BULLETIN OF THE POLISH ACADEMY OF SCIENCES
TECHNICAL SCIENCES, Vol. 69(4), 2021, Article number: e137733
DOI: 10.24425/bpasts.2021.137733

POWER SYSTEMS AND POWER ELECTRONICS

Research on hybrid modified pathfinder algorithm for optimal reactive power dispatch

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Abstract. Hybridization of meta-heuristic algorithms plays a major role in the optimization problem. In this paper, a new hybrid meta-heuristic algorithm called hybrid pathfinder algorithm (HPFA) is proposed to solve the optimal reactive power dispatch (ORPD) problem. The superiority of the Differential Evolution (DE) algorithm is the fast convergence speed, a mutation operator in the DE algorithm incorporates into the pathfinder algorithm (PFA). The main objective of this research is to minimize the real power losses and subject to equality and inequality constraints. The HPFA is used to find optimal control variables such as generator voltage magnitude, transformer tap settings and capacitor banks. The proposed HPFA is implemented through several simulation cases on the IEEE 118-bus system and IEEE 300-bus power system. Results show the superiority of the proposed algorithm with good quality of optimal solutions over existing optimization techniques, and hence confirm its potential to solve the ORPD problem.

Key words: optimal reactive power dispatch (ORPD); real power losses; pathfinder algorithm (PFA); modified pathfinder algorithm (mPFA); hybrid pathfinder algorithm (HPFA).

1. INTRODUCTION

The meta-heuristic algorithm based on swarm intelligence plays a vital role in the optimal reactive power dispatch in the complex power system planning and operation. Most of the modern engineering problems considered meta-heuristic algorithms for their fewer parameters and operators used. The ORPD problem is important in the operation of power system planning and operation of the power system. The reactive power generation changes on every load variation in the power system operation and tends to lead to variations in load voltage. By proper management of reactive power, the voltage profile will be maintained easily. ORPD main objective is the minimization of real power loss and satisfing power balance equations and different equality and inequality constraints. The minimization of real power loss is achieved through control variables which consist of generator voltage magnitude, transformer tap settings and shunt capacitors. Therefore, the proper handling of voltage profile results to minimize the real power losses in the transmission lines easily.

Several classical techniques [1] have been implemented for solving ORPD problem. The difficulties of the conventional optimization approaches (COA) arise when we incorporate system constraints, trapped in local minima. They suffer from complex objective functions and require high computational time. An additional problem is associated with these techniques and their lack of efficiency, local convergence and dealing with discrete control variables. These techniques also suffer from nonlinear functions and problems having multiple local minimum points.

Three classes of meta-heuristic algorithms are mainly classified: Evolutionary-based optimization methods [2], physical-based optimization methods [3] and swarm intelligence-based optimization methods [4]. Evolutionary based optimization algorithm begins with the initial population and evaluates the objective using several operators like crossover, mutation, and selection. Furthermore, these methods do not carry previous population information. Physical-based optimization methods are based on the physical rules in the universe. They explore the search space by physic rules. The third class is swarm-based optimization algorithms, based on the behavior of the swarm of animals in nature. These methods collect the information of intelligence of animals and save the information about optimization problem over the process.

Nature of the differences of algorithms, the optimization process in the meta-heuristic algorithms depends on two characteristics, exploration, and exploitation. In exploration, a sample of unknown regions find randomly searchability, too much exploration deploys with random search and no convergence. In exploitation we try to improve the best-so-far individuals, too much exploitation results in only local search and converge to the local optimum. So, the proper balance between exploration and exploitation plays a major role in meta-heuristic algorithms [5]. Pathfinder algorithm (PFA) is a new meta-heuristic algorithm that was created by Yapici and Cetinkaya (2019) [6]. This method is based on finding the best food or prey area depending on the collective movement of the animal group and mimics the leadership hierarchy of swarms. The searching behavior of the swarms to find the prey or food area depends on the leadership of an individual. The position of swarms is not orderly, all of them are randomly moved. PFA gives the best performance to some of the optimization problems. PFA mainly depends on mathematical formulas when the prob-

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Manuscript submitted 2021-04-26, revised 2021-05-28, initially accepted for publication 2021-06-03, published in August 2021

lem is increased, the potential of these algorithm decreases. To overcome these problems a hybridization is employed. The evolutionary-based optimization algorithm DE is incorporated with the swarm intelligence-based PFA algorithm. The differential evolution (DE), introduced by storn and price [7] gives better convergence, searching local optima and good robustness. The superiority of the Differential Evolution (DE) algorithm is the fast convergence speed, a mutation operator in DE algorithm incorporated into the pathfinder algorithm (PFA).

