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Optimum Reactive Power Dispatch Solution using Hybrid Particle Swarm Optimization and Pathfinder Algorithm

SAMSON A. ADEGOKE, YANXIA SUN

Department of Electrical and Electronic Engineering Science, University of Johannesburg, South Africa, e-mail (adsam4u@gmail.com, ysun@uj.ac.za)

Corresponding author: Samson A. Adegoke (e-mail: adsam4u@gmail.com).

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ABSTRACT Optimum reactive power dispatch (ORPD) significantly impacts the operation and control of electrical power systems (EPS) due to its undeniable benefit in the economic operation and reliability of the systems. ORPD is a sub-problem of optimal power flow (OPF). The main aim is to reduce/minimize the real power loss. Among the swarm intelligence (SI) metaheuristic algorithms is particle swarm optimization (PSO), which has fast convergence speed and gives the optimum solution to a particular problem by moving the swarm in the intensification (exploitation) search space. Also, the pathfinder algorithm (PFA) mimics the collective movement of the swarms with a leading member. Therefore, combining the fast convergence of PSO with PFA to form a hybrid technique is considered a viable approach in this study to avoid decreasing PFA searchability when the dimension of the problem increases. In this article, a hybrid algorithm based on a particle swarm optimization and pathfinder algorithm (HPSO-PFA) is proposed for the first time to study the combination of the control variables (generator voltage, transformer tap, and sizing of reactive compensation to obtain the objective function (total real power loss). The proposed method is tested on the IEEE 30 and 118 bus systems. The losses were reduced to 16.14262 MW and 107.2913 MW for the IEEE 30 and 118 test systems. Furthermore, the percentage (%) reduction for the IEEE 30 and 118 test systems are 9.8% and 19.25%, respectively. The result demonstrates the performance of HPSO-PFA gives a better solution than the other algorithms.

KEYWORDS optimum reactive power dispatch HPSO-PFA; pathfinder algorithm (PFA); minimization of power loss.

I. INTRODUCTION

DUE to modern equipment running on electricity, electrical power systems (EPS) have undergone several disturbances. As the demand for electricity goes higher, consumption will gradually be higher. EPS is a process of generating, transmitting, and distributing electric energy to the consumers (house, industry, and transportation use). Indisputably, optimum reactive power dispatch ORPD significantly impacts the operation and control of EPS due to its undeniable benefit in economic operation, security, and reliability of the systems. ORPD is a sub-problem of OPF; it is a nonlinear optimization problem in a power system involving continuous and discrete control variables while obeying the equality and inequality constraints [1–6]. The change in reactive power generation (RPG) on every load variation in power system operation leads to varying/changes in load voltage. However, proper/adequate reactive power management will maintain the voltage profile at each bus/node. The main objective of ORPD is the reduction/minimizing of actual/real power loss while keeping the power balance equality and inequality constraints. The control variables in achieving the objective function are the transformer tap settings, generator voltage magnitude, and shunt capacitors. Moreover, improvement in voltage profile leads to a reduction in real power loss [6].

Many methods have been reported in the literature in finding the solution to the ORPD problem; such techniques include conventional/traditional methods and meta-heuristic methods. Some of the conventional methods are gradient-based, Newton methods, interior point method [7], nonlinear programming, quadratic programming [8], and linear programming [9, 10]. However, these methods are not accurate in dealing with discrete variables and nonlinear functions [1, 11].

Among the meta-heuristic methods which has high quality solutions are: particle swarm optimization (PSO) [12], tight-and-cheap conic relaxation approach (TCCR) [13], different approaches are semi-definite programming (SDP) [14], enhanced Jaya optimization method (e-JAYA) [15], modified stochastic fractal search algorithm (MSFSA) [16], improved social spider algorithm (ISSA) [17], improved ant lion optimizer (IALO) [18], modified version of sine–cosine method (ISCA) [19], success history-based adaptive differential evolution (SHADE) [20], tree seed algorithm (TSA) [21], Jaya optimization algorithm (JAYA) [22, 23], backtracking search (BS) method [24], whale optimization algorithm (WOA) [25], Gaussian bare-bones water cycle optimizer (GBBWCO) [26], moth–flame optimizer (MFO) [6], ant lion optimizer (ALO) [27], chaotic krill herd algorithm (CKHA) [28], particle swarm optimization with an ageing leader and challengers (ALC-PSO) [29], grey wolf optimizer (GWO) [2] modified teaching–learning algorithm with differential evolution (MTLA-DE) [30], artificial bee colony (ABC) [31], gravitational search algorithm (GSA) [32], big bang–big crunch (BB-BC) [33], comprehensive learning particle swarm optimization (CLPSO) [34].

The meta-heuristic algorithms are based on two important characteristics: diversification (exploration) and intensification (exploitation). In diversification, an unknown space is chosen for a random search. The best individual is trying to improve intensification, but too much intensification stocks into local search and converges to local optimal minimal. However, balancing diversification and intensification is essential in presenting effective algorithms [35–38].

