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Diminishing Active Power Loss and Improving Voltage Profile Using an Improved Pathfinder Algorithm Based on Inertia Weight

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Abstract: Part of the widely discussed problem in electrical power systems is the optimal reactive power dispatch (ORPD) due to its reliability and economical operation of electrical power systems. The ORPD is a complex and nonlinear optimization problem. The pathfinder algorithm (PFA) is a newly developed algorithm that inspires the group movement of prey with a leader called a pathfinder when hunting for food. The inertia weight is added to the PFA and is called an improved pathfinder algorithm (IPFA) to support the proper random work of the swarm to avoid the decrease in searchability of the PFA. The IPFA was proposed in this work to diminish the active power loss while improving the voltage profile. The IPFA was validated on the IEEE 30 and 118 bus systems along with particle swarm optimization (PSO) and the teaching–learning-based optimizer (TLBO). The proposed IPFA provides the best result as the losses of the IEEE 30 and 118 test systems were reduced to 16.035 and 115.048 MW from the initial base of 17.89 and 132.86 MW, respectively. The losses of PSO and the TLBO were 16.1568 and 16.1607 MW for the IEEE 30 bus system, respectively, while for the IEEE 118 bus system, the PSO provided 117.9129 MW and the TLBO provided 118.0524 MW. The two test systems' reduction percentages (%) were 10.37% and 13.41%, respectively. The results were compared with those of other algorithms in the literature, and the IPFA provided a superior result, thereby suggesting the superiority of IPFA methods in diminishing the power loss and improving the system's voltage profile.

Keywords: diminished active power loss; improved pathfinder algorithm; ORPD; pathfinder algorithm

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1. Introduction

The challenge facing the power system is the complexity of the network. A power system consists of a generation, transmitting, and distributing network; it expects to consume little resources while providing adequate reliability and the security of the system. At present, the power system has experienced an increase in voltage instability, leading to voltage collapse and blackouts in many countries, which has resulted in economic losses. Another challenge is increased transmission losses that lead to low efficiency and limit the power system's operation. Considering these challenges, this study motivates future research into how the optimal reactive power dispatch (ORPD) is important for the optimal power flow (OPF), which dramatically impacts the system's security, operation, and economy. The objective of the ORPD is to redistribute the reactive power, which diminishes the system's active power loss while improving the voltage profile and maintaining the constraints [1–3]. The control variables provided by the ORPD are the generator voltage magnitude, shunt capacitors, and transformer tap settings. Many classical optimization techniques have been applied to solve the ORPD problems but failed because of low precision and the inability to determine the global optimal [1,4]. Examples of such classical optimization techniques are linear programming, interior point, quadratic programming, Newton techniques, and gradient point [4–8].

In order to overcome the demerits of classical techniques, researchers have applied metaheuristic and evolutionary algorithms. These include the genetic algorithm (GA) [9], particle swarm optimization (PSO) [10], the enhanced Jaya optimization method (e-JAYA) [11], differential evolution (DE) [12], the modified stochastic fractal search algorithm (MSFSA) [13], the improved social spider algorithm (ISSA) [14], the improved ant lion optimizer (IALO) [15], a modified version of the sine–cosine method (ISCA) [16], success-history-based adaptive differential evolution (SHADE) [17], the tree seed algorithm (TSA) [18], the Jaya optimization algorithm (JAYA) [12,19], the backtracking search (BS) method [20], the whale optimization algorithm (WOA) [21], the Gaussian bare-bones water cycle optimizer (GBBWCO) [22], the moth–flame optimizer (MFO) [23], the ant lion optimizer (ALO) [24], the chaotic krill herd algorithm (CKHA) [25], particle swarm optimization with an aging leader and challengers (ALC-PSO) [26], the grey wolf optimizer (GWO) [27], the modified teaching–learning algorithm with differential evolution (MTLA-DE) [28], the artificial bee colony (ABC) [29], the gravitational search algorithm (GSA) [30], the big bang–big crunch (BB-BC) [31], comprehensive learning particle swarm optimization (CLPSO) [32], the modified pathfinder algorithm (mPFA) [33], and the HPSO-PFA [34].

The PFA has been applied to solve the ORPD problem combined with other techniques due to its simplicity and because it has few parameters to tune without changing the whole process of the algorithm. However, the PFA decreases searchability when the problem's dimensions increase [33]. To overcome this challenge, this study proposed using inertia weight (w) to improve the vibration coefficient (ε) and the fluctuation coefficient (A) of the PFA. It provided adequate support for random prey walks at the diversification stage and enabled the prey to reach the optimum global minimum in the search space. This proposed method is called the improved PFA (IPFA). Two other algorithms were tested along with the IPFA: PSO and the teaching–learning-based optimizer (TLBO). This study aimed to diminish the transmission active power loss and improve the voltage profile while the system constraints were maintained. The optimized control variables were the transformer tap setting, generator voltage, and reactive compensator. The IPFA method was tested on the IEEE 30 and 118 bus systems. The result of the IPFA was compared with other algorithms to establish its favorable performance for these applications. The proposed IPFA also provided superior results compared with other methods reported in the literature. The contribution of this paper is as follows:

a. Inertia weight (w) was added to the parameter of the PFA (i.e., the vibration coefficient (ε) and fluctuation coefficient (A)) to improve the random walk of prey. The w that was added to ε and A enhanced the ability to transit between exploration and exploitation and was proposed to solve the ORPD problem to diminish active power loss and to overcome the challenges of the PFA in reducing the searching ability when the problem becomes complex for the reliability and effective operation of the power systems.
b. The penalty function combined with the objective function for better performance by including the load bus voltage, reactive power generation, and apparent power flow to avoid violation.
c. The results obtained from the proposed IPFA with other algorithms showed that the proposed IPFA provided superior results compared with others.