This paper proposes a new hybrid pathfinder algorithm to solve ORPD problems of power systems. The efficiency of the HPFA algorithm is tested on a medium scale, larger and large-scale test systems namely IEEE-118 and IEEE-300 bus are selected to demonstrate the performance. The simulations of the proposed methods are compared with other results of recently published algorithms such as Chaotic parallel vector evaluated interactive honey bee mating optimization PSO with an aging leader and challengers (ALC-PSO) [8], Modified imperialist competitive algorithm and invasive weed optimization (MICA-IWO) [9], Imperialist competitive algorithm (ICA) [10], Invasive weed optimization (IWO) [9], Quasi opposition teaching-learning based optimization (QOTLBO) [11], Double differential evolution (DDE) [10], Modified teaching-learning algorithm MTLA [10], Teaching-learning algorithm (TLA) [10], Binary real coded firefly algorithm (BRCFF) [10], Artificial bee colony (ABC) [10], Ant lion optimizer (ALO) [12], Chaotic bat algorithm-IV (CBA-IV) [13], Chaotic bat algorithm-III (CBA-III) [13], Bat algorithm (BA) [13], Specialized genetic algorithm (SGA) [14].

The rest of the paper is structured as follows: ORPD problem is mathematically formulated in Section 2. In Section 3, the PFA is described briefly. HPFA algorithm is briefly explained in Section 4. Section 5 of the paper is reserved to give the simulation results along with comparison with recently developed meta-heuristic algorithms. The conclusion is made in Section 6.

2. MATHEMATICAL FORMULATION

In general view, the mathematical formulation of ORPD issue is described in two classes: the real power minimization and second class is constraints. The real power loss minimization is subjected to equality and inequality constraints in transmission lines while it should satisfy it. Mathematically ORPD problem can be formulated as follows:

$$\begin{aligned} f &= \min P_{\text{loss}} = f_{\text{obj}}(x,u) \\ &= \sum_{\substack{k \in N_l \\ k \in (i,j)}} g_k \left(V_i^2 + V_j^2 - 2V_iV_j \cos\theta_{ij}\right). \end{aligned} \tag{1}$$

Subject to:

$$g(x,u) = 0, \tag{2}$$

$$h(x,u) \le 0, \tag{3}$$

$$u^{\min} \le u \le u^{\max}, \tag{4}$$

$$x^{\min} \le x \le x^{\max}. \tag{5}$$

In the above equation, $f(x,u)$ describes the objective function, $\min P_{\text{loss}}$ is the objective function of real power losses in transmission network to be minimized, N_l is overall transmission networks, g_k is the branch k conductance, V_i and V_j are the i-th and j-th bus voltage respectively, θ_{ij} is the difference of i-th and j-th bus voltage phase, $g(x,u)$ referred to as equality constraints which consist of the power balance equation, $h(x,u)$ refers as inequality constraints, x refers to dependent variables consisting of

1. Load bus voltage magnitude V_L.
2. Reactive power output-based generator Q_g.
3. Apparent line loading S_l.

Mathematically the dependent vector can be examined as follows:

$$x^T = [V_{L1} \ldots V_{LNQ},\ Q_{g1} \ldots Q_{gNg},\ S_{l1} \ldots S_{lNl}]. \tag{6}$$

u is the control variable vector described as follows:

1. Generator bus voltage restriction V_g.
2. Transformer tap ratio t.
3. Compensation of reactive power (Capacitor banks) Q_c.

$$u^T = [V_{g1} \ldots V_{gNg},\ t_1 \ldots t_{NT},\ Q_{c1} \ldots Q_{cNc}], \tag{7}$$

where N_{PQ} is the total PQ buses, N_l is the number of transmission lines, N_g is the total generator buses, N_T is the total transformer in the system and N_c is the total bank of the capacitor.

2.1. Objective constraints

2.1.1. Equality constraints

The equality constraints are real and reactive power balance and they can be illustrated as follows:

$$P_{gi,\text{slack}} - P_{di} - V_i \sum_{j=1}^{N_B} V_j \left(G_{ij}\cos\theta_{ij} + B_{ij}\sin\theta_{ij}\right) = 0, \quad i = 1,2,\ldots,N_B - 1, \tag{8}$$

$$Q_{gi} - Q_{di} + Q_{ci} - V_i \sum_{j=1}^{N_B} V_j \left(G_{ij}\sin\theta_{ij} - B_{ij}\cos\theta_{ij}\right) = 0, \quad i = 1,2,\ldots,N_{PQ}, \tag{9}$$

where $P_{gi,\text{slack}}$ and Q_{gi} are the generation of real and reactive power at i-th bus, P_{di} and Q_{di} is the demand of real power and reactive power at i-th bus, Q_{ci} is the capacitor of reactive power, G_{ij} and B_{ij} are real and reactive part of admittance matrix at i-th and j-th bus, N_B is the total buses, $N_B - 1$ is the excluding slack bus, respectively.

