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Optimal Reconstruction of Photovoltaic Distribution Networks Based on an Enhanced Random Weight Particle Swarm Algorithm

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Abstract

This study proposes an innovative and improved random weighted particle swarm optimization algorithm with the goal of effectively resolving the static reconfiguration issue of PV distribution networks. The algorithm, tailored to suit the unique characteristics of distributed PV distribution grids, not only enhances the search's efficiency and precision, but also successfully avoids the algorithm's premature convergence by incorporating the Tabu search approach. This significantly augments the comprehensive capability for global search and local optimization. Simulation is utilized to authenticate the algorithm's efficacy, and a comprehensive comparison, such as search speed and accuracy, is conducted with the particle swarm algorithm, the improved particle swarm algorithm, and the stochastic weighted particle swarm algorithm, all of which are based on the IEEE 33-node distribution network model with distributed photovoltaic. The comparison results demonstrate that the upgraded algorithm exhibits remarkable performance in terms of search efficiency, global search aptitude, and accuracy, far surpassing the other comparison algorithms.

Keywords: Tabu search, distributed photovoltaic, network reconfiguration, particle swarm optimization (PSO).

1. Introduction

The integration of distributed photovoltaic (PV) generation into power grids is becoming increasingly prevalent due to its significant advantages such as abundant solar resources and its environmentally friendly, pollution-free nature [1]. The integration of electrical power systems is transforming their operational modes, resulting in power flow issues in distribution networks (DNs) caused by PV power injection, which can lead to voltage fluctuations and even serious safety incidents[2-4]. Consequently, the reliability of distributed PV networks is of paramount importance. By improving reliability, the occurrence of accidents can be decreased, thereby guaranteeing the safety of electricity usage. This research aims to enhance the system reliability by restructuring the DN, thus reducing network losses and voltage fluctuations.

Network reconfiguration is a relatively economical means to enhance reliability [5, 6]. By altering the state of switches within the DN, the system's topology is largely altered. The ultimate purpose of this alteration, based on energy balance, voltage, and power limit regulations, is to diminish network losses and augment voltage distribution [7, 8].

Currently, experts, both domestically and internationally, have primarily adopted three strategies to address issues in distributed PV networks: mathematical optimization techniques, heuristic methods, and intelligent algorithms, with intelligent algorithms seeing extensive application and development in this field [9-11].

Several studies have proposed innovative solutions. A study blending the PSO with the genetic algorithm resulted in the binary quantum PSO (BQPSO) [12], which serves as an example. This algorithm incorporates a method for tackling infeasible solutions, thus augmenting its global search capacity and computation speed, although the optimization speed still needs to be enhanced. Another study combined the fireworks algorithm with Cauchy mutation to propose an improved fireworks algorithm (IFWA) [13], which enhances the optimization algorithm's solution speed and accuracy. The development of Chicken Swarm PSO (CSOPSO) [14] was the result of a comparison between chicken and particle swarm algorithms. This algorithm broadens the search scope and eliminates local optima, thus producing higher-quality feasible solutions. Nevertheless, its optimization speed and accuracy require further refinement. In a study, an analytic hierarchy process was employed to model the reconfiguration of distributed power source DNs, with a genetic algorithm as the optimization algorithm. Furthermore, a set-based update strategy was introduced to tackle combinatorial issues, and the dynamic multi-swarm PSO algorithm (DMS-PSO) [15] was then combined with this. Proposed by another was an improved PSO algorithm (IPSO) [16] to tackle the reconfiguration model of hydrogen energy DN systems, thereby improving the system's security and load balance. This algorithm was further enhanced by a neighborhood learning strategy. Despite this, these investigations rarely delve deeply into the global search aptitude and premature convergence of optimization algorithms, and certain papers present intricate algorithm executions, leaving room for betterment in optimization velocity and precision.

This research proposes an improved random weight particle swarm optimization (IRWPSO) algorithm to tackle these issues, aiming to balance and enhance the particle swarm algorithm's global and local search capabilities and velocity. By utilizing tabu search techniques, the algorithm strives to elude local optima to the greatest extent feasible, harmonizing local and global searches to achieve successful global optimization.

2. Optimized Reconstruction Model for Distributed Photonic Power Distribution Networks

2.1 Objective function

An optimization restructuring model for a distributed photovoltaic DN is established by this work, with network loss and voltage deviation chosen as two optimization indicators to attain a comprehensive optimum of both as the ultimate outcome.