The remaining part of the paper is organized as follows: Section 2 discusses the ORPD formulation, and Section 3 discusses the overviews of the PFA and IPFA. Section 4 presents the results and discussion of the simulation, and Section 5 includes the conclusion and future recommendation of the study.

2. Problem Formulation

This research aimed to diminish/reduce the active power loss while keeping the constraints. Equation (1) was used as the objective function [1]:

$$\text{Min } f = P_{loss} = \sum_{K=1}^{N_L} G_k \left(v_i^2 + v_j^2 - 2V_i V_j \cos\theta_{ij} \right) \tag{1}$$

where P_{loss} is the active power loss, G_k is the branch, N_L is the overall number of transmission losses, k is the branch between bus i and j, θ_{ij} is the voltage angle between bus i and j, V_i is the voltage at the ith bus, V_j is the voltage at the j-th bus.

2.1. Equality Constraints

The equality constraint in the transmission networks arethe LF equations, given as:

$$P_{gi} - P_{di} - V_i \sum_{K=1}^{N_B} V_j (G_k \cos\theta_{ij} + B_K \sin\theta_{ij}) = 0 \tag{2}$$

$$Q_{gi} - Q_{di} - V_i \sum_{K=1}^{N_B} V_j (G_k \sin\theta_{ij} + B_K \cos\theta_{ij}) = 0 \tag{3}$$

where N_B is the overall number of buses/nodes, P_{gi} is the real power generation, Q_{gi} is the reactive power generation, P_{di} and Q_{di} are the active and reactive load power demand at the ith bus, and B_K is the mutual susceptance.

2.2. Inequality Constraints

The inequality constraints are given in upper and lower limits.

2.2.1. Generator Constraints

These are the generators of the bus voltage, together with the generations of the active and reactive power:

$$V_{gi}^{min} \leq V_{gi} \leq V_{gi}^{max} \; i = 1 \ldots, N_g \tag{4}$$

$$Q_{gi}^{min} \leq Q_{gi} \leq Q_{gi}^{max} \; i = 1..., N_g \tag{5}$$

$$P_{gi}^{min} \leq P_{gi} \leq P_{gi}^{max} \; i = 1..., N_g \tag{6}$$

where N_g = the overall number of generators.

2.2.2. Reactive Power Compensation Limits

The reactive power compensator limits are constraints by minimum and maximum limits, as shown below.

$$Q_{ci}^{min} \leq Q_{ci} \leq Q_{ci}^{max} \; i = 1 \ldots, N_C \tag{7}$$

where N_C = the overall number of reactive power compensations.

2.2.3. Transformer Tap Ratio Constraints

The transformer tap setting are constraints by minimum and maximum limits.

$$T_k^{min} \leq T_k \leq T_k^{max} \; i = 1 \ldots, N_T \tag{8}$$

where N_T = the overall number of transformers.

2.2.4. Line Flow Limits

The line flow limits are the voltage restriction on transmission line loading and load buses. Their limits are shown below.

$$V_{ki}^{min} \leq V_{ki} \leq V_{ki}^{max}\ i = 1\ldots, N_B \tag{9}$$

$$S_k \leq S_k^{max}\ i = 1\ldots, N_K \tag{10}$$

Of all the variables mentioned above, the reactive power generation (RPG), load bus voltage, and apparent power flow were the dependent variables combined with the objective function and the use-penalty coefficient to avoid unrealistic solutions. Therefore, the objective function in Equation (1) has now become,

$$f_T = f + \lambda_V \sum_{K=1}^{N_B} (V_i - V_i^{\lim})^2 + \lambda_g \sum_{K=1}^{N_B} (Q_{gi} - Q_{gi}^{\lim})^2 + \lambda_T \sum_{K=1}^{N_B} (S_i - S_i^{\lim})^2 \tag{11}$$

Here,

$$\lambda_V,\ \lambda_g,\ \lambda_T \text{ are the penalty factors} \tag{12}$$

$$V_i^{lim} = \begin{cases} V_i^{lim}, if\ V_i < V_i^{min} \\ V_i^{lim}, if\ V_i > V_i^{max} \end{cases} \tag{13}$$

$$Q_{gi}^{lim} = \begin{cases} Q_{gi}^{lim}, if\ Q_{gi} < Q_{gi}^{min} \\ Q_{gi}^{lim}, if\ Q_{gi} > Q_{gi}^{max} \end{cases} \tag{14}$$

$$S_i^{lim} = \begin{cases} S_i^{lim}, if\ S_i < S_i^{\min} \\ S_i^{lim}, if\ S_i > S_i^{max} \end{cases} \tag{15}$$