2.1.2. Inequality constraints

The inequality constraints include:

Constraints related to Generator consist of their minimum and maximum limits as:

1. Real power generation at slack bus

$$P_{gi,\text{slack}}^{\min} \le P_{gi,\text{slack}} \le P_{gi,\text{slack}}^{\max}, \quad i \in N_g. \tag{10}$$

2. Restrictions on generator voltage

$$V_{gi}^{\min} \le V_{gi} \le V_{gi}^{\max}, \quad i \in N_g. \tag{11}$$

3. Reactive power outputs

$$Q_{gi}^{\min} \le Q_{gi} \le Q_{gi}^{\max}, \quad i \in N_g, \tag{12}$$

where $P_{gi,\text{slack}}^{\min}$ and $P_{gi,\text{slack}}^{\max}$ define min and max of real power generator at slack bus, $V_{gi}^{\min}$ and $V_{gi}^{\max}$ define minimum and maximum generator voltage, $Q_{gi}^{\min}$ and $Q_{gi}^{\max}$ define min and max of reactive power generator.

Transformer tap ratio are restricted by their minimum and maximum limits as:

$$t_k^{\min} \leq t_k \leq t_k^{\max}, \quad k \in N_T, \tag{13}$$

where $t_k^{\min}$ and $t_k^{\max}$ define minimum and maximum of transformer tap setting at branch k.

Shunt VAR reactive power source (capacitor banks) are restricted by their minimum and maximum limits as:

$$Q_{ci}^{\min} \leq Q_{ci} \leq Q_{ci}^{\max}, \quad i \in N_c, \tag{14}$$

where $Q_{ci}^{\min}$ and $Q_{ci}^{\max}$ define minimum and maximum of i-th capacitor bank.

Line flow limits: includes the load bus voltage and the transmission line loading are restricted by their minimum and maximum limits as:

$$V_{li}^{\min} \leq V_{li} \leq V_{li}^{\max}, \quad i \in N_l, \tag{15}$$

$$S_l \leq S_l^{\max}, \qquad l \in N_l, \tag{16}$$

where $V_{li}^{\min}$ and $V_{li}^{\max}$ define minimum and maximum load bus voltage of i-th unit, S_l defines apparent line flow of i-th unit, $S_l^{\max}$ defines maximum apparent line flow of i-th unit.

In the proposed work, dependent variables constraints are incorporated to the objective function to avoid an unfeasible solution. The control variables are self-constrained, but the dependent variables are violated. By using the penalty function method these problems will be controlled and feasible solution obtained. Therefore the modified objective function is changed to the following form:

$$f' = f + \mu_{g1}\left(P_{g1} - P_{g1}^{\lim}\right)^2 + \mu_v \times \sum_{i=1}^{N_{PQ}} \Delta V_i + \mu_q \times \sum_{i=1}^{N_g} \Delta Q_i + \mu_s \times \sum_{i=1}^{N_l} \Delta S_i, \tag{17}$$

where μ_{g1}, μ_v, μ_q and μ_s are the penalty terms with the slack real power generation, load bus voltage, reactive power generation and the apparent line flow limit violations, $x^{\min} \leq x \leq x^{\max}$ are the minimum and maximum value of the dependent variables.

$$\Delta V_i = \begin{cases} \left(V_i^{\min} - V_i\right)^2 & \text{if } V_i < V_i^{\min}, \\ (V_i - V_i^{\max})^2 & \text{if } V_i > V_i^{\max}, \\ 0 & \text{if } V_i^{\min} \leq V_i \leq V_i^{\max}; \end{cases} \tag{18}$$

$$\Delta Q_i = \begin{cases} \left(Q_i^{\min} - Q_i\right)^2 & \text{if } Q_i < Q_i^{\min}, \\ (Q_i - Q_i^{\max})^2 & \text{if } Q_i > Q_i^{\max}, \\ 0 & \text{if } Q_i^{\min} \leq Q_i \leq Q_i^{\max}; \end{cases} \tag{19}$$

$$\Delta S_i = \begin{cases} (S_i - S_i^{\max})^2 & \text{if } S_i > S_i^{\max}, \\ 0 & \text{if } S_i^{\min} \leq S_i \leq S_i^{\max}. \end{cases} \tag{20}$$

3. PATHFINDER ALGORITHM

The pathfinder algorithm (PFA) is a Swarm intelligence (SI)-based optimization algorithm inspired by the behaviour of swarms with a leader. This technique permits all individuals from swarms to choose randomly to investigate the search space, while the member chooses to move towards any area by following the leader. In numerical, the behaviour of the leader and the member is completely different from each other. Note that we called the leader of a swarm a pathfinder. The pathfinder stores the best solution on each iteration. The PFA have three positions:

1. Initialization position.
2. Pathfinder's position.
3. Follower's position.

Initialization position

In this initialization process, some positions are selected randomly in the search space. In equation (21) there is generated a randomly positioned vector. This individual vector find the best solution and it is chosen as the pathfinder:

$$X_{i,j}^G = X_j^{\min} + rand[0,1]\left(X_j^{\max} - X_j^{\min}\right), \qquad i \in [1, N_p], \quad i \in [1, D], \tag{21}$$

where N_p is the number of swarms and D is the total control variables. $X_j^{\min}$ and $X_j^{\max}$ minimum and maximum value of each control variable j.

