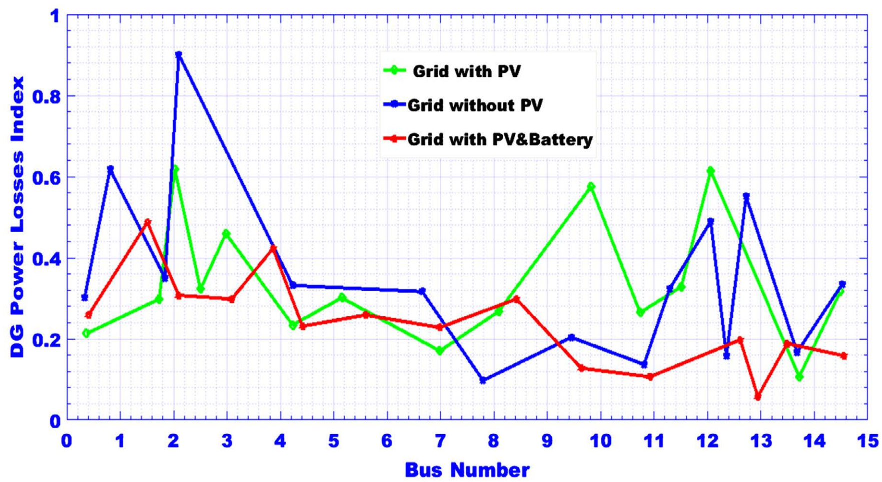

Figure 6. Power losses profiles on IEEE 14 bus after DGs integration.

high power loss at 2, 3, 12 and 13. In the absence of the energy storage system and the photovoltaic (PV) generator, the power losses are enormous. However, as the number of DGs increases, these power losses are reduced and stabilize at around 0.5 MW. The presence of a battery bank makes it possible to compensate for reactive energy. This has enabled the power profile to be stabilized by maintaining the frequency of the electrical network in the presence of the DGs.

6.4. Optimization the System Using Improved PSO (IPSO)

After evaluating the size of the proposed system as a whole, the objective function was used to optimize the system by reducing power losses on the IEEE14 bus standard test. Figure 7 shows that the improved PSO reduces power losses compared with the conventional PSO. The same applies to the convergence of the improved PSO, which remains constant from n = 40 iterations. The speed of convergence of the fitness function allows us to make a conjecture about the robustness of the proposed system as well as the feasibility of its implementation.

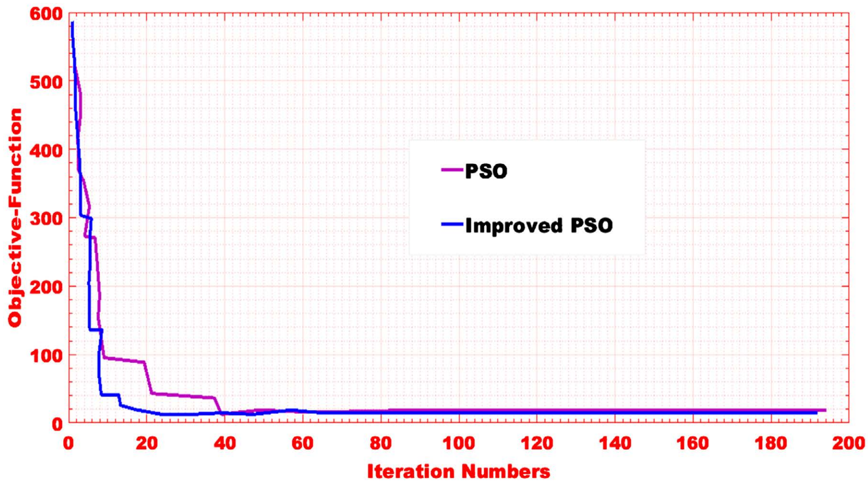

Figure 7. Evaluation of the performance of IPSO compared to the classical PSO.

Table 1. Comparison of the proposed algorithm.

Types of DGs	GA [31]	PSO [32]	WOA [33]	BPSO [34]	**Proposed PSO**
Grid/PV	20.4 MW	32.6 MW	21 MW	23.8 MW	**45 MW**
PV/ESS	15.1 MW	25.4 MW	18.4 MW	17.5 MW	**35 MW**
Grid/PV/ESS	24.6 MW	30.1 MW	22.3 MW	44.2 MW	**62 MW**

Based on the different results obtained on the IEEE 14 bus standard test, the evaluation of the size of the proposed system is given in Table 1. A number of algorithms have been proposed, based on the same configurations and the same scenarios. A comparison is made. It can be seen that the proposed system is cost-effective in terms of performance and the size of the system, which has led to an improvement in the active power produced by the system as a whole. A good speed of convergence is observed compared to the data provided by techniques such as GA, PSO, WOA, and BPSO.

7. Conclusion

After evaluating the size of the entire system composed of distributed generators (DGs), PSO algorithms improved the energy quality by reducing power losses. The voltage profile was observed during the testing of the IEEE 14 bus standard. The assessment and sizing of the proposed system yielded better performance. A comparison between standard PSO and improved PSO leads to the conclusion that the proposed technique enhances energy quality better than classical PSO. This study can be more intriguing if the harmonic distortion rate is calculated at a common coupling point. The aim of this study was to investigate an algorithm capable of reducing power losses in the entire system consisting of distributed generations, and to examine the behavior of voltage profiles on the test of the IEEE 14-bus standard. After studying the size of the overall system, it was found that the proposed model could significantly improve the active power profile.

This study could therefore be an effective contribution to the optimization of the energy efficiency of systems incorporating distributed generation.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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