3. Pathfinder Algorithm

The PFA was proposed [35]. It is a swarm intelligence technique (SIT). The PFA mimics the animal movement group with a leading member. This algorithm allows random movement in the search location and follows the pathfinder/leader. If a member finds a better place, the member is selected as a leader. The leading member is called the pathfinder. The movements of the members and pathfinder are different [33]. The PFA consists of three positions: the initialization, pathfinder, and followers. Mathematically, Equation (16) is used for initialization, allowing all the swarm/prey to randomly move in the search area. Equation (17) is used to move other members to the next phase, while the pathfinder uses Equation (18):

$$x_{i,j}^G = x_j^{min} + rand\left(x_j^{max} - x_j^{min}\right) \tag{16}$$

$$x_i^{k+1} = x_i^k + R_1\left(x_j^k - x_i^k\right) + R_2\left(x_p^k - x_i^k\right) + \varepsilon \tag{17}$$

$$x_p^{k+1} = x_p^k + 2r_3\left(x_p^k - x_i^{k-1}\right) + A \tag{18}$$

$$R_1 = \alpha r_1 \text{ and } R_2 = \beta r_2 \tag{19}$$

$$\varepsilon = \left(1 - \frac{k}{k_i}\right) u_1 D_{ij} \tag{20}$$

$$k_i = k_{max} \tag{21}$$

$$D_{ij} = \|x_i - x_j\| \tag{22}$$

$$A = u_2 e^{-\frac{2k}{k_i}} \tag{23}$$

where R_1 and R_2 are random variables, x_p is the vector position of the pathfinder, k is the current iteration, x_i and x_j are the positioned vector of members i and j, r_1 and r_3 are random variables between (0,1) and α, and β are chosen between (1,2), k_{max} is the total number of iterations, D_{ij} is the distance between two members and u_1 and u_2 are random vectors between $(-1, 1)$, A is the fluctuation coefficient, ε is the vibration coefficient.

3.1. Proposed Improved PFA (IPFA)

In order to obtain a global optimum solution and avoid the reduction in searchability of problems with the PFA, this study improved the PFA by introducing inertia weight (w) into the A and ε of the PFA. The reason for this modification was to provide proper fluctuation (A) and vibration (ε) coefficients with a random movement and to transit between the diversification (exploration) and intensification (exploitation). Since the inertia weight w has been effective in PSO to improve the particle search to explore more search areas [36], this principle was adopted and we added the inertia weight to the A and ε of the PFA for a better search and to obtain a global solution.

The inertia weight provided adequate support when moving the prey/swarm to the next stage, which controlled the movement in the search area and reduced premature convergence, which was achieved using Equation (24). The inertia weight added to ε in Equation (25) supported the prey to attain a global optimum solution in the search place. The proper value for A and ε helped in achieving the best solution. Therefore, the w incorporated is given in Equation (26) [2,37]. The flowchart of the proposed IPFA is presented in Figure 1.

$$x_p^{k+1} = x_p^k + 2r_3\left(x_p^k - x_i^{k-1}\right) + w \times A \tag{24}$$

$$x_i^{k+1} = x_i^k + R_1\left(x_j^k - x_i^k\right) + R_2\left(x_p^k - x_i^k\right) + w \times \varepsilon \tag{25}$$

$$w_1 = w_{max} - \frac{w_{max} - w_{min}}{k_i} \times z \tag{26}$$

where w_{max} and w_{min} = maximum and minimum inertia weight, z is the current iteration.