Pathfinder's position

By using equation (22) the location of the pathfinder is a move to the next level. The best solution is taken by comparing the two position vectors i.e., a new position of pathfinder and the past one:

$$X_p^{G+1} = X_p^G + 2r_3\left(X_p^G - X_p^{G-1}\right) + A, \tag{22}$$

where X_p is the pathfinder position vector, G is the current iteration and r_3 is the random vector within the range $[0,1]$. A is the variation coefficient is calculated as follows:

$$A = U_2 e^{-\frac{2G}{G_{\max}}}. \tag{23}$$

U_2 is a random vector range in $[-1,1]$, $G_{\max}$ is the maximum number of iteration

Follower's position

By using equation (24) the position of the follower is updated. The pathfinder is replaced with the follower in case that the follower finds the best fitness solution. The follower's position is calculated as follows:

$$X_i^{G+1} = X_i^G + R_1\left(X_j^G - X_i^G\right) + R_2\left(X_p^G - X_i^G\right) + \varepsilon, \tag{24}$$

$$i \in [2, N_p], \quad R_1 = \alpha r_1, \quad R_2 = \beta r_2,$$

$$\varepsilon = \left(1 - \frac{G}{G_{\max}}\right) U_1 D_{ij}, \qquad D_{ij} = \left\| x_i - x_j \right\|, \tag{25}$$

where X_i is the position vector of i-th follower, X_j is the position vector of member j-th follower, U_1 is a random vector range in $[-1,1]$, D_{ij} is the position between two follower members: In this direction, r_1, and r_2 are random values range in $[0,1]$, ε is the vibration coefficient. Likewise, α and β are selected randomly in the range of $[1,2]$ in each iteration.

4. MODIFIED PATHFINDER ALGORITHM

In this detailed study, the pathfinder algorithm has both its advantages and disadvantages. The main advantage of PFA is that all members are randomly moved. When the dimensions of the problem increase PFA performance is decreased because it mainly depends on mathematical formulas. They restricted the exploration and exploitation process of the ORPD problem by two randomly generated values ε and A. When ε and A are close to zero the swarm movement of the next position with small steps; ε and A are greater than one the swarm gets large steps. To develop the new solutions, the position vectors are moved in the search space with small steps. Therefore, some modifications are needed to get the best feasible solution by adjusting two values ε and A. In this aspect, different experimental analyses have been taken into account, the five most powerful modifications.

$$\text{Proposed mPFA modification}: \begin{cases} \varepsilon = 0.1\varepsilon \\ A = 0.001A; \end{cases} \tag{26}$$

$$\text{First modification}: \begin{cases} \varepsilon, \\ A = 0.1A; \end{cases} \tag{27}$$

$$\text{Second modification}: \begin{cases} \varepsilon = 0.1\varepsilon, \\ A = 0.1A; \end{cases} \tag{28}$$

$$\text{Third modification}: \begin{cases} \varepsilon = 0.001\varepsilon, \\ A = 0.1A; \end{cases} \tag{29}$$

$$\text{Fourth modification}: \begin{cases} \varepsilon = 0.001\varepsilon, \\ A = 0.001A. \end{cases} \tag{30}$$

5. HYBRID PATHFINDER ALGORITHM

Many of the researchers have been focused on the hybridization of meta-heuristic algorithms with local optima solution. In this proposed work a new meta-heuristic algorithm called hybrid pathfinder algorithm (HPFA) is introduced. The evolutionary-based optimization algorithm based differential evolution (DE) algorithm is the most powerful. The superiority of the Differential Evolution (DE) algorithm is the fast convergence speed, a mutation operator in the DE algorithm incorporates into the pathfinder algorithm (PFA) to produce the optimal change between exploration and exploitation, escape from local optima and get the better convergence rate.

Implementation of HPFA for ORPD

The implementation of HPFA for ORPD problem based on the series operation of optimization which gives equal possibilities to all the members of swarms in the evolution of each generation. The main operation in the DE algorithm is the mutation operator (F). The superiority of the Differential Evolution (DE) algorithm is the fast convergence speed, a mutation operator in DE algorithm incorporated into the pathfinder algorithm (PFA) to form a new meta-heuristic algorithm called hybrid pathfinder algorithm (HPFA). A mutation operator is added after the follower's position. The following steps are used to incorporate mutation phase after follower's phase and the rest part of the PFA are the same. For each follower X_i in the swarm, do the following steps:

Step 1: From the follower's phase pick three different followers, X_r, X_p and X_q which is not equal to X_i.