Therefore, the Pathfinder algorithm (PFA) is a recently developed meta-heuristic algorithm that was developed by (Yapici and Cetinkaya in 2019) [39]. PFA simulates the behavior of the animal group movement and mimics the swarm leadership. Depending on the individual leader, the swarm moves randomly to find the best food location. The PFA gives an effective result to some of the optimization problems. Majorly, PFA depends on the size of the problem. When the dimension of the problem increases, the performance of the PFA is reduced because it depends on mathematical formulas [36]. Also, the superiority of PSO is the fast convergence speed and fewer parameters to be adjusted, but stock to local optimal leads to unsatisfactory results.

Therefore, the HPSO-PFA is proposed to solve the ORPD problem in power system networks to overcome the challenges of PSO and PFA mentioned above. Combining PSO and PFA enable the prey to jump from the local optimal, which implies moving away from undesirable solutions and allows the swarm to locate the most prominent food (i.e., exploitation) without reduction in the searchability. The performance of the proposed method is tested on standard IEEE systems (i.e., IEEE 30 and 118 bus systems). The effective performance simulation of the proposed method is compared with other algorithms, and HPSO-PFA demonstrates satisfactory results. The contributions of this work are as follows:

a. Proposed a novel hybrid algorithm based on particle swarm optimization and pathfinder algorithm for the first time to optimize the control parameter of the ORPD problem to minimize real power loss. Also, to overcome local optimal, reducing searchability at high dimension problem, and premature convergence for the best quality solution, effective operation, and reliability of the power system network.
b. The penalty function is effectively considered for comparison of the performance by including the line constraint, shunt capacitor, and bus voltage.
c. Comparing the results obtained from the proposed HPSO-PFA with other algorithms involving hybrid and single techniques reveals that the proposed algorithm performed better than others.

The rest of the paper is structured as follows: Section 2 gives the materials and methods, Section 3 reports the HPSO-PFA and implementation to ORPD, Section 4 present the result and discussion, while the last Section is the conclusion and future work recommendation

II. MATERIALS AND METHODS

A. OBJECTIVE FUNCTION

This research aims to minimize the real power loss, which is the main target of the ORPD problem, while keeping the constraints. Formulation of the ORPD problem as the minimizing/reduction function (x, u) is as follows

$$f = P_{loss} = f(\mathrm{x}, \mathrm{u}) = \sum_{K=1}^{N_L} G_k \left(v_i^2 + v_j^2 - 2V_iV_j \cos\theta_{ij}\right), \quad (1)$$

which satisfying

$$\begin{cases} g(x,u) = 0 \\ h(x,u) \le 0' \end{cases} \quad (2)$$

$$u^{min} \le u \le u^{max}, \quad (3)$$

$$x^{min} \le x \le x^{max}, \quad (4)$$

where $f(\mathrm{x},\mathrm{u})$ is the objective function to be optimized, P_{loss} is real total losses, 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 jth bus, $g(x,u)$ *and* $h(x,u)$ are the equality and inequality constraints, x is the vector of the dependent variables, u is the vector of the control variables, and min and max are the minima and maximum limit values.

B. EQUALITY CONSTRAINTS

The equality constraints in transmission networks are the load flow (LF) equations

$$P_i - V_i \sum_{K=1}^{N_B} V_j (G_k \cos\theta_{ij} + B_K \sin\theta_{ij}) = 0, \quad (5)$$

$$Q_i - V_i \sum_{K=1}^{N_B} V_j (G_k \sin\theta_{ij} + B_K \cos\theta_{ij}) = 0, \quad (6)$$

where N_B is the overall number of buses/nodes, P_i is the real power generation, Q_i is the reactive power generation, and B_K is the mutual susceptance.

C. INEQUALITY CONSTRAINTS

The inequality constraints are given in upper and lower limits

1) Generator constraints: These are the generation of bus voltage, together with the generation of real and reactive power are kept to their limits

$$V_{gi}^{min} \leq V_{gi} \leq V_{gi}^{max} \qquad i = 1 \ldots, N_g, \tag{7}$$
$$Q_{gi}^{min} \leq Q_{gi} \leq Q_{gi}^{max} \qquad i = 1\ldots, N_g, \tag{8}$$
$$P_{gi}^{min} \leq P_{gi} \leq P_{gi}^{max} \qquad i = 1\ldots, N_g, \tag{9}$$

N_g= Overall number of generators

2) *Reactive power compensation limits*

$$Q_{ci}^{min} \leq Q_{ci} \leq Q_{ci}^{max} \qquad i = 1 \ldots, N_C, \tag{10}$$

N_C= Overall number of reactive power compensation

3) *Transformer tap ratio constraints*

$$T_k^{min} \leq T_k \leq T_k^{max} \qquad i = 1 \ldots, N_T, \tag{11}$$

N_T= Overall number of transformers

4) *Line flow limits*

$$V_{ki}^{min} \leq V_{ki} \leq V_{ki}^{max} \qquad i = 1 \ldots, N_B\,, \tag{12}$$
$$S_k \leq S_k^{max} \qquad i = 1 \ldots, N_K, \tag{13}$$

where N_K is the load flow branch, and V_{ki} is the voltage of the load bus/node.