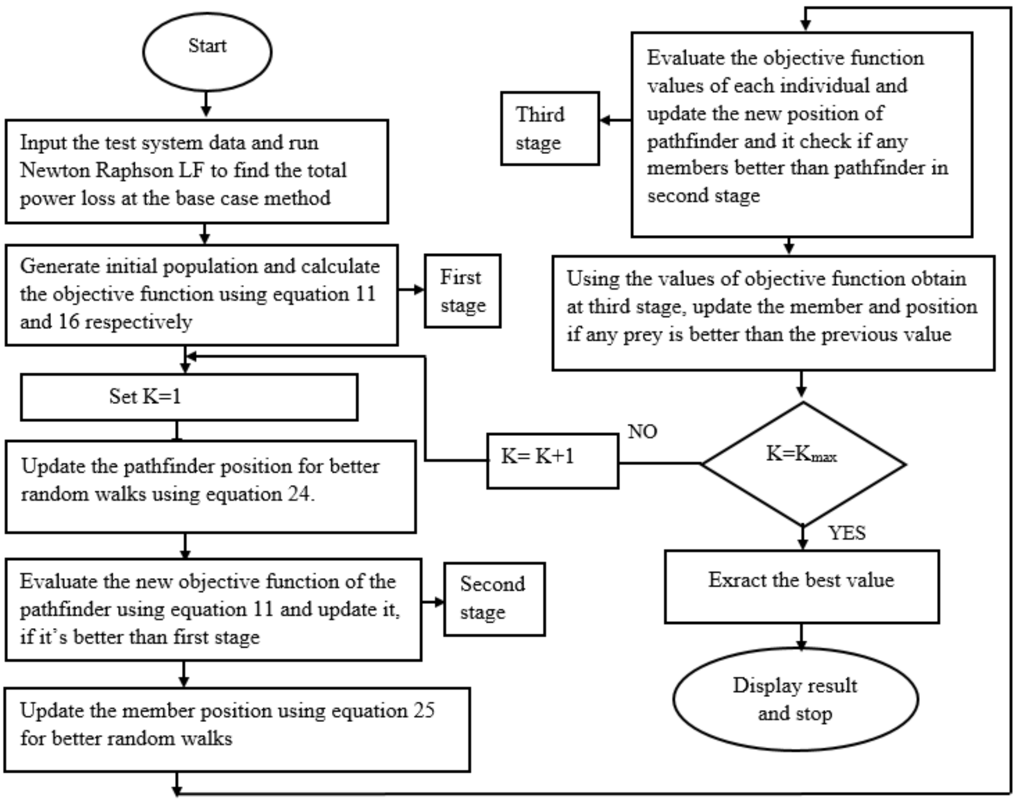

Figure 1. Flow chart of the proposed IPFA.

3.2. Implementation of the IPFA to the ORPD Problem

1. Parameter initialization (size of the population, number of iterations, search space size, and system data).
2. Run Newton–Raphson (NR) LF and calculate the fitness.
3. Update counter (i.e., k = k + 1).
4. Allow the swarms to randomly move using Equation (16).
5. Determine the total power loss using Equation (11).
6. Use Equations (24) and (25) to update and move the pathfinder and follower to the next position.
7. Check the control variable if it is in a permissible range.
8. Then select and store the best value.
9. Are the stopping criteria satisfied? If not, go back to step 2; if YES, go to step 10.
10. Display the result and end.

4. Result and Discussion

For the adequate verification of the proposed IPFA to solve the ORPD problem, the IEEE 30 and 118 bus systems were used to investigate the method's performance in diminishing the active power loss in electric transmission systems. The differences between the two considered systems were (1) the 30 bus system consisting of 30 small nodes, while the 118 bus system consisted of 118 nodes; (2) the 30 bus system consisted of six generators, of which node/bus 1 was a reference/slack bus, and the others were 2, 5, 8, 11, and 13. It consisted of 4 transformer taps located at branches 6–9, 6–10, 4–12, and 28–27. The shunt compensation was 2 and was situated on buses 10 and 24. Moreover, the number of variables that were optimized was 12, while the 118 bus system contained 77 control variables, of which 9 were transformer taps (5–8, 25–26, 17–30, 37–38, 59– 63, 61–64, 65–66, 68–69, and 80–81), 54 were generators (1, 4, 6, 8, 10, 12, 15, 18, 19, 24, 25, 26, 27, 31, 32, 34, 36, 40, 42, 46, 49, 54, 55, 56, 59, 61, 62, 65, 66, 69, 70, 72, 73, 74, 76, 77, 80, 85, 87, 89, 90, 91, 92, 99, 100, 103, 104, 105, 107, 110, 111, 112, 113, and 116), and 14 were reactive compensations (5, 34, 37, 44, 45, 46, 48, 74, 79, 82, 83, 105, 107, and 110). The setting of the algorithm is tabulated in Table 1. MATLAB 2018b software was used for the simulation for this research on a personal HP computer consisting of the following specifications: a corei5, 2.6 GHz processor, 8 GB of RAM, and 500 HDD. Each test case was run for 30 independent trials. The population size was set to 50 for the two cases, and the number of iterations was 200 and 300 for the IEEE 30 and 118 test systems, respectively. The maximum and minimum inertia weights W_{max} and W_{min} were set to 0.9 and 0.4, respectively. The boundary of the control variables of the IEEE 30 test system is given in Table 2 [38]. The individual test case parameters are shown in Table 3.

Table 1. Settings of the algorithms.

Parameter Name	Value
Number of iterations	200 and 300
Particle number	50
W_{max}	0.9
W_{min}	0.4
A	$w\times$ A
ε	$w \times \varepsilon$

Table 2. The control variable boundaries of the IEEE 30 bus system, reproduced with permission from [38], Institution of Engineering and Technology (IET), 2007.

Variables	Upper Limits (p.u)	Lower Limits (p.u)
The voltage of the load bus	1.1	0.9
Transformer tab	1.1	0.9
Shunt compensator	0.04	0

Table 3. Parameter of the test systems.

IEEE Test Systems	30 Bus System	118 Bus System
Number of buses	30	118
Generators	6	54
Transformers	4	9
Shunt compensator	2	14
Control variables	12	77
Base case power loss (MW)	17.89	132.86

4.1. IEEE 30 Bus System

This test system contained six (6) generators, of which the node/bus one (1) was a reference/slack bus, and the others were 2, 5, 8, 11, and 13. It consisted of 4 transformer taps located at branches 6–9, 6–10, 4–12, and 28–27. The shunt compensation was 2 and was situated on buses 10 and 24. The number of variables to optimize was 12. The schematic diagram is given in Figure 2. The upper and lower limits of the load bus voltage were 1.1 and 0.9 p.u, respectively. Moreover, the transformer tap setting was 1.1 and 0.9 p.u, and the shunt compensations were 0.04 and 0 with a base 100 MVA. The convergence curve is shown in Figure 3, and the proposed improved pathfinder algorithm (IPFA) method gave the best result out of the particle swarm optimization (PSO), teaching–learning-based optimization (TLBO), and pathfinder algorithm (PFA). It is noticed that TLBO had a disappointing performance at the final stage. This showed a weakness in attaining diversity to the final stage, whereas, at the initial stage, it had a good performance.