Step 2: The new position vector is carried out for each D in the total control variables depending on CR. CR in the range of $[0,1]$. From equation (31) the new position vector is selected by transformation one dimension of X_i.

$$Y_{ij} = X_{rj} + F\left(X_{pj} - X_{qj}\right), \tag{31}$$

where i, r, p and q are random modification integers that are not equal. F is the mutation vector range in $[0,2]$. j is selected randomly index between $[1,D]$.

Step 3: Determine the best objective solution of the new position vector.

Step 4: In the selection process, a new position vector gives a better objective solution than the old one. Replace the old vector with the new position vector. Otherwise, the old is the best objective solution value. Figure 1 shows the implementation of HPFA.

6. NUMERICAL RESULTS AND DISCUSSIONS

To verify the performance and efficiency of the proposed HPFA algorithm, a MATLAB platform is used for the ORPD problem [20–23]. The simulation results are conducted on a personal computer "2.30 GHz of Turbo Boost up system, Core i5-2410M Processor with the range of 2.90 GHz – 4 GB RAM". For power flow examination the MATPOWER 6.0 software (Zimmerman et al. 2005) is used [15]. The proposed HPFA is implemented through several simulation cases on IEEE 118-bus power system and large-scale power system IEEE 300-bus power system. For each optimization methods, 50 individual trials were solved to get the optimal solutions. For minimization parameter settings for the proposed HPFA algorithm, the mPFA values as chosen, mutation factor (F) is 0.7, population size is 40 and number of generations is 300.

Test system 1: Results of IEEE 118-bus system

Firstly IEEE 118-bus system is tested to show the effectiveness of the proposed HPFA algorithm. The system has 186 branches which fifty-four 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 at buses, nine transformer tap settings 5–8, 25–26, 17–30, 37–38, 59–63, 61–64, 65–66, 68–69, 80–81 buses and fourteen capacitors are placed at buses 5, 34, 37, 44, 45, 46, 48, 74, 79, 82, 83, 105, 107, 110. The boundary condition for control variables like

