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Comparative Analysis of Nature Inspired Algorithms Applied to Reactive Power Planning Studies

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Abstract

Reactive power optimization is one of the efficient ways of improving power system reliability and efficiency which is beneficial in power planning studies. ORPD problems are best solved using different algorithms to achieve optimization. This paper deals a comparative study of three algorithms PSO, GSA and hybrid PSOGSA algorithm. The ORPD multi-objective problem is tested over standard IEEE system. The test is performed under two conditions with and without penalty function added to the objective function. And all results obtained are summarized and best optimal solution is obtained from the hybrid PSOGSA algorithm.

Keywords: ORPD (Optimal Reactive Power Dispatch) Problem, GSA (Gravitational Search algorithm), PSO (Particle swarm Optimization), Hybrid PSOGSA

1. Introduction

Reactive power optimization plays a vital role in maintaining a healthy power system. Power demands are to be met without affecting the reliability and security of the system.

The ORPD problem satisfies the reactive power needs of any system to achieve optimal results[1].

The ORPD problem minimizes the multi-objective function comprising of real power loss, voltage deviation and penalty. The problem consists of control variables such as generator voltages, position of the tap changing transformers, shunt reactors in the system. It converges by satisfying all equality and inequality constraints.

Minimising the real power losses of the system obtains good reactive power optimization results[2]. Minimizing the voltage deviation improves the voltage profile of the system[3]. Penalty is added to the system whenever there is a violation in the thermal limits of lines, reactive power limits of generators, voltage limits of load bus and real power limits of slack bus. Penalty check ensures the purity of results obtained. And also it stands as a proof for the reliability and security of the system[4].

Power system optimization has evolved with developments in computing and optimization algorithms. Soft Computing Techniques (Artificial Neural Networks[5], Genetic Algorithms and Fuzzy Logic Models) provide better performance than conventional methods to solve

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the ORPD problem. Heuristic algorithms are more efficient than classical algorithms for solving the ORPD problem. Among those algorithms Particle Swarm algorithm[6], and Gravitational Search Algorithm (GSA)[2] are the most recent ones.

This paper focuses in hybridization of both the algorithms to obtain best results[7,8]. Goodness of the algorithms is used for hybrid PSOGSA. The results of all three algorithms are obtained and analysed.

These algorithms are tested on standard IEEE30-bus system for effective application using MATLAB simulations. Results obtained from hybrid PSOGSA show better performance than the parent algorithms.

2. Formaulation of the ORPD Problem

Two ORPD problems are formulated and tested using all three algorithms. The first problem deals a system without penalty and the second problem includes penalty. Both the cases have different augmented objective function. But the equality constraints, inequality constraints and control variables remains the same.

2.1 Objective Function

The objective function of this problem is to find the optimal settings for reactive power control variables which minimize the function.

1) Without penalty[1]:

The objective function is expressed as in equation (1a):

$$f = (w * P_l) + (1-w)*VD \qquad (1a)$$

P_l is the real power loss of the system,

VD is the load bus voltage deviations,

W is the weighting factor and is set to 0.7.

2) With penalty[4,9,10]:

The objective function 1b describes the fitness value of the system with quadratic penalties. And k_1, k_2, k_3, k_4 are chosen to be 10 (from trial and error method)

$$f = (w * P_l) + (1-w) * VD + k_1 \sum_{i=1}^{nl} L_i^2 + k_2 \sum_{i=1}^{npq} V_i^2 + k_3 \sum_{i=1}^{npv} Q_i^2 + k_4 P_{sl}^2 \qquad (1b) \qquad (1b)$$

Where,

w is the weighing factor and is set to 0.7,

P_l is the real power losses,

VD is the voltage deviation of the load buses,

L_i is the sum of thermal limit violation of all lines,

V_i is the sum of voltage limit violation of all load buses,

Q_i is the sum of reactive power limit violation of all generating buses,

P_{sl} is the slack bus real power limit violation,

nl is the total number of branches (lines),

npq is the total number of load buses,

npv is the total number of generator buses.

$$L_i = \begin{cases} L_i - L_i^{max}, & if\ L_i > L_i^{max}; \\ L_i^{min} - L_i, & if L_i < L_i^{min}; \\ & else\ 0; \end{cases}$$

$$V_i = \begin{cases} V_i - V_i^{max}, & if\ V_i > V_i^{max}; \\ V_i^{min} - V_i, & if\ V_i < V_i^{min}; \\ & else\ 0; \end{cases}$$

$$Q_i = \begin{cases} Q_i - Q_i^{max}, & if\ Q_i > Q_i^{max}; \\ Q_i^{min} - Q_i, & if\ Q_i < Q_i^{min}; \\ & else\ 0; \end{cases}$$

$$P_{sl} = \begin{cases} P_{sl} - P_{sl}^{max}, & if\ P_{sl} > P_{sl}^{max}; \\ P_{sl}^{min} - P_{sl}, & if\ P_{sl} < P_{sl}^{min}; \\ & else\ 0; \end{cases}$$

i) Real power loss minimization (P_l)