Table 4 compares the best power loss, worst MW, mean MW, standard deviation (STD), and the percentage of reduction (%) of the proposed IPFA compared with other algorithms. It shows that IPFA reduced the loss to 16.035 MW from the base case of 17.89 MW and provided the highest percentage reduction of 10.37%. Also, the proposed IPFA method was compared with PSO [39], evolutionary programming (EP) [40], differential evolution (DE) [38], etc., which provided the losses of 16.1810, 16.3896, and 16.4939 MW, respectively. The IPFA method outperformed the other reported algorithms in the literature. This provided adequate suitability of the proposed method for solving the ORPD problem. The voltage profile of PSO, the PFA, TLBO, and the IPFA were compared with the base case, which is given in Figure 4. It is seen that the Newton–Raphson (NR) method (i.e., the conventional method) showed lower voltage magnitude at the base case than the IPFA, the PFA, PSO, and TLBO, which were the optimization methods, due to the inability of NR to explore different search space to give the optimum solution. This suggested the effectiveness of the IPFA, the PFA, PSO, and TLBO in improving the voltage magnitude more than the NR method. However, the proposed IPFA increased the voltage profile more than the other methods for most of the buses of the test system. Moreover, the voltage profile was within the limits of 1.1 p.u for the upper limits and 0.9 for the lower limits of all buses. It can be seen that there was an increase in voltage between buses 10 to 15; this was due to the generator at buses 11 and 13 providing reactive support to avoid the voltage falling below the limits. This showed that the proposed IPFA method effectively improved the bus voltage profile.

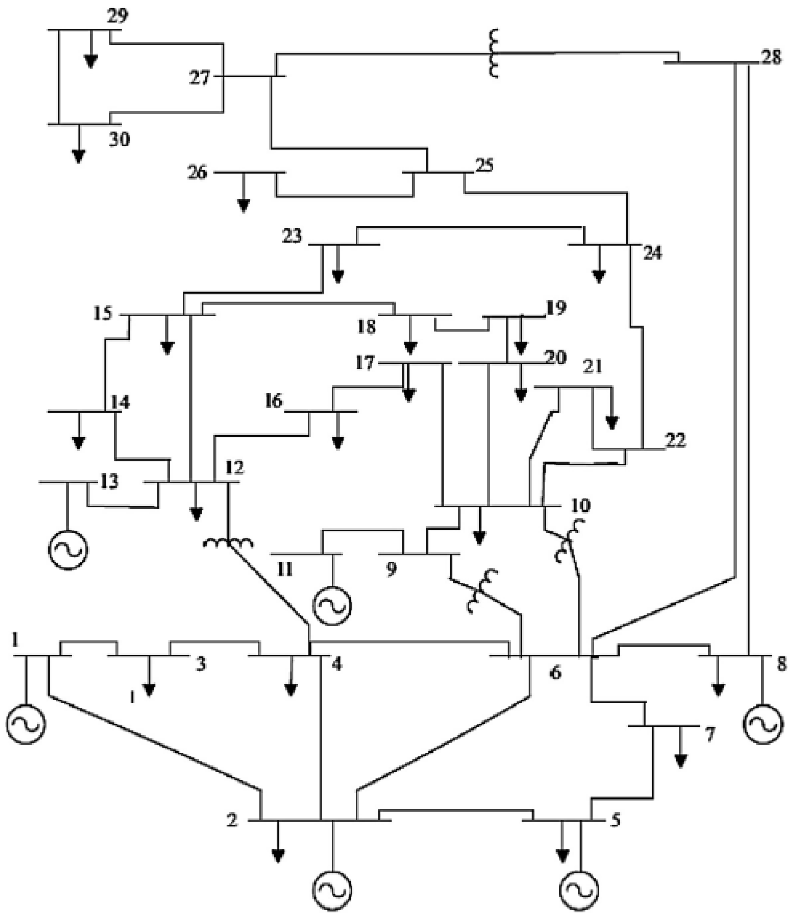

Figure 2. A schematic diagram of the IEEE 30 bus system, reproduced with permission from [22], Elsvier, 2017.