(1) Network loss in the DN

The current and impedance of the lines dictate the loss of the DN. The negligible reactance of the distribution line is expressed thus:

$$P_{Loss} = \sum_{k=1}^{N} \gamma_k I_k^2 R_k \tag{1}$$

The total number of branches in the DN is represented by N. P_{Loss} is the active power loss, which is caused by the current and resistance that flow through the branches. The binary value of the switch state γ_k is 1 for closed switches and 0 for open ones. I_k is the magnitude of the current passing through the k-th branch. R_k is the resistance of the k-th branch. I_k and R_k determine the power loss on that branch.

(2) Voltage deviation in the DN

To ascertain the electric power quality, the voltage deviation in the DN is gauged by the divergence of the node voltage from the rated voltage.

$$\Delta U = \sum_{i=1}^{M} \left| U_i - U_r \right| \tag{2}$$

The voltage deviation of the DN, denoted by ΔU, is represented by the total system voltage, M being the total number of nodes, and Ui and Ur being the actual value of the *i* node voltage and rated voltage of the DN, respectively.

Analyzing the optimization restructuring model of the DN inclusive of distributed photovoltaic systems reveals that this restructuring process is a multi-objective optimization endeavor. Here, a multi-objective weighting approach is utilized to streamline the multi-objective optimization process, with the standardization of the two objective functions. The specific steps are outlined as:

$$\min f = \min\left(\lambda_1 \frac{P_{Loss}}{P_{NV}} + \lambda_2 \frac{\Delta U}{U_{NV}}\right) \tag{3}$$

where, λ1 and λ2 respectively represent the weighting coefficients for objective functions 1 and 2, λ1,λ2 ∈ (0,1) and λ1+λ2=1, with a focus on the impact of network loss, accepting a certain range of voltage deviation, thus setting λ1=0.8, λ2=0.2. The particle swarm algorithm, which standardizes parameters, initially determined the nominal value of network loss and baseline voltage deviation, denoted by PNV and UNV, respectively, to address the inconsistency of values and units between the two optimization indicators. The optimization process is affected by the weighting coefficients, which act as a gauge of focus, determining solutions that are in line with the goals.

2.2 Constraints

Active distribution network reconfiguration necessitates adherence to the following constraints [17].

(1) The initial move is to abide by the network's load flow regulations, which encompass both the power balance limitations and the production of distributed energy sources. The energy balance constraints within the distribution network are delineated by Eq. (4).

$$\begin{cases} P_i + P_{PVi} = P_{Li} + U_i \sum_{i=1}^{M} U_j \left(G_{ij}\cos\theta_{ij} + B_{ij}\sin\theta_{ij}\right) \\ Q_i + Q_{PVi} = Q_{Li} + U_i \sum_{i=1}^{M} U_j \left(G_{ij}\sin\theta_{ij} - B_{ij}\cos\theta_{ij}\right) \end{cases} \tag{4}$$

where, M represents the total number of nodes. Q_i and P_{PVi} signify the active and reactive power injected at node *i*, P_{PVi} and Q_{PVi} signify the active and reactive power supplied by PV systems, and P_{Li} and Q_{Li} signify the active and reactive power load at node *i* The second term on the right side of the equation symbolizes the active and reactive power losses of each branch, respectively. U_i and U_j denote the voltage at nodes *i* and j, respectively. G_{ij} and B_{ij} are conductance and susceptance of branches *i* and *j*, with θ_{ij} representing the phase angle difference between them.

$$P_{PV}^{\min} \le P_{PV} \le P_{PV}^{\max} \tag{5}$$

Equation (5) delineates the processing restrictions of distributed photovoltaic systems, with P_{PV}^{min} and P_{PV}^{max} representing the minimum and maximum limits of output power from distributed photovoltaic sources, respectively.

(2) Essential for the operation of DNs are operational constraints, like node voltages and branch currents.

$$\begin{cases} V_i^{\min} \le V_i \le V_i^{\max} \\ I_l \le I_l^{\max} \end{cases} \tag{6}$$

where, V_i^{min} and V_i^{max} represent the minimum and maximum voltages of the nodes in the DN, respectively. I_l^{max} stands for the maximum capacity of the branches in the network.

(3) Furthermore, network topology constraints are imperative to prevent the occurrence of closed loops and isolated islands within the DN. It is mandatory that the network maintains a radial configuration both before and after any restructuring processes.

3. Improved Random Weight PSO for Solving Models

3.1 Standard PSO algorithm

The standard PSO is an artificial intelligence algorithm and inspired by the foraging habits of birds, and generates a swarm of particles, each randomly assigned a velocity and position [18]. As they move, the direction of both the best individual and the best swarm particles influences them.