The total real power of the system is given in equation (2)

$$P_l = \sum_{k=1}^{N_l} G_k \left(V_i^2 + V_j^2 - 2V_iV_j \cos(\delta_i - \delta_j) \right) \qquad \mathbf{(2)}$$

Where, N_l is the total number of transmission lines in the system; G_k is the conductance of the line k ; V_i and V_j are the magnitudes of the sending end and receiving end voltages of the line; δi and δj are angles of the end voltages.

ii) Load bus Voltage Deviation minimization (VD)

Bus voltage magnitude is maintained within the allowable limit to ensure quality service. As shown in equation (3) voltage profile is improved by minimizing the deviation of the load bus voltage from the reference value (it is taken as 1.0 p.u.).

$$VD = \sum_{k=1}^{N_{pq}} |(V_k - V_{ref})| \quad (3)$$

2.2 Constraints

The minimization problem is subjected to the equality and inequality constraints as follows.

Equality constraints:

Load Flow Constraints:

The real and reactive power constraints are according to equation (4) and (5) respectively as given below:

$$P_{Gi} - P_{Di} - \sum_{j=1}^{N_B} V_i V_{ij} Y_{ij} \cos(\delta_{ij} + \gamma_j - \gamma_i) = 0 \quad (4)$$

$$Q_{Gi} - Q_{Di} - \sum_{j=1}^{N_B} V_i V_{ij} Y_{ij} \sin(\delta_{ij} + \gamma_j - \gamma_i) = 0 \quad (5)$$

Inequality Constraints:

Generator bus voltage ($V_{Gi}\ V_{Gi}$) inequality constraint:

$$V_{Gi}^{min} \le V_{Gi} \le V_{Gi}^{max}, i\varepsilon ng$$

Load bus voltage ($V_{Li}\ V_{Li}$) inequality constraint:

$$V_{Li}^{min} \le V_{Li} \le V_{Li}^{max}, i\varepsilon nl$$

Switchable reactive power compensation ($Q_{Ci}\ Q_{Ci}$) inequality constraint:

$$Q_{Ci}^{min} \le Q_{Ci} \le Q_{Ci}^{max}, i\varepsilon nc$$

Reactive power generation ($Q_{Gi}\ Q_{Gi}$) inequality constraint:

$$Q_{Gi}^{min} \le Q_{Gi} \le Q_{Gi}^{max}, i\varepsilon ng$$

Transformer tap setting ($T_i\ T_i$) inequality constraint:

$$T_i^{min} \le T_i \le T_i^{max}, i\varepsilon nt$$

Where nc, ng, and nt are the numbers of the switchable reactive power sources, generators and transformers.

3. Algorithm Description

3.1 Particle Swarm Optimization (PSO)

PSO algorithm has been used for several optimization problems and stands good for ORPD problems. The features of the method are as follows:

a) It is based on researches conducted on swarms.

b) It is a simple process.

c) It is used for nonlinear optimization problems with continuous variables.

PSO algorithm is from the following conceptual things that birds find food flocking together. Therefore it is assumed that all information is shared within them. This is the basic concept of PSO. PSO is developed through simulation of a flock of birds in two-dimension.

The updated velocity of each agent is obtained from the velocity and distance from pbest and gbest values from:

$$v_i^{k+1} = w_i v_i^k + c_1 rand \times (pbest_i - s_i^k) + c_2 rand \times (gbest_i - s_i^k) \quad (6)$$

Where, v_i^k is the velocity of agent i at k^{th} iteration, v_i^{k+1} modified velocity of agent, rand is a random number between 0 and 1, s_i^k is the current position of agent at iteration, *pbest*$_i$ is the *pbest* of agent, *gbest* is the *gbest* of the group, w_i is the weight function for velocity of agent, c_i is the weight coefficients for each term.

And the current position can be calculated from the following equation,

$$s_i^{k+1} = s_i^k + v_i^{k+1} \quad (7)$$

Particle swarm optimisation is extremely simple and effective for wide range of functions[6]. Conceptually, it lies between genetic algorithms and evolutionary programming algorithm. The updating of *pbest* and *gbest* by the PSO is similar to the crossover operation of the genetic algorithms.