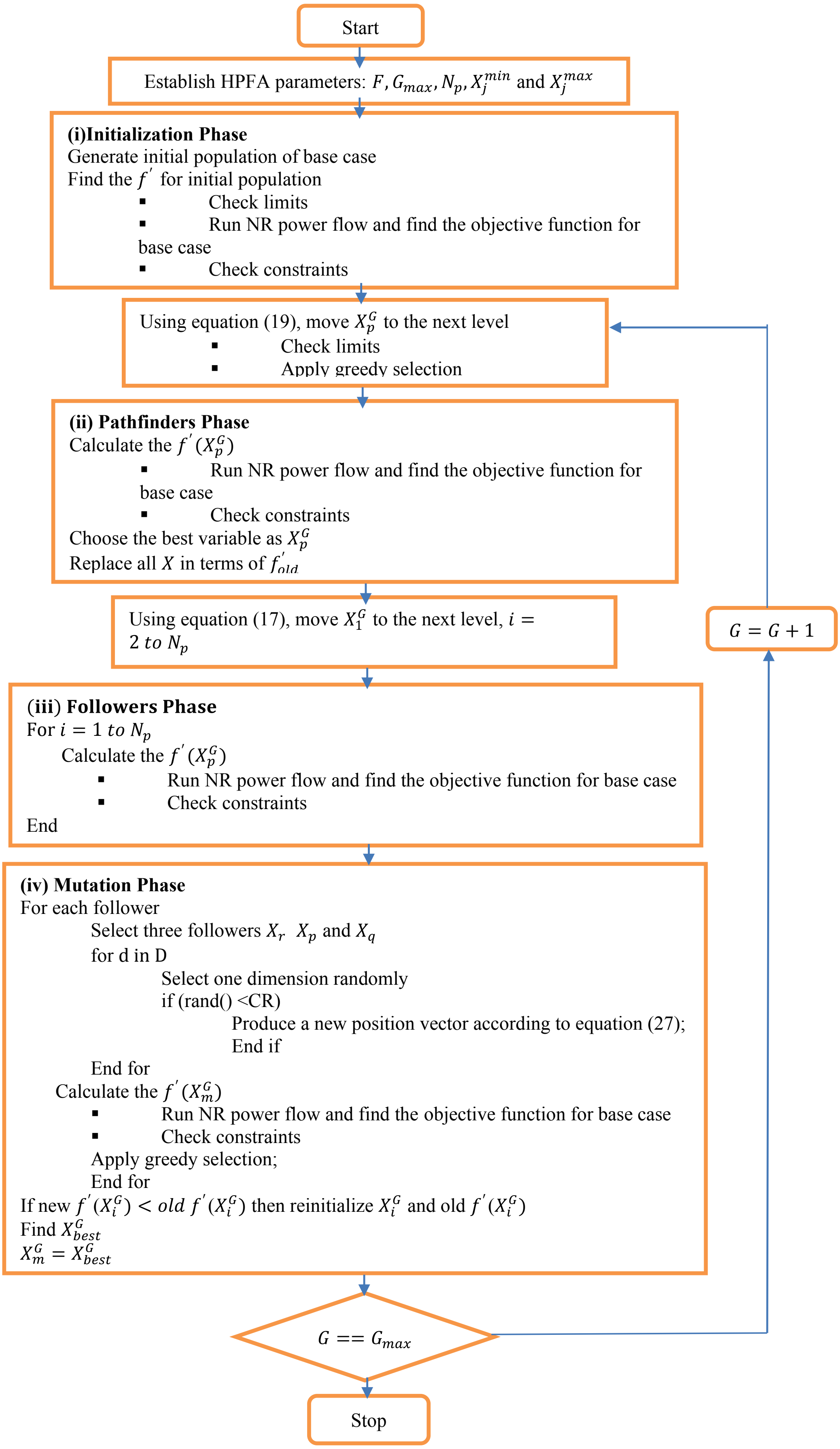

Fig. 1. HPFA flow chart

the generator voltage magnitude is 0.95–1.1, transformer taps is 0.95–1.1 and shunt capacitor limits is 0–0.18. Line data and bus data are taken from [11].

The system loads are given as follows:

$$P_{\text{load}} = 4242.0\ \text{MW}, \quad Q_{\text{load}} = 1438.0\ \text{MVAr},$$
$$\sum P_G = 4374.9\ \text{MW}, \quad \sum Q_G = 795.7\ \text{MVAr},$$
$$P_{\text{loss}} = 132.863\ \text{MW}.$$

Table 1 summarizes the minimum real power losses (minimum), median real power losses (median), maximum real power losses (worst), standard deviation (std), real power losses saving percentage ($\%P_{\text{Save}}$) and the average CPU times (s) to execute the results. From Table 1, it is seen that the percentage of power saving for HPFA algorithm is 18.6455% compared to base case value. To show the effectiveness of the proposed algorithms 50 individual trials were taken to get the best optimal solution. The minimum real power loss is obtained by the HPFA algorithm is 108.090 MW. It can be seen that the optimal solution of real power loss is less when compared to mPFA and other existing algorithms. The results confirm that the real power loss reduced to 3.8754% less than QOTLBO [11], 5.4505% less than MTLA-DDE [13], 5.5047% less than MICA-IWO [9], 5.6724% less than MTLA [10], 7.3811% less than TLA [10], 7.7613% less than DDE [10], 7.8555% less than BRCFF [10], 9.1611% less than ABC [10], 10.8143% less than ALO [12] and 12.4341% less than ALC-PSO [8].

It may be observed that all the control variables are within their limits. The performance characteristics of real power loss by HPFA, mPFA, mPFA1, mPFA 2, mPFA 3, mPFA 4 and PFA is illustrated in Figs. 2 and 3. From Fig. 2, the optimal solution is achieved and these solutions show substantial improvements, which will be more accurate with the large scale problem. The optimum real power loss obtained within less executed time is found to be a more promising one. Figure 3 illustrates the statistical details of the IEEE 118-bus system. It shows the best, mean and worst optimal value of all proposed algorithms.