The dependent variable constraints are added to the objective function to avoid unrealistic solutions. The self-constraints are the control variable, but the dependent variable is violated. Therefore, the objective function and penalty factor can be expressed together, as shown in the equation (14).

$$f_T = f + \lambda_V \sum_{K=1}^{N_B} (V_i - V_i^{lim})^2 + \lambda_g \sum_{K=1}^{N_B} (Q_{gi} - Q_{gi}^{lim} + \lambda_T \sum_{K=1}^{N_B} (S_i - S_i^{lim})^2. \tag{14}$$

Here,

$$\lambda_V, \lambda_g, \lambda_T \quad \text{are the penalty factors,} \tag{15}$$
$$V_i^{lim} = \begin{cases} V_i^{lim}, if\ V_i < V_i^{min} \\ V_i^{lim}, if\ V_i > V_i^{max}, \end{cases} \tag{16}$$
$$Q_{gi}^{lim} = \begin{cases} Q_{gi}^{lim}, if\ Q_{gi} < Q_{gi}^{min} \\ Q_{gi}^{lim}, if\ Q_{gi} > Q_{gi}^{max}, \end{cases} \tag{17}$$
$$S_i^{lim} = \begin{cases} S_i^{lim}, if\ S_i < S_i^{\min} \\ S_i^{lim}, if\ S_i > S_i^{max} \end{cases}. \tag{18}$$

D. THE PFA

The PFA is a swarm intelligence technique based on the swarm's movement with a leader-member and was proposed by [39]. The leader-member is called the pathfinder. PFA allows all the swarms to move toward any location in the search area by following the pathfinder and moving randomly in the search space. When a member's best optimum place is located, this individual member is chosen as a leader/pathfinder. PFA has three stages: initialization, the position of the pathfinder, and the position of followers. The initialization allows all the prey members to move randomly in the search area, as given in (19). The pathfinder position enables the prey to move to another location, and the present best solution is compared to the previous one. Equation (20) moved the pathfinder to the next position. Lastly, equation (21) was used to update the position of the follower. When the follower chooses the best solution, the pathfinder replaces the follower. PFA has the advantage of encouraging the random movement of all members. However, it has the disadvantage of reducing the searchability performance at high-dimension problems. Therefore it restricted the intensification and diversification of the ORPD problem [36].

$$x_{i,j}^G = x_j^{min} + rand(x_j^{max} - x_j^{min}), \tag{19}$$
$$x_p^{k+1} = x_p^k + 2r_3(x_p^k - x_i^{k-1}) + A\,, \tag{20}$$
$$x_i^{k+1} = x_i^k + R_1(x_j^k - x_i^k) + R_2(x_p^k - x_i^k) + \varepsilon, \tag{21}$$
$$R_1 = \alpha r_1 \text{ and } R_2 = \beta r_2, \tag{22}$$
$$\varepsilon = \left(1 - \frac{k}{k_i}\right) u_1 D_{ij}, \tag{23}$$
$$k_i = k_{max}, \tag{24}$$
$$D_{ij} = \|x_i - x_j\|, \tag{25}$$
$$A = u_2 e^{-\frac{2k}{k_i}}, \tag{26}$$

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, A and ε are fluctuation and vibration coefficient, respectively, r_1 *and* r_3 are random variables between (0,1), 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 coefficients, ε is the vibration coefficients.

E. MODIFIED PFA (mPFA)

The Modified PFA was proposed [40]. A and ε are the fluctuation and the vibration coefficients, which are modified for a better search, since both have the capability for random movements and transition between diversification and intensification. Therefore, there should be a proper value for A and ε to maintain the random movement. Hamza Yapici has proposed the value for both A and ε as $\varepsilon = 0.1\varepsilon$ and A= 0.001A

F. THE PSO

Among the SI techniques is PSO, inspired by the social behaviors of birds and fish schooling. In PSO, each individual/particle moves with velocity and keeps the best position within the search space. The best position of each particle of the population/swarm is communicating with other particles. The swarm moved randomly in the d-dimensional search area, and each particle kept/maintained the velocity and position [41]. Each particle updates its position and velocity at every iteration and learns from its own/personal position and the swarm's overall best position [42]. The updated velocity and position are defined by equations (27) and (31). The advantage of PSO is that it has few parameters to be tuned. It has a low computational burden and fast convergence and does not require preconditions such as differentiability or continuity objective functions. However, PSO still encountered some demerits, such as premature convergence and inability to tend to the global optimal. The reason is in two ways 1). When particles converge to the local optimal in the search space, they cannot move out. 2). When particles are attracted too much to the swarm leader, they will quickly converge without exploring the different search spaces [43].