The following flow chart in Figure 1 describes the PSO algorithm,

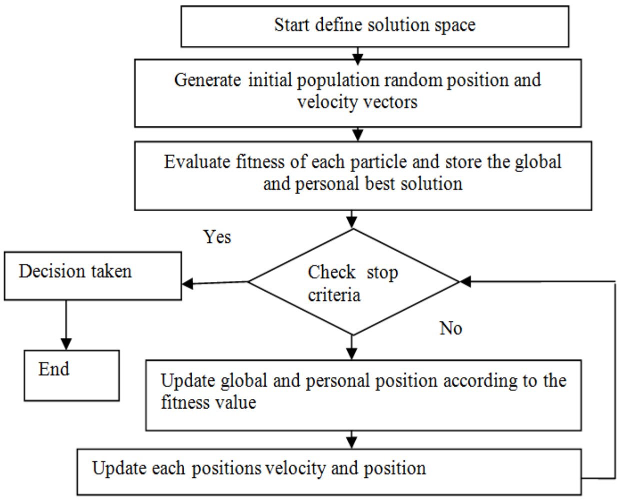

Figure 1. PSO algorithm flow chart.

3.2 Gravitational Search Algorithm (GSA)

Gravitational Search Algorithm is the most recent population based search algorithm. It is based on the Newtonian laws of gravity and interaction of masses. The algorithm considers agents to be objects consisting of different masses[1,2]. The entire agents move due to the gravitational attraction force acting between them and the progress of the algorithm directs the movements of all agents globally towards the agents with the heavier masses. Each agent in GSA is denoted by four parameters[11]: Position of the mass in d_{th} dimension, inertia mass, active gravitational mass and passive gravitational mass. The way Newton's gravitational force behaves is called "action at a distance". This indicates that gravity acts between separated particles without any intermediary and without any delay.

The GSA is considered to be an isolated system consisting of masses. It assumes a small artificial world of masses that obeys the Newton's laws[11]. Most commonly, masses obey the following laws:

Law of gravity and Law of motion

The algorithm can be summarized as[11–14].

Step 1: Initialization of the agents:

The position of N number of agents is randomly selected and initialized within the limits.

$$\mathbf{X_i = \left(x_i^1 \dots x_i^d \dots x_i^n\right) \quad for\ i = 1, 2, 3 \dots N} \tag{6}$$

Where, X^d_i represents the position of i^{th} agent in the d^{th} dimension.

Step 2: Evaluation of the fitness value for each agent:

Compute best and worst values for each agent at each iteration to get fitness value.

$$best(t) = (_j \in \{1, \dots m\}^{min} fit_j(t) \tag{7}$$

$$worst(t) = (_j = \{1, \dots m\}^{max} fit_j(t) \tag{8}$$

Equation (10) and (11) is for minimisation problem. Where fit_j *(t) is* the fitness of the j^{th} agent at time t.

Step 3: Calculation of gravitational constant:

The gravitational constant G at time *t* is

$$G(t) = G_0 e^{\frac{\alpha t}{T}} \tag{9}$$

Where, G_0 is set to 1, α to 20 and T is the total number of iterations.

Step 4: Calculation of the mass of the agents:

The gravitational and inertial masses are,

$$M_{ai} = M_{pi} = M_{ii} = M_i, \qquad i = 1,2 \dots N$$

$$m_i(t) = \frac{fit_i(t) - worst(t)}{best(t) - worst(t)} \tag{10}$$

$$M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{N} m_j(t)} \tag{11}$$

Where, M_{ai} is the active gravitational mass of i^{th} agent, M_{pi} is the passive gravitational mass of the i^{th} agent, M_{ii} is the inertia mass of the i_{th} agent.

Step 5: Calculating the total force and acceralation:

The total force acting on the i^{th} agent $(F_i^d(t))$ is,

$$F_i^d(t) = \sum_{j \in k_{best}, j \neq 1}^{N} rand_j F_{ij}^d(t) \tag{12}$$

Where, k_{best} is k agents with best fitness and becomes 2% of the initial population. F_{ij}^d (t) is the force on 'ith' agent,

$$F_{ij}^d(t) = G(t)\frac{M_i(t) \times M_j(t)}{R_{ij}(t) + \varepsilon}\left(x_j^d(t) - x_i^d(t)\right) \tag{13}$$

Where, F_{ij}^d (t) is the force on agent 'i' from agent 'j' at d^{th} dimension and t^{th} iteration, R_{ij} (t) is the Euclidian distance between agents 'i' and 'j' at iteration t, G(t) is the calculated gravitational constant for the same iteration, ε is a constant with small value.

Acceralation of the i^{th} agent is,

$$a_i^d(t) = \frac{F_i^d(t)}{M_{ii}(t)} \tag{14}$$

Step 6: Updating the velocity and position:

The velocity and position for next (t+1) iteration is given by,

$$V_i^d(t+1) = rand_i \times V_i^d(t) + a_i^d(t) \tag{15}$$

$$X_i^d(t+1) = X_i^d(t) + V_i^d(t+1) \tag{16}$$

Step 7: Repeat the steps 2-6 till the stopping condition is reached. The best fitness value is the global fitness of the problem and the position of the corresponding agent at the same iteration is the global solution of the agent.