The following is the formula for adjusting particle velocity and location.

$$\begin{cases} \mathbf{V}_i^{t+1} = \omega \mathbf{V}_i^t + c_1 r_1 \left(p_i^t - \mathbf{X}_i^t \right) + c_2 r_2 \left(\mathbf{S}_i^t - \mathbf{X}_i^t \right) \\ \mathbf{X}_i^{t+1} = \mathbf{X}_i^t + \mathbf{V}_i^{t+1} \end{cases} \tag{7}$$

The search space's dimensions, denoted by t=1, 2,…, G and G, the population's size, i =1,2,…,N and N, and the inertia weight ω, are all factors in this equation. c_1 and c_2 are the local and global learning factors, respectively. If too small, optimization becomes sluggish; if too large, the optimal solution may be overlooked. Typically, is chosen in [0.2, 2.0]; and r_1 and r_2 are random numbers following a normal distribution; p_i^t and $\boldsymbol{S}_i^t$ represent the local and global optimum values, respectively.

This approach meticulously balances the exploration and exploitation phases in the search space, aiming to efficiently converge towards the optimal solution by dynamically adjusting the influence of personal and collective experiences on the movement of particles.

3.2 Random weight PSO algorithm

The PSO algorithm ascertains the trajectory and magnitude of a particle's motion by both its individual historical peak position and the collective historical peak position. While this mechanism facilitates rapid convergence of the particle swarm, it also makes the algorithm susceptible to premature convergence on local optima, thereby undermining its ability to locate global optima. The inertia's magnitude has a direct bearing on the algorithm's local and global search aptitude: a greater inertia weight boosts global search capacity, while a lesser inertia weight increases local search capability, thus encouraging convergence. In order to address the premature convergence of the PSO algorithm towards local optima, this study introduces a Random Weight PSO (RWPSO) algorithm. By adjusting the correlation between a particle's past speed and its present velocity, this algorithm broadens the search range, preventing premature convergence on local optima, while simultaneously accelerating the rate of convergence and improving solution precision.

The calculation of the random weight employs the following formula

$$\begin{cases} \omega = \mu + \sigma N(0,1) \\ \mu = \mu_{\min} + \left(\mu_{\max} - \mu_{\min} \right) \cdot \mathrm{rand}(0,1) \end{cases} \tag{8}$$

N (0,1), a random number within the normal range (0,1), and rand(0,1) within the uniform range (0,1) are both denoted by a parameter adjustment factor μ.

3.3 Improved random weight PSO algorithm

The RWPSO algorithm augments global search aptitudes, yet these aptitudes are inherently random. he algorithm, even in operation, still faces the possibility of attaining local optima. An improved version of the RWPSO, the IRWPSO, is presented in this paper, combining the Tabu Search algorithm [19] with the aim of diminishing its randomness and enhancing its proficiency in finding optimal solutions.

This paper presents the Tabu search algorithm to alleviate the cyclical searching that may arise from unintentional repetition of exploration paths. The algorithm, by setting the population's optimal solution as a Tabu particle,

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systematically liberates and pardons particles. The paper proposes an improved random weight particle swarm algorithm for resolving this issue, as seen in Figure 1 - *ger* representing the termination iteration count and *iter* the current iteration number. This method increases the algorithm's global search aptitude and local convergence, thus enhances the chances of discovering the global optimal solution.