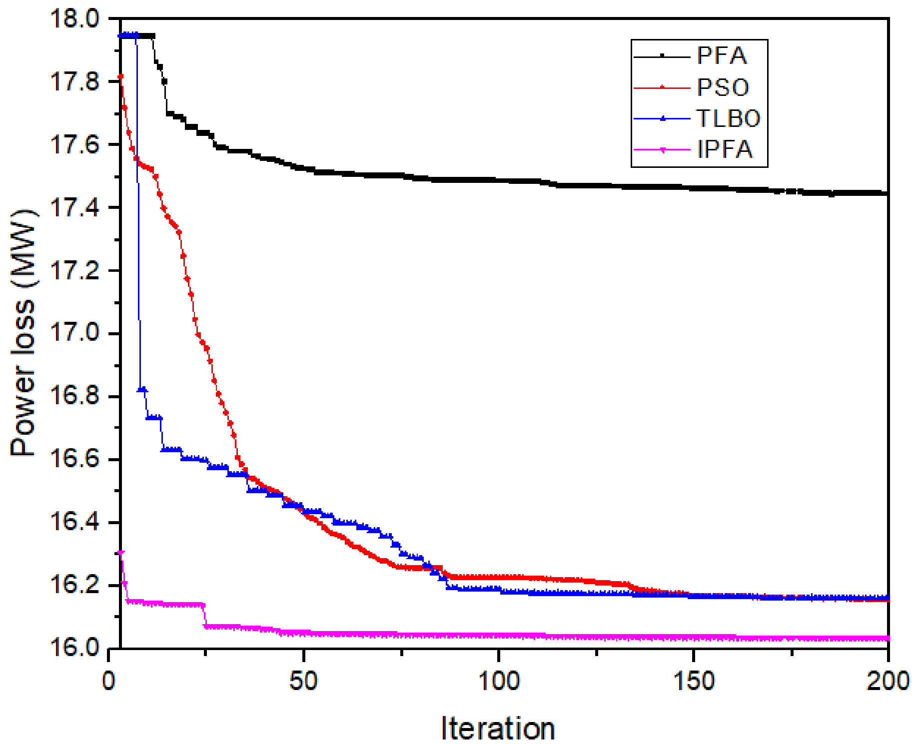

Figure 3. Convergence curve of the IEEE 30 bus system for diminished power loss.

Table 4. Comparison of IPFA with other algorithms.

Algorithms	Best MW	Worst MW	Mean	STD	% of Loss Reduction
IPFA	16.035	17.053	16.544	0.71983	10.37
PFA	17.4469	17.982	17.71445	0.37844	2.52
PSO	16.1568	18.214	17.206	1.42553	9.58
TLBO	16.1607	17.983	17.07185	1.28856	9.67
DE [41]	16.2184	16.6060	-	0.0895	-
DE-ABC [41]	16.2163	16.2164	-	2.34×10^{-5}	-
ABC [41]	16.2325	17.693	-	0.34919	-
PSO [39]	16.1810	-	-	-	-
DE [38]	16.4939	-	-	-	-
EP [40]	16.3896	-	-	-	-

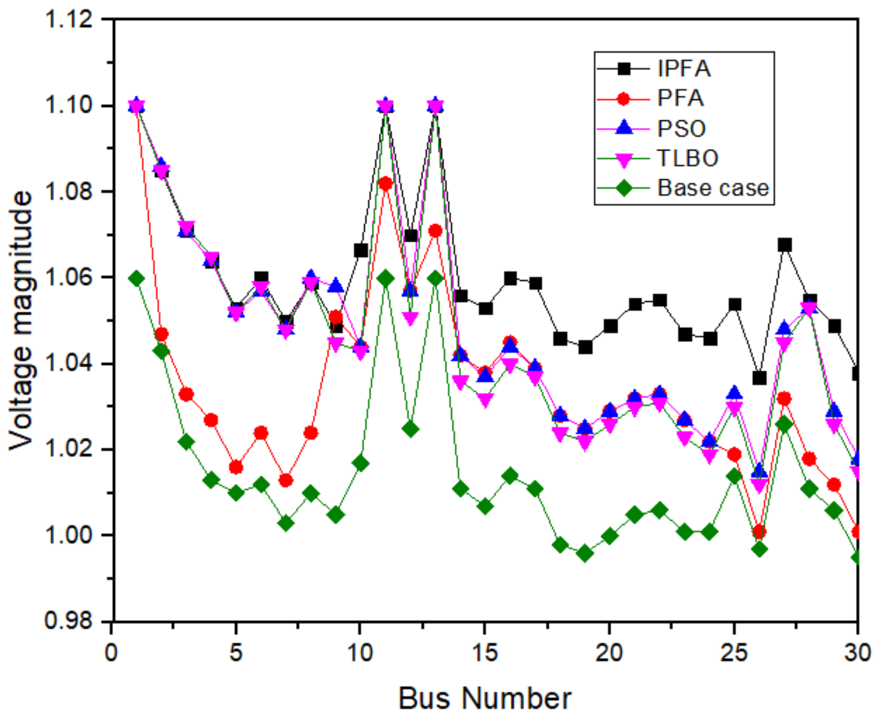

Figure 4. Voltage profile of the IEEE 30 bus system against the bus number.

4.2. IEEE 118 Bus System

The ORPD problem was performed on the IEEE 118 bus system, which contained 77 control variables, of which 9 were the transformer taps, 54 were generators, 186 were transmission lines, and 14 were reactive compensations. Furthermore, the load demand was 4242 MW and the P_{loss} was 132.863 MW. The limit of the control variable was reported [23] with a base of 100 MVA. The upper and lower limits of the load bus voltage were 1.1 and 0.95 p.u, respectively. Moreover, the transformer tap settings were 1.1 and 0.9 p.u and the shunt compensations were 20 and -40 MVar [23]. The test case schematic diagram is given in Figure 5.