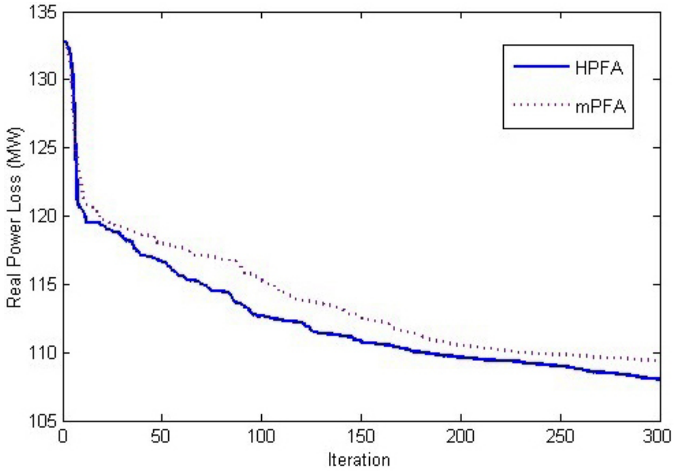

Fig. 2. Real power loss analysis for IEEE-118 bus system using HPFA, and mPFA

Table 1

The test power system of IEEE 118 bus based statistical details

Methods	Best Solution, MW	Median Solution, MW	Worst Solution, MW	Standard deviation	$\%P_{\text{Save}}$	Average CPU time, s
HPFA	108.090	109.2265	111.0862	0.5974	18.6455	39.120
mPFA	109.400	110.6587	112.4245	0.6373	17.6595	39.318
mPFA1	109.484	113.7257	119.4001	2.2180	17.5963	39.289
mPFA2	109.550	111.9117	114.7864	1.5193	17.5466	39.403
mPFA3	111.211	112.6254	114.0518	0.6522	16.2965	39.412
mPFA4	109.695	111.5693	113.0648	0.7930	17.4375	39.300
PFA	109.848	115.1558	121.6239	3.447	17.3223	39.255
QOTLBO [11]	112.2789	113.7693	115.4516	0.0244	NR	NR
MTLA-DDE [10]	113.9814	114.0852	114.4975	2.8755*10-4	14.53	792.49
MICA-IWO [9]	114.04	114.44	114.97	2.4288*10-4	14.48	835.32
MTLA [10]	114.2213	115.8446	116.2458	2.458*10-3	14.35	821.54
TLA [10]	116.0682	119.9652	123.4688	1.956*10-2	12.96	844.86
DDE [10]	116.4792	120.4789	133.2587	5.752*10-2	12.66	838.32
BRCFF [10]	116.581	117.20	119.90	2.135*10-3	12.58	787.47
ABC [10]	117.9922	118.47	119.684	2.2807*10-3	11.52	815.26
ALO [12]	119.7792	NR	NR	NR	9.847	716.7
ALC-PSO [8]	121.53	123.14	132.99	91*10-6	8.245	1045.10

NR means Not Reported

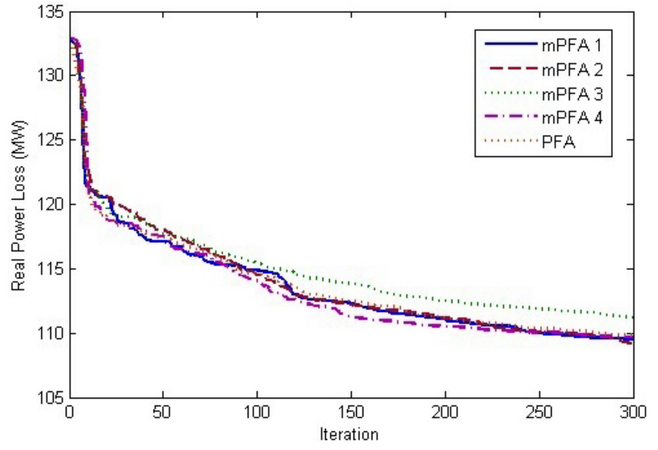

Fig. 3. Real power loss analysis for IEEE-118 bus system using mPFA 1, 2, 3, 4, and PFA

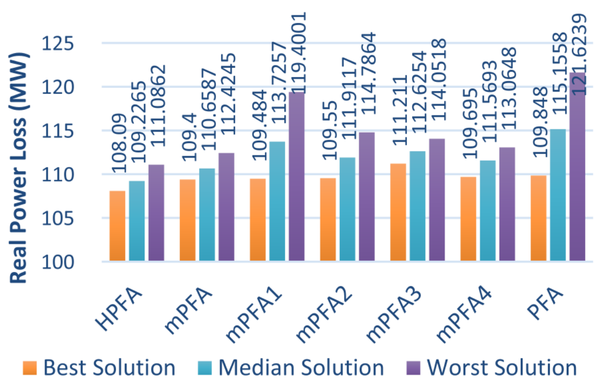

Fig. 4. Statistical results of IEEE 118-bus system

Test System 2: Results of IEEE-300 bus system

Large scale power system is taken to shows the effectiveness of the proposed HPFA algorithm. The large-scale IEEE 300-bus system consists of 411 transmission lines; 69 generator buses, 107 transformer tap-setting, 8 capacitor banks and 6 reactors are used. The minimum and maximum limits for control variables like magnitude voltage of the generator is 0.95–1.1, transformer taps are 0.95–1.1, capacitor limits are 0–3.25 and reactors is 0 to –0.3. Line data and bus data are taken from [13].

The system loads are given as follows:

$$P_{\text{load}} = 4242.0\ \text{MW}, \quad Q_{\text{load}} = 1438.0\ \text{MVAr},$$

$$\sum P_G = 4374.9\ \text{MW}, \quad \sum Q_G = 795.7\ \text{MVAr},$$

$$P_{\text{loss}} = 408.316\ \text{MW}.$$

To get the best optimal solution 50 individual trials were taken to show the potential of the HPFA algorithm and other proposed methods. The proposed HPFA approach can yield the minimum real power losses as 353.750 MW, which is the globally optimal solution when compared to mPFA and other existing algorithms. The results confirm that the real power loss reduced to 1.1307% less than SGA [14], 5.6304% less than CBA-IV [13], 7.3997% less than CBA-III [13], 8.7381% less than BA [13].