$$V_i^{k+1} = \varphi\left(w_1 v_i^k + c_1 r_1 \left(p_{best} - s_i^k\right) + c_2 r_2 \left(g_{best} - s_i^k\right)\right), \tag{27}$$

where φ and w_1,

$$\varphi = \frac{2}{\left|2 - \psi - \sqrt{\psi^2 - 4\psi}\right|}. \tag{28}$$

$$\psi = c_1 + c_2 \tag{29}$$

$$w_1 = w_{max} - \frac{w_{max} - w_{min}}{iter_{max}} \times z. \tag{30}$$

$$s_i^{k+1} = s_i^k + V_i^k. \tag{31}$$

III. THE PROPOSED HPSO-PFA

The most prominent task in the meta-heuristic algorithm is to obtain an optimum solution balance between diversification and intensification. Therefore, PSO and PFA are merged to form a new algorithm. The hybrid algorithm is expected to perform well in local and global search and gives better results than single algorithms.

PSO can converge faster, and it requires fewer parameters to be tuned. This makes it easy to combine with other algorithms to form a hybrid method. It controls the balance between the local and global search space. A disadvantage of PSO is that it stocks to local optimal. On the other hand, PFA has the advantage of transits between the exploration (diversification) and exploitation (intensification) phases, which makes all members move randomly. A disadvantage of PFA is that there is a decrease in searchability as the dimension of the problem increases. At the start of every iteration, a global exploration of the search area is necessary to examine the wide area for perspective solutions and then look for a prominent solution in the search area. PSO can quickly identify the promising region in the search area, while PFA is used to move the swarm to another phase to locate the best solution. The best solution of PFA is then combined with the velocity of PSO to obtain the most prominent solution. A new hybrid is proposed to overcome the shortcomings of PSO and PFA. Therefore, combining the fast convergence of PSO with PFA to form a hybrid technique is considered a viable alternative method to avoid decreasing PFA searchability when the dimension of the problem increases.

However, HPSO-PFA enables the new solution to produce in the iteration process, thus encouraging movement from the diversification and intensification stage. It was observed from this work that HPSO-PFA did not stock to local optimal, and searchability did not reduce at the high dimension problem, i.e., at the higher test bus system. Therefore, HPSO-PFA has the advantage of attaining global optimum.

In the prey movement of PFA, the prey moves randomly to look for a prominent solution; if the prey cannot get a superior solution, the position of PFA is updated, and the prey that gets a better solution is chosen as a pathfinder/leader. The position of the follower is also updated for a better search space. After that, the pathfinder is combined with PSO velocity to improve the search space when looking for a better solution. The flowchart of HPSO-PFA represents Fig. 1.

A. IMPLEMENTATION OF HPSO-PFA TO ORPD PROBLEM

1. Initialization of the parameters
2. Run Newton Raphson (NR) LF and calculate the fitness
3. Update counter, i.e., iter = iter +1
4. Update G_{best} and P_{best}
5. Check the control variable if it's in a permissible range
6. Store the best fitness
7. Generate new followers and pathfinder, as given in equations (21 and 20).
8. Select the best solution and generate the new one.
9. Update the velocity and position given in equations (27) and (31).
10. Run the NR method LF
11. Then select and store the best value
12. Is the stopping criteria satisfied? If not, go back to step 2, and if YES, move to step 13
13. Display the result and stop

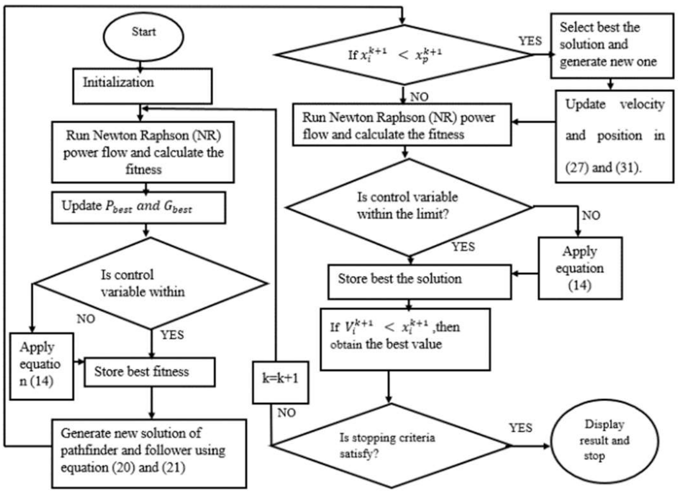

Figure 1. Flow chart of HPSO-PFA

IV. RESULT AND DISCUSSION

A. THE IEEE 30 TEST SYSTEM WITH 12 CONTROL VARIABLES

The IEEE 30 bus system consists of 4 transformer tabs, 2 reactive power compensation, and 6 generator buses/nodes. The total number of the control variable is 12, and the initial power loss is 17. 8984 MW [44, 45]. Table. 1. Give the settings of the algorithms. The value of the limit control variables of the system is shown in Table 2. For this test system, the simulation was run for 30 independent trials. The minimum P_{loss} of PFA is 17.4450 MW, PSO is 16.1980 MW, and the HPSO-PFA is 16.14262 MW. The convergence curve of the algorithms of the test system is given in Fig. 2. Table 3 illustrates the comparison of the best control variable of the IEEE 30 bus system after optimization.