Table 5 illustrates the best power loss, worst, mean, STD, and the percentage of reduction (%) of the proposed improved pathfinder algorithm (IPFA) compared with other algorithms. The IPFA (this study) reduced the active power loss to 115.048 MW, while the CSA [14], MFO [23], HICA-PSO [42], GWO [27], and ALC-PSO [26] reduced the losses to 130.96, 116.4254, 127.82, 120.65, and 121.53 MW, respectively. From the compared results, the proposed IPFA provided the best results in finding the optimum solution to the ORPD problem among the algorithms reported in the literature. The convergence curve of the improved pathfinder algorithm (IPFA) is provided in Figure 6. It can be seen that the proposed improved pathfinder algorithm (IPFA) provided the best result out of particle swarm optimization (PSO), teaching–learning-based optimization (TLBO), and the pathfinder algorithm (PFA). From Figure 6, the IPFA and PFA looked like they did not have a convergent power loss value at the iteration of 0 steps, but it was a value (i.e., a number). Also, if it were a zero value, it would have passed the origin line, but it did not draw to the origin line in this case. This showed that the IPFA method effectively reduced the active power loss and provided the optimum result. This validated the superiority of the proposed IPFA in obtaining the optimum solution without stocking to the local optimum when handling the ORPD problem.

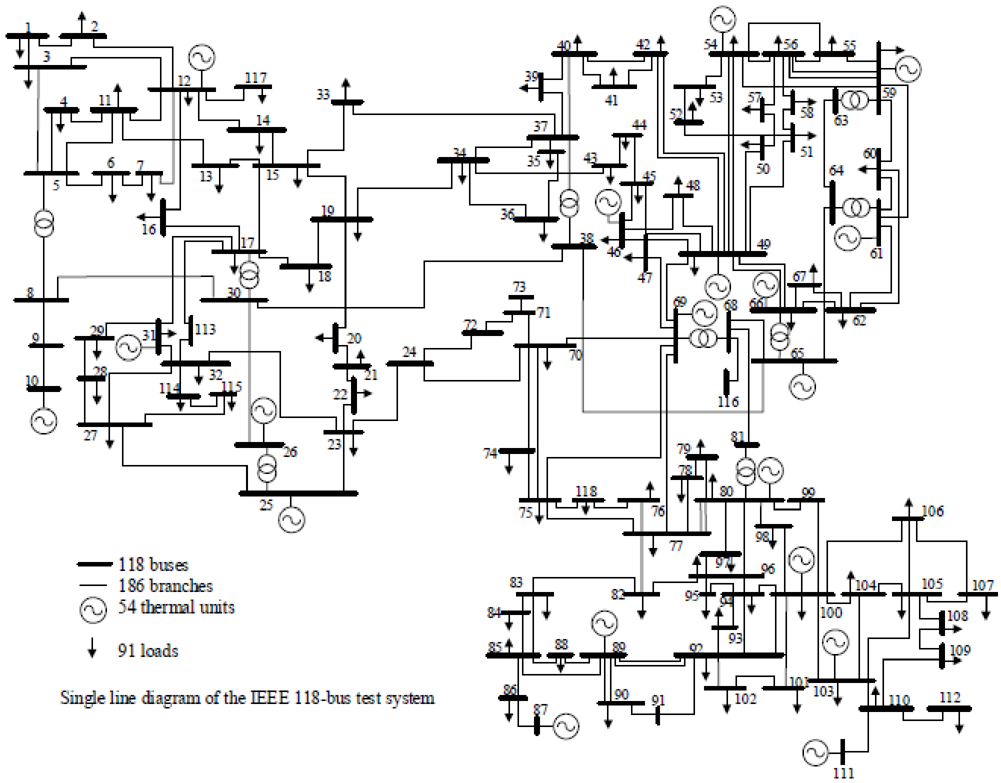

Figure 5. A schematic diagram of the IEEE 118 bus system, reproduced with permission from [43], John Wiley and Sons, 2018.

Table 5. Comparison with other techniques.

Algorithms	Best MW	Worst MW	Mean MW	STD	% Save
IPFA	115.048	118.758	116.903	2.62337	13.41
PFA	120.1287	123.425	121.7769	2.3308	9.58
PSO	117.9129	123.873	120.8930	4.2144	9.75
TLBO	118.0524	119.895	118.9737	1.30291	11.15
MFO [23]	116.4254	-	-	-	12.37
HICA-PSO [42]	127.82	-	-	-	-
GSA [30]	127.76	-	-	-	3.84
FA-APTFPSO#4 [6]	129.8815	146.6919	136.9296	4.2154	46.60

Table 5. *Cont.*

Algorithms	Best MW	Worst MW	Mean MW	STD	% Save
ALC-PSO [26]	121.53	132.99	-	91×10^{-10}	-
CPVEIHBMO [44]	124.098	-	-	-	6.60
GWO [27]	120.65	-	-	-	9.19