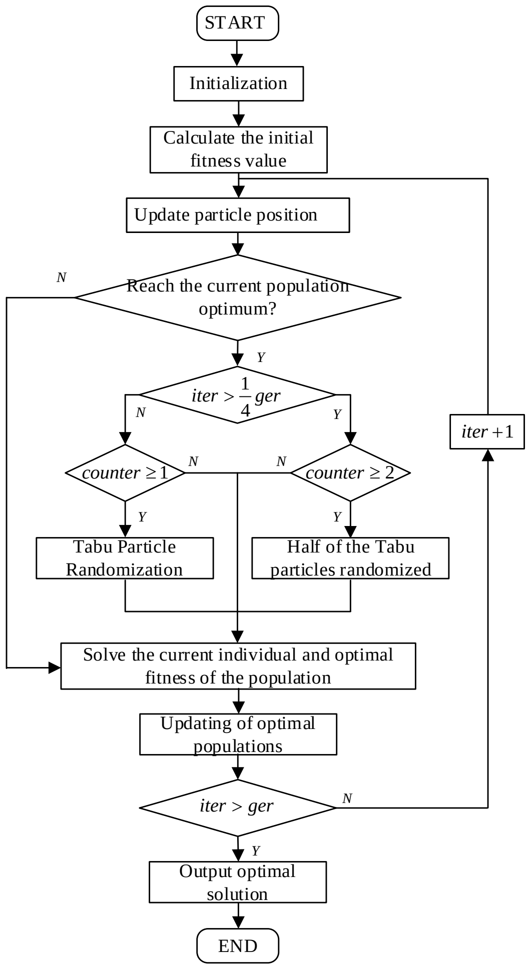

Figure 1. Flowchart of IRWPSO

The procedure for optimizing distributed photovoltaic operations within DNs through PSO involves the following steps:

1. Initialize the parameters of the power DN. Then set the operational parameters, power flow calculations, and constraints for distributed photovoltaics.

2. Determine the start positions of the particle swarm and configure the algorithm's parameters, initializing the iteration count to 1.

3. Employ Eq. (3) as the fitness function to ascertain initial fitness values. Designate the particle with the minimum fitness value as the initial taboo particle, setting its term of office accordingly.

4. Assess whether the algorithm has reached its maximum number of iterations. If so, report the optimal fitness value of the swarm and the corresponding states of the power DN switches. If not, iterate the particle swarm, updating the positions and velocities of particles according to Equation (7).

5. Examine the term of office for the taboo particle. If the term is not zero, proceed with the process, randomizing particles that meet the criteria. If the term is zero, apply the principle of contempt, proceed to step 6, and check the position of each particle in the new population to determine if it is a taboo particle. If it is, regenerate the particle with new corresponding velocity and position.

6. Calculate the fitness values of particles in the new population and compare them with the current individual's optimal fitness value. If a particle's fitness value surpasses the current optimum, update the individual's optimal position and fitness value; otherwise, maintain the status quo.

7. Compare the new optimal fitness values with those of the existing group. If a value exceeds the current group's optimum, replace it with the optimal population and corresponding fitness value. If not, maintain the current state but refresh the information of the taboo particles. Adjust the term of office for taboo particles if the conditions above are not met, namely $T = T - 1$. If the term of office is zero or negative, extend the term of the taboo particle $T = L$ and return to step 4.

4. Simulation Case Study Analysis

Taking the IEEE-33 node distribution system (illustrated in Figure 2) as an example, this study integrates distributed PV into the DN and employs an IRWPSO algorithm to optimize and restructure the DN. The effectiveness of this optimization algorithm is demonstrated.

The system comprises 33 nodes, with solid lines indicating sectionalizing switches between each node and dashed lines representing tie switches between each branch. A network system of distributed photovoltaic power distribution is formed by connecting a 0.2 MW photovoltaic input to nodes 2, 6, 10, and 14.

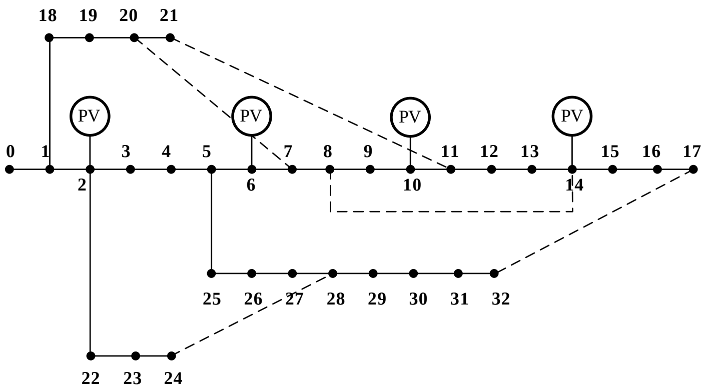

Figure 2 IEEE-33-bus radial distribution system containing distributed photovoltaic

Table 1 shows the parameters of the enhanced stochastic weight particle swarm algorithm.

Table 1 Improved random weight particle swarm parameterization.