To show the superiority of the proposed algorithm, the minimum P_{loss}, maximum P_{loss}, mean, and standard deviation (STD) are given in Table 4. Subbaraj and Rajnarayanan [44] reported a minimum loss of 16.3896 MW, and Liang et al. [45] reported their minimum loss to be 16.4939 MW. By comparison, this literature reported the minimum losses higher than the losses obtained from the proposed algorithm in this study. It can be seen that HPSO-PFA gives a better loss reduction than all the algorithms, thereby suggesting the superiority of the technique used in this study. A details comparison with other algorithms is presented in Table 4.

Therefore, HPSO-PFA is more effective in power loss reduction. The percentage (%) loss reduction of PFA is 2.52%, mPFA is 2.6%, PSO is 9.5%, and HPSO- PFA is 9.8%. HPSO-PFA gives a higher percentage loss reduction, giving it superiority over the others.

Table 1. Settings of the algorithms

Parameter name	Value
Number of iterations	200
Particle number	50
Acceleration constant for PSO	$C_1 = C_2 = 2$
Constriction factor	0.729
W_{max}	0.9
W_{min}	0.4
A	0.001A
ε	0.1ε

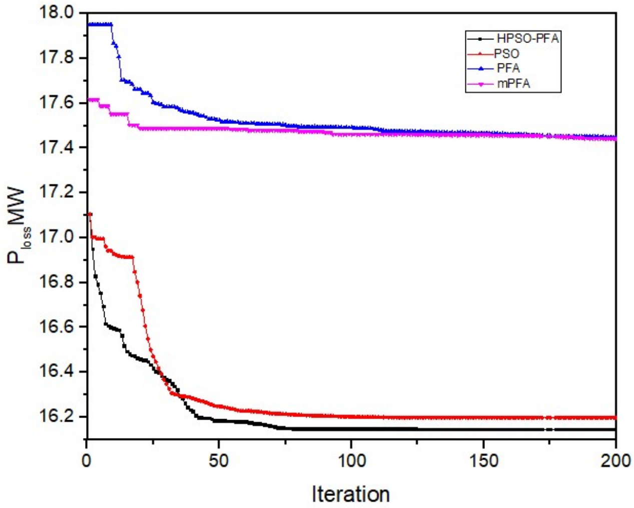

Figure 2. Convergence curve of IEEE 30 bus system

Table 2. The setting of control variables of the test system [45]

Control variables	Maximum (p.u)	Minimum (p.u)
The voltage of the load bus	1.05	0.95
The voltage of the generator (Vg) bus	1.1	0.9
Transformer tab	1.1	0.9
Q_{C10}	0.2	0
Q_{C24}	0.04	0

Table 3. Best control variable of the IEEE 30 bus system

Control variable	Algorithms			
	HPSO-PFA	EP [44]	SARGA [44]	PSO [46]
Vg_1	1.1015	-	-	1.0995
Vg_2	1.0863	1.097	1.094	1.0778
Vg_5	1.0542	1.049	1.053	1.0459
Vg_8	1.0609	1.033	1.059	1.0576
Vg_{11}	1.1001	1.092	1.099	1.0526
Vg_{13}	1.1001	1.091	1.099	1.0330
T_{6-9}	1.0433	1.01	0.99	1.0050
T_{6-10}	0.9210	1.03	1.03	1.0239
T_{4-12}	1.0546	1.07	0.98	1.0183
T_{28-27}	0.9803	0.99	0.96	0.9927
Q_{c10}	0.0408	0.19	0.19	0.1840
Q_{c24}	0.0421	0.04	0.04	0.1315

Table 4. Comparison of HPSO-PFA with other algorithms

Algorithms	Minimum P_{loss}MW	Maximum P_{loss}MW	Mean	STD	% loss reduction
PFA	17.4469	17.982	17.71445	0.37844	2.52
mPFA	17.4413	17.9762	17.70875	0.37823	2.6
PSO	16.1980	18.214	17.206	1.42553	9.5
HPSO-PFA	**16.14262**	17.1065	16.62456	0.68157	9.8
DE [47]	16.2184	16.6060	-	0.089508	-
DE-ABC[47]	16.2163	16.2164	-	2.34E-05	-
ABC [47]	16.2325	17.693	-	0.34919	-
PSO [46]	16.1810	-	-	-	-
DE [45]	16.4939	-	-	-	-
EP [44]	16.3896	-	-	-	-