The following flow chart in Figure 2 describes the GSA algorithm,

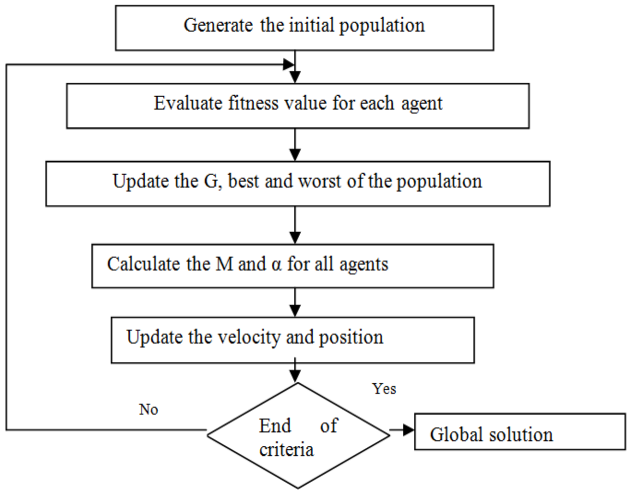

Figure 2. GSA algorithm flow chart.

3.3 Hybrid PSOGSA

Hybridization of different algorithms aims to combine different properties and improve the solution quality. Among the well-known algorithms, PSO and GSA algorithms are the two new algorithms that are used in many fields by researchers and these algorithms are proven to be very powerful optimization tools. Each algorithm has different strong features. PSO generally avoids the solution from trapping into local minima by using its diversity and it's very simple. GSA provides stable convergence characteristics.

The hybridization is a low-level binding because we combine both the algorithm's functions. It also is co-evolutionary because we do not use both algorithm's one after other. Indeed they run in parallel. It is heterogeneous as there are two different algorithms that are involved to produce single final results[15].

The main objective of the hybrid algorithm is to combine the social thinking ability of PSO with the local search capability of GSA. Hence we have arrived at a new formula for the hybrid PSOGSA and velocity updation is obtained as,

$$v_i(t+1) = w \times v_i(t) + c_1' \times rand \times ac_i(t) + c_2' \times rand \times \left(gbest - X_i(t)\right) \quad (21)$$

Where $v_i(t)$ is the velocity of agent *i* at iteration *t*, c_j' is the weighting factor, *w* is the weighting function, rand is a random number between 0 and 1, $ac_i(t)$ is the acceleration of agent i at iteration *t*, and *gbest* is the best solution so far. Position updation is done by,

$$X_i(t+1) = X_i(t) + V_i(t+1) \quad (22)$$

The agents are initialized randomly and each agent is considered as a candidate solution. Then gravitational Mass, gravitational constant, force on each agent are calculated step by step. Next the acceleration of the particle is calculated and best solution so far is updated for all iteration. Velocities of all agents are calculated and best positions are identified. When iteration reaches the stopping criteria the velocity and position updation is stopped. Thus the globally best solution is obtained.

The following flow chart in Figure 3 describes the algorithm,

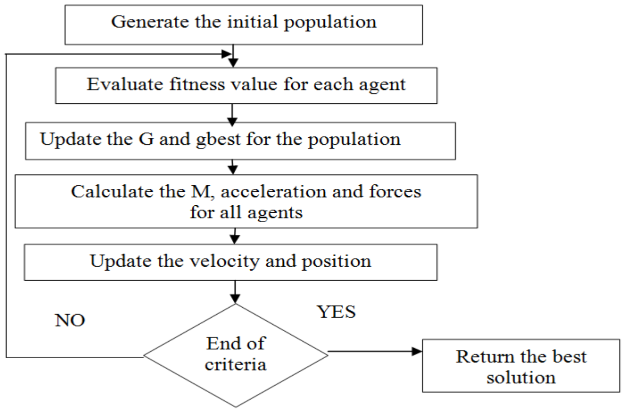

Figure 3. Hybrid PSOGSA algorithm flow chart.

4. Simulation Results

All the three algorithms are tested on a standard IEEE 30 bus system[16] using MATLAB. AC Newton-Raphson load flow is run by using MATPOWER simulation software package. MATPOWER[15] is open-source Matlab power system simulation software. It is used mostly in research and education for AC and DC power flow and Optimal Power Flow (OPF) simulations. Matpower is designed to give the best performance possible while keeping the code simple to understand and modify[17]. And the results are proposed. The system has 6 generating buses 1, 2, 5, 8, 11 and 13. The transformer tap settings were made at 4 lines and shunt capacitors are added