Parameters	Values	Parameters	Values
M	50	c_1	0.7
ger	50	c_2	0.7
G	37	P_{NV}	123.75kW
μ_{max}	0.8	U_{NV}	12.66kV
μ_{min}	0.2	λ_1	0.8
σ	0.2	λ_2	0.2

The swarm's optimization speed is significantly impacted by M's essential role. It is not advisable to be too small; hence, a value of 50 is selected. The iteration termination count ger serves as a boundary for concluding the optimization process. The PSO algorithm's search space dimension, G, is a critical factor. The inertia weight parameter's mean is set to μ_{max} and μ_{max}, respectively. The variance of the inertia weight, σ, is intended to remain around 0.4 and this setup allows for a certain level of adjustment without considerable dispersion, thus establishing the values of these parameters. The objective function differentiates the weights of network loss and voltage deviation, λ1 and λ2, with a heightened focus on the former to demonstrate its greater importance. The effectiveness of the optimization procedure is determined by the self-learning and social learning elements of the particle swarm, c_1 and c_2, both established at 0.7. P_{NV} and U_{NV} are the baseline values for network loss and voltage deviation within the objective function are established, guiding the optimization focus.

Table 2 shows the parameters of IEEE-33 with distributed photovoltaic distribution system.

Table 2 IEEE-33 with distributed photovoltaic distribution system parameters

Parameters	Values	Parameters	Values
P_{PV}	0.2MW	V_b	12.66kV
$\cos\theta$	0.9	S_b	10MW

P_{PV}, the active power output of each distributed photovoltaic system, is denoted, and $cos\theta$, the power factor attained or surpassed by reactive power compensation, is referenced. V_b, the voltage in the DN, and S_b, the power in the same network, are both denoted.

In the context of an IEEE-33 distribution system incorporating distributed photovoltaic sources, this study conducts a comparative analysis by applying various control algorithms. Standardization of algorithms on parameters such as inertia weight, self-learning factor, social learning factor, and convergence criteria guarantees a fair comparison. Specifically, the PSO [20], IPSO) [21], RWPSO [22], and IRWPSO algorithms are used to tackle the reconfiguration of DNs. Given the stochastic initial states inherent to particle swarm algorithms, each algorithm is executed 20 times to guarantee a fair comparative analysis, as illustrated in Table 3, with typical results selected for further comparison and analysis as shown in Table 4. The analysis reveals that the IRWPSO algorithm achieves the highest frequency of global optimal fitness values and the highest success rate, surpassing that of IPSO and significantly outperforming PSO and RWPSO. The IRWPSO algorithm's global search capabilities are clearly demonstrated by this result.

Table 3 Comparison of results from 20 runs (IRWPSO, RWPSO, IPSO, PSO, INIT)

Algorithms	IRWPSO	RWPSO	IPSO	PSO
Number of occurrences of global optimal fitness	18	8	15	6
Optimal solution probability	90%	40%	75%	30%

Table 4 Distribution grid reconfiguration results (IRWPSO, RWPSO, IPSO, PSO, INIT)

Algorithms	IRWPSO	RWPSO	IPSO	PSO	INIT
Disconnected branches	6,8,13,31,36	6,10,13,27,31	5,8,13,31,36	6,8,13,26,31	32,33,34,35,36
Voltage deviation /p.u.	1.019 0	0.956 5	1.055 4	0.986 3	1.469 1
Network losses /kW	115.292 7	118.363 2	115.210 6	121.302 1	121.302 1
Optimal fitness	0.949 1	0.956 5	0.955 9	0.981 4	/
Number of iterations for Optimal solution	6	7	10	4	/

Figure 3 illustrates the changes in fitness function values with iteration numbers before and after the restructuring of the power DN. The iteration numbers are shown on the horizontal axis, while the fitness function values are displayed on the vertical axis. INIT refers to the value of the fitness function before the restructuring of the DN. IRWPSO, RWPSO, IPSO, and PSO represent the changes in the fitness function values when the corresponding optimization algorithms are used for the restructuring of the DN.

The IRWPSO algorithm, after eight iterations, has achieved an optimal fitness function value of 0.9491, whereas the IPSO algorithm requires up to 90 iterations to reach the same outcome. In comparison, the PSO and RWPSO algorithms are observed to be ensnared in local optima, unable to escape these boundaries. Furthermore, IRWPSO exhibits IRWPSO demonstrates a greater likelihood of discovering the optimal solution in comparison to IPSO, indicating that IRWPSO possesses superior global search and local convergence capabilities.