B. THE IEEE 118 BUS SYSTEM

To prove the performance of HPSO-PFA in a large test case system, the IEEE 118 test system was used. The system contains 77 control variable, of which 9 is transformer taps (5–8, 25–26, 17–30, 37–38, 59– 63, 61–64, 65–66, 68–69, 80–81), 54 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, 116), and 14 reactive compensations (5, 34, 37, 44, 45, 46, 48, 74, 79, 82, 83, 105, 107, 110). The limit of the control variable has been reported [6]. Furthermore, the load demand and base case is P_{loss} are given below

$$P_{load} = 4242 \text{ MW},$$
$$Q_{load} = 1438 \text{ MVar},$$
$$P_{loss} = 132.863 \text{ MW}.$$

The settings of the algorithms are the same as the one given in Table 1, except for the number of iterations that were set to 300 in this case. For the test system, the simulation was run for 30 independent trials. From the simulation result, HPSO-PFA offers outstanding development in minimizing real power loss. The losses significantly reduce from 132.863 MW of the base case to 107.2913 MW. The convergence curve of the IEEE 118 bus system is shown in Fig. 3. The best control variable after optimization is given in Table 5. By comparing the result of the proposed approach with some algorithms like MFO, chaotic parallel vector evaluated interactive honey bee mating optimization (CPVEIHBMO), HPFA, CLPSO, and GWO; the proposed HPSO-PFA gives an outstanding smallest/lowest power loss result. Comparing HPSO-PFA with CPVEIHBMO, CLPSO, GWO, MFO, and HPFA gives 12.65%, 17.81%, 10.05%, 6.88%, and 0.6%, respectively. This achievement proved the superiority of the proposed hybrid approach since it gives a more desirable solution with the lowest power loss in solving the ORPD problem

Table 6 illustrate the minimum, maximum, mean, and STD of real power loss with other techniques, and it can be seen that HPSO-PFA gives the most superior result. Table 7 illustrates the percentage (%) of reduction with different techniques; by comparison, the proposed method gives 19.247%, while MOF, CPVEIHBMO, CLPSO, and GWO give 12.37%, 6.6%, 1.43%, and 9.19%, respectively. However, this also indicates the achievement of HPSO-PFA in power loss reduction.

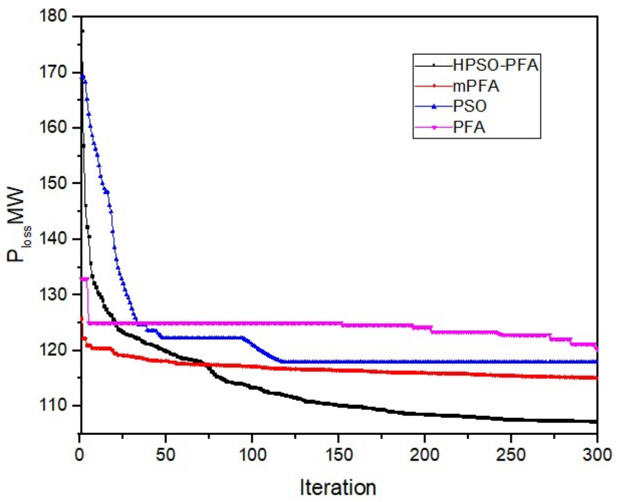

Figure 3. Convergence curve of IEEE 118 bus system

Table 5. Comparison of result with other methods of IEEE 118 bus system after optimization