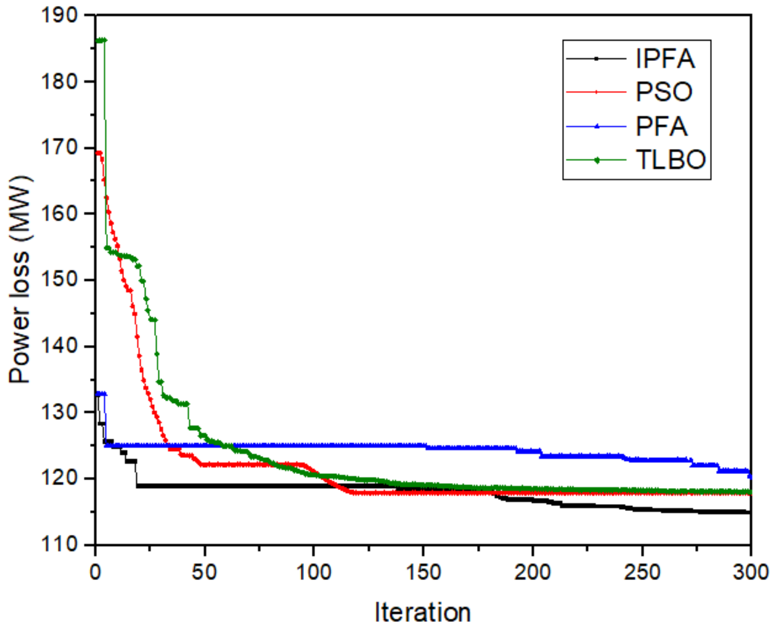

Figure 6. Convergence curve of the IEEE 118 bus system for diminished power loss.

5. Conclusions

In this work, the IPFA was proposed to solve the ORPD problem by introducing inertia weight (w) to the A and ε of the PFA to support the proper random work of prey at the initial stage and to allow the prey to reach the best location when searching for food without reducing the searchability that arises in PFA. The proposed method maintained the balance between diversification and intensification in the search area and attained the optimum solution. The inertia weight supported the proper movement of the swarm to the next stage, which regulated the movement in the search area and lowered premature convergence. In other words, it helped to attain the best solution to a problem. The proper value for A and ε helped in achieving the best solution. The method was tested on the IEEE 30 and 118 bus systems to diminish the active power loss. The active power loss of the IEEE 30 bus system was reduced to 16.035 MW for the IPFA, 17.4469 MW for the PFA, 16.1568 MW for PSO, and 16.1607 MW for TLBO from the initial value of 17.89 MW.

The proposed method was compared with DE, DE-ABC, ABC, PSO, and EP, providing losses of 16.2184, 16.2163, 16.2325, 16.1810, and 16.3896 MW, respectively. The proposed IPFA provided a lower loss reduction than all the compared methods. Moreover, for the IEEE 118 bus system, the losses were reduced to 115.048 MW for the IPFA, and 120.1287, 117.9129, and 118.0524 MW for the PFA, PSO, and TLBO, respectively, from the initial case of 132.863 MW. The proposed IPFA was compared with the CSA, MFO, HICA-PSO, GWO, and ALC-PSO, which had higher losses of 130.96, 116.4254, 127.82, 120.65, and 121.53 MW, respectively. This showed the feasibility and superiority of the proposed IPFA to attain optimum power loss reduction. The percentage reduction for the two test systems was 10.37% and 13.41%, respectively. The result obtained was compared with other techniques in the literature, and the result of IPFA yielded the best solution. This proved the superiority of the proposed method over other techniques for effectively diminishing the power loss in electrical power systems and improving the voltage profile of the systems. Future work should focus on optimizing more objective functions and using the method to solve the ORPD problem and for the optimum placement of distributed generation to improve the systems' voltage profile. Also, the IPFA is an efficient technique that can solve several complex problems in engineering fields.

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Abbreviations

Symbols	Meaning
P_{loss}	is the active power loss
G_k	is the k branch
N_L	is the overall number of transmission losses
k	is the branch between bus i and j
θ_{ij}	is the voltage angle between bus i and j
V_i and V_j	are the voltages at the ith and jth bus, respectively
N_B	is the overall number of buses/nodes
P_{gi} and Q_{gi}	are the active and reactive power generations, respectively
P_{di} and Q_{di}	are the active and reactive load power demands at the ith bus, respectively
B_K	is the mutual susceptance
N_g	is the overall number of generators
N_C	is the overall number of reactive power compensation
N_T	is the overall number of transformers
R_1 and R_2	are random variables equal to αr_1 *and* βr_2, respectively
x_p	is the vector position of the pathfinder
k_p	is the current iteration
x_i and x_j	are the positioned vectors of members i and j
α and β	are randomly chosen between (1,2) in each iteration
$r_1, r_2,$ and r_3	are the random variables between (0,1)
k_{max}	is the total number of iterations
D_{ij}	is the distance between two members
u_1 and u_2	are the random vectors between $(-1, 1)$
A and ε	are the fluctuation and vibration coefficients, respectively
w_{max} and w_{min}	are the maximum and minimum inertia weights, respectively
z	is the current iteration
w	is the inertia weight
V_{gi}^{max} and V_{gi}^{min}	are the maximum and minimum of the generator voltage, respectively
Q_{gi}^{max} and Q_{gi}^{min}	are the maximum and minimum of the reactive power generated, respectively
P_{gi}^{max} and P_{gi}^{min}	are the maximum and minimum active power generated, respectively
Q_{ci}^{max} and Q_{ci}^{min}	are the maximum and minimum of the reactive power compensation, respectively
T_k^{max} and T_k^{min}	are the maximum and minimum of the transformer tabs setting, respectively
V_{ki}^{max} and V_{ki}^{min}	are the maximum and minimum of the load bus voltage, respectively
S_k	is the apparent line flow
S_k^{max}	is the maximum apparent line flow

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