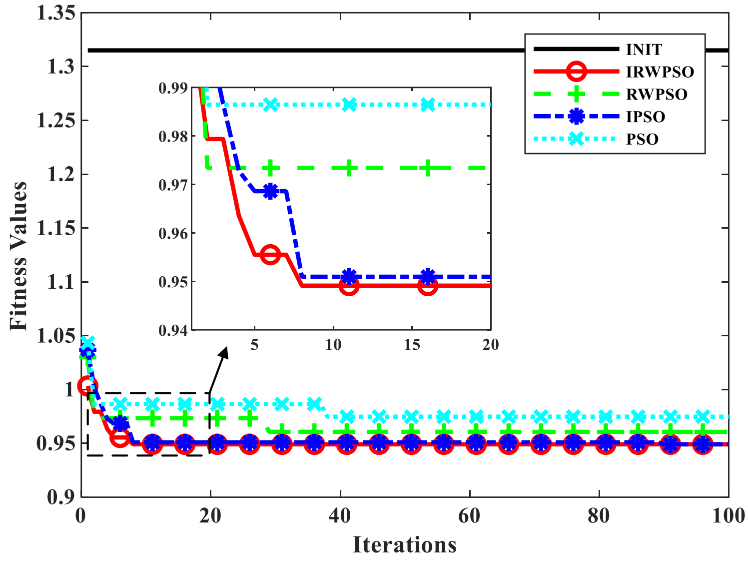

Figure 3 Iterative process of DN reconfiguration algorithms (INIT, IRWPSO, RWPSO, IPSO, PSO)

The IEEE-33 distribution system's node voltage, denoted by "INIT", is the consequence of the integration of distributed photovoltaics, signifying the initial voltage distribution of the network.

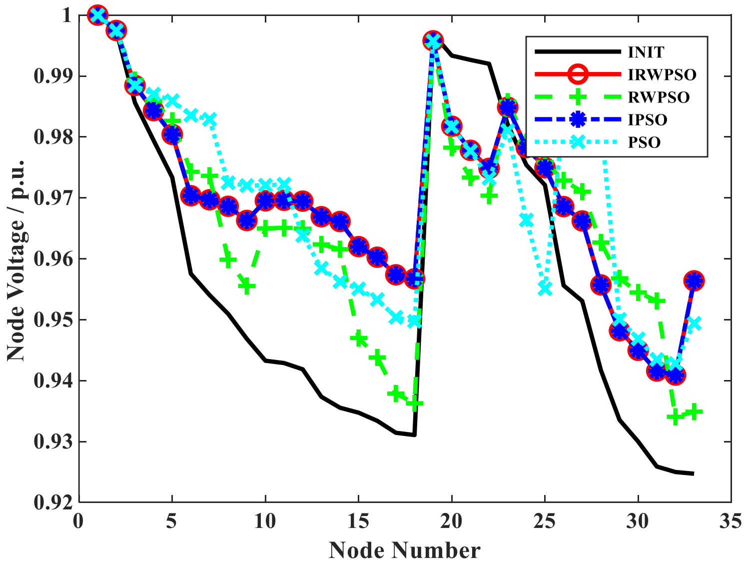

Figure 4 Voltage at each node before and after reconfiguration of the DN

Figure 4 illustrates the voltage conditions of the nodes before and after reconfiguration with various algorithms, with the node numbers on the horizontal axis and the voltage per unit on the vertical axis. Optimization algorithms used for reconfiguration have determined the optimal node voltage distribution of the network, which is represented by "IRWPSO," "RWPSO," "IPSO," and "PSO." After the restructuring of the DN using the IRWPSO algorithm, the voltage levels across various nodes have become more uniform, with minimal deviations, meeting the required standards. The lowest voltage at any node is recorded at 0.9410 p.u. IRWPSO's solution, with a slight divergence in voltage deviation and minimum voltage level, stands out as the most suitable globally, taking into account the total power loss, in comparison to other algorithms. The original system's voltage condition across the nodes of the DN has been improved by this restructuring.

5. Conclusion

This study introduces an IRWPSO algorithm for reconfiguring the DN. This algorithm unites the emergency search approach with the random weighted particle swarm algorithm, thereby significantly increasing the algorithm's ability to bypass the local optimum during the search process. The IEEE-33 node distribution system, containing distributed photovoltaic, has been verified for this algorithm, which integrates active loss and voltage deviation indexes into a single-objective optimization problem via weight scalarization. The optimization objectives are then taken into account.

The IRWPSO algorithm has been shown to be exceptionally successful in optimizing voltage deviation and active loss, with the voltage deviation being reduced to 1.0190 p. The simulations yielded outcomes of 115.2927 kW active loss and 0.9491- fitness index, which made the IRWPSO a clear performance leader in comparison to the other three PSO algorithms. The results of 20 runs, when compared, demonstrate that IRWPSO has the highest success rate in searching for the global optimal solution, thus demonstrating its superiority in both global search capability and search efficiency.

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