Control variables	HPSO-PFA	MFO [6]	GWO [2]	GSA [32]	CPVEI HBMO [5]	FA-APTFPSO #4 [48]
Vg_1	1.0566	1.0173	1.0204	0.9600	0.9926	1.0141
Vg_4	1.0809	1.0402	1.0257	0.9620	1.0108	0.9494
Vg_6	1.0703	1.0292	1.0208	0.9729	1.0037	1.0013
Vg_8	1.0898	1.0600	1.0419	1.0570	0.9976	1.0044
Vg_{10}	1.0996	1.0374	1.0413	1.0885	1.0215	1.0111
Vg_{12}	1.0669	1.0250	1.0232	0.9630	1.0093	0.9937
Vg_{15}	1.0600	1.0268	1.0207	1.0127	1.0075	0.9898
Vg_{18}	1.0608	1.0298	1.0270	1.0069	1.0259	0.9567
Vg_{19}	1.0593	1.0275	1.0204	1.0003	0.9943	1.0300
Vg_{24}	1.0793	1.0483	1.0137	1.0105	1.0179	0.9540
Vg_{25}	1.0999	1.0600	1.0270	1.0102	1.0177	1.0383
Vg_{26}	1.1004	1.0600	1.0386	1.0401	0.9990	0.9656
Vg_{27}	1.0561	1.0267	1.0188	0.9809	1.0084	0.9229
Vg_{31}	1.0476	1.0101	1.0138	0.9500	0.9838	0.9169
Vg_{32}	1.0542	1.0226	1.0135	0.9552	0.9827	1.0238
Vg_{34}	1.0804	1.0556	1.0261	0.9910	1.0065	0.9379
Vg_{36}	1.0773	1.0548	1.0261	1.0091	1.0190	0.9936
Vg_{40}	1.0592	1.0419	1.0125	0.9505	1.0267	0.9173
Vg_{42}	1.0641	1.0429	1.0233	0.9500	0.9865	0.9242
Vg_{46}	1.0859	1.0450	1.0272	0.9814	1.0084	1.0113
Vg_{49}	1.0982	1.0589	1.0401	1.0444	1.0035	1.0638
Vg_{54}	1.0761	1.0284	1.0230	1.0379	0.9806	0.9865
Vg_{55}	1.0752	1.0289	1.0221	0.9907	0.9969	1.0216
Vg_{56}	1.0761	1.0283	1.0226	1.0333	0.9881	0.9221
Vg_{59}	1.1001	1.0512	1.0379	1.0099	1.0197	1.0496
Vg_{61}	1.0996	1.0534	1.0241	1.0925	0.9956	1.0092
Vg_{62}	1.0954	1.0506	1.0199	1.0393	1.0064	1.0007
Vg_{65}	1.1005	1.0596	1.0465	0.9998	0.9883	0.9703
Vg_{66}	1.1012	1.0600	1.0378	1.0355	1.0101	0.9861
Vg_{69}	1.1005	1.0600	1.0501	1.1000	0.9931	0.9961
Vg_{70}	1.0729	1.0600	1.0243	1.0992	1.0127	0.9676
Vg_{72}	1.0668	1.0526	1.0187	1.0014	1.0145	0.9431
Vg_{73}	1.0693	1.0600	1.0397	1.0111	1.0174	0.9368
Vg_{74}	1.0632	1.0600	1.0170	1.0476	1.0025	0.9653
Vg_{76}	1.0595	1.0390	1.0080	1.0211	0.9842	1.0033
Vg_{77}	1.0865	1.0502	1.0192	1.0187	0.9914	1.0075
Vg_{80}	1.1002	1.0600	1.0329	1.0462	1.0257	0.9617
Vg_{85}	1.0992	1.0600	1.0224	1.0491	0.9876	1.0407
Vg_{87}	1.1003	1.0599	1.0361	1.0426	1.0213	0.9594
Vg_{89}	1.1019	1.0600	1.0558	1.0955	1.0069	0.9824
Vg_{90}	1.0847	1.0431	1.0290	1.0417	1.0298	0.9726
Vg_{91}	1.0848	1.0496	1.0127	1.0032	0.9839	0.9744
Vg_{92}	1.0984	1.0600	1.0360	1.0927	1.0021	0.9606
Vg_{99}	1.0837	1.0551	1.0297	1.0433	0.9853	0.9589
Vg_{100}	1.0888	1.0584	1.0360	1.0786	1.0281	0.9846
Vg_{103}	1.0704	1.0442	1.0232	1.0266	0.9802	1.0369
Vg_{104}	1.0552	1.0333	1.0180	0.9808	1.0187	0.9931
Vg_{105}	1.0499	1.0281	1.0176	1.0163	1.0209	0.9853
Vg_{107}	1.0318	1.0161	1.0201	0.9987	1.0234	0.9057
Vg_{110}	1.0388	1.0215	1.0207	1.0218	0.9842	0.9361
Vg_{111}	1.0431	1.0280	1.0261	0.9852	1.0000	0.9529
Vg_{112}	1.0206	1.0042	1.0066	0.9500	0.9930	0.9198
Vg_{113}	1.0666	1.0350	1.0251	0.9764	1.0200	0.9417
Vg_{116}	1.0999	1.0484	1.0342	1.0372	1.0016	0.9524
T_{8-5}	0.9850	1.01360	1.0208	1.0659	1.0255	0.9595
T_{26-25}	1.0901	1.10000	1.0279	0.9534	0.9891	1.0012
T_{30-17}	1.0153	1.00380	1.0323	0.9328	0.9932	0.9378
T_{38-37}	0.9798	0.98263	1.0209	1.0884	0.9873	0.9699
T_{63-59}	0.9539	0.98430	1.0091	1.0579	0.9868	0.9879
T_{64-61}	1.0338	1.01390	1.0366	0.9493	1.0235	0.9810
T_{65-66}	1.0555	1.10000	1.0301	0.9975	1.0090	0.9999
T_{68-69}	0.9693	1.10000	1.0234	0.9887	1.0075	0.9987
T_{81-80}	0.9769	0.96831	1.0211	0.9801	0.9872	1.0002
Q_{C5}	0.1210	0	-39.76	0	0	1.2528
Q_{C34}	0.1443	0	13.79	7.4600	6.0111	0.4362
Q_{C37}	0.1164	-0.03126	-24.73	0	0	3.5249
Q_{C44}	0.0645	10	9.957	6.0700	6.0057	2.1925
Q_{C45}	0.1377	0	9.868	3.3300	3.0001	1.5462
Q_{C46}	0.1342	0	9.919	6.5100	5.9838	2.2228
Q_{C48}	0.1248	0.000842	14.89	4.4700	3.9920	0.8434
Q_{C74}	0.1319	0.220540	11.972	9.7200	7.9862	1.3999
Q_{C79}	0.0184	20	19.649	14.250	13.9892	2.6851
Q_{C82}	0.2292	0	19.890	17.490	17.9920	1.0367
Q_{C83}	0.1725	10	9.9515	4.2800	4.0009	2.4714
Q_{C105}	0.0209	0	19.968	12.040	10.9825	2.8861
Q_{C107}	0.0381	6	5.9136	2.2600	2.0251	1.8803
Q_{C110}	0.2073	6	5.8834	2.9400	2.0272	3.2001

Table 6. Comparison with other techniques

Algorithms	Minimum $P_{loss}\ MW$	Maximum $P_{loss}\ MW$	Mean	STD
PFA	120.1287	123.425	121.7769	2.3308
mPFA	115.0687	119.213	117.1409	2.9305
PSO	117.9129	123.873	120.8930	4.2144
HPSO-PFA	**107.2913**	119.567	113.4292	8.6802
mPFA [40]	117.0690	118.0053	117.3823	0.2969
SDP [14]	113.17	-	-	-
MSFS [16]	114.6351	116.6677	115.4278	0.4678
IALO [18]	114.795	-	117.299	-
ALO [18]	116..86	-	119.712	-
HPFA [36]	108.090	109.2265	-	0.5974
ISSA [17]	114.5297	121.1127	115.651	1.4889
MFO [6]	116.4254	-	-	-
GSA [32]	127.76	-	-	-
FA-APTFPSO#4 [48]	129.8815	146.6919	136.9296	4.2154
ALC-PSO [29]	121.53	132.99	-	-

Table 7. Comparison of percentage of reduction after optimization

Algorithms	Base case	HPSO-PFA	MOF [6]	GWO [2]	CPVEIH BMO [5]	CLPSO [34]
P_{loss} MW	132.863	107.2913	116.4254	120.65	124.098	130.96
% of loss reduction		**19.247**	12.37	9.19	6.60	1.43

V. CONCLUSION AND FUTURE WORK

In this research, a novel HPSO-PFA was proposed to find the solution to the ORPD problem. The PSO and PFA parameters, the maximum number of iterations, and the population size were done at the initialization stage. PFA was used to move the swarm to the next position. The best result was combined with the velocity of PSO to update and give the most optimum result. HPSO-PFA has fast convergence speed and offers the most prominent solution. Also, it can attain a good balance between diversification and intensification in the search location. The ORPD problem is a constraint optimization problem in which real power losses have been considered the objective function. The HPSO-PFA has been examined and tested on the standard IEEE 30 and 118 bus test system, and the result was compared with other algorithms that suggest the superiority of the HPSO-PFA algorithm. The real power loss of HPSO-PFA is 16.14262 MW, PFA is 17.4469 MW, mPFA is 17.4413 MW, and PSO is 16.1980 MW for IEEE 30 bus system. The reduction percentage for PFA, mPFA, PSO, and HPSO-PFA are 2.52%, 2.6%, 9.5%, and 9.8%, respectively. HPSO-PFA has a high percentage of loss reduction of 9.8%, IEEE 30 bus/node system. Also, for the IEEE 118 test system, the base case loss is 132.863 MW, HPSO-PFA, PSO, PFA, and mPFA reduce the losses to 107.2913 MW, 117.9129 MW, 120.1287 MW, and 115.0687 MW, respectively.

Furthermore, the percentage (%) reduction for the IEEE 118 test system are 19.25%, 11.25%, 9.59%, and 13.39% for HPSO-PFA, PSO, PFA, and mPFA, respectively. HPSO-PFA proved effective in large/extensive test systems in minimizing power loss. It can be seen from the simulation result that HPSO-PFA has an adequate high capacity in global search and adequate converge rate in reducing losses than others. Moreover, the comparison shows the superiority of the proposed HPSO-PFA over the other techniques. The future work is to test the proposed HPSO-PFA on the multi-objective function.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

S.A. Adegoke carried out the research under the supervision of Prof. Y. Sun, and the authors approved the final version.

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SAMSON A. ADEGOKE received his B.Tech degree in Electrical and Electronic Engineering from Ladoke Akintola University of Technology, Ogbomoso, Oyo State, Nigeria, in 2020. Currently, he is a master's student. His research interests are Power Systems and Optimization

YANXIA SUN received her joint qualification: DTech in Electrical Engineering, at Tshwane University of Technology, South Africa and PhD in Computer Science, University Paris-EST, France in 2012. Currently, she is serving as a Professor at the University of Johannesburg, South Africa. She has more than 10 years of teaching and research experience. She is an IEEE senior member. Her research interests include control systems, nonlinear dynamics, optimization and renewable energy.