Table 2 shows the minimum real power losses (minimum), median real power losses (median), maximum real power losses (worst), standard deviation (std), real power losses saving percentage ($\%P_{\text{Save}}$) and the average CPU times (s) to execute the results for IEEE 300-bus large scale power system. From Table 2 it is seen that the percentage of power saving for HPFA algorithm is 13.3637% compared to the base case value.

The performance characteristics of real power loss by HPFA, mPFA, mPFA1, mPFA 3 illustrates in Fig. 5. From Fig. 5, the optimal solution is achieved and these solutions show substan-

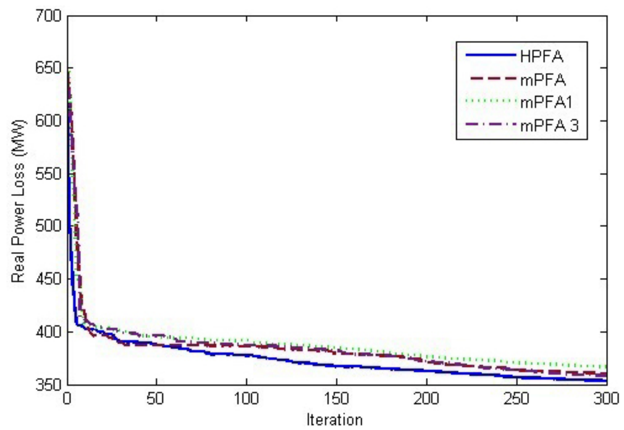

Fig. 5. Real power loss analysis for IEEE-300 bus system using HPFA, mPFA, mPFA 1 and 3

Table 2
The test power system of IEEE 300 bus based statistical details

Methods	Best Solution, MW	Median Solution, MW	Worst Solution, MW	Standard deviation	$\%P_{\text{Save}}$	Average CPU time, s
HPFA	353.750	354.949	356.3145	0.6134	13.3637	75.9561
mPFA	355.491	356.7497	358.5155	0.6356	12.9373	76.0354
mPFA 1	356.665	360.9067	366.5811	2.1189	12.6498	76.1568
mPFA 3	358.849	360.2634	361.8735	0.6635	12.1149	77.1083
SGA [14]	357.10	371.7911	405.4689	8.4040	NR	77.4805
CBA-IV [13]	373.6675	375.5762	380.065	1.6047	NR	NR
CBA-III [13]	379.9265	385.5483	392.973	2.1774	NR	NR
BA [13]	384.6609	387.7787	419.145	5.0014	NR	NR

NR means Not Reported

tial improvements, which will be more accurate with the large scale problem. The optimum real power loss is obtained within less executed time is found to be more promising one. Figure 6 illustrates the statistical details of the IEEE 300-bus system. It shows the best, mean and worst optimal value of all proposed algorithms.

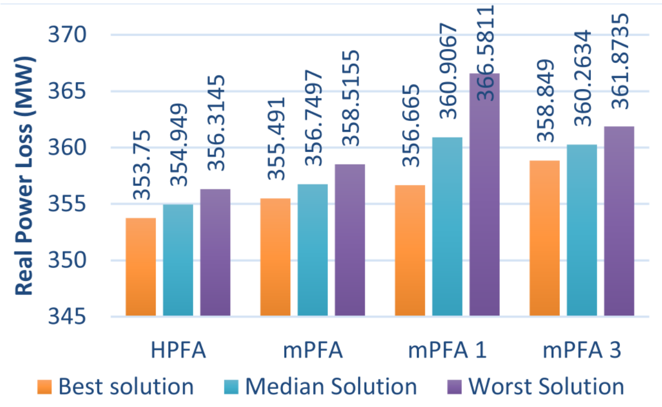

Fig. 6. Statistical results of IEEE 300-bus system

7. CONCLUSIONS

In this work, ORPD based HPFA, mPFA and PFA are proposed to reduce real power loss in large scale test systems. The proposed HPFA helps to manipulate the large scale test systems with less computation time. This demonstrates that the large scale systems are progressively accurate through powerful execution and capacity. The simulations are carried out on the IEEE 118-bus and IEEE 300-bus test systems. The investigations of the outcomes can produce the minimum power loss compared to existing methods. The optimal solution is achieved and these solutions show substantial improvements, which will be more accurate with the large scale problem. It is seen that the percentage of power-saving for HPFA algorithm is very high compared to the base case value. The obtained results show the potential of HPFA method to find the near-optimum solution compared to other meta-heuristic algorithms. For future research, convergence, as well as better quality solutions, will be encourage as the most promising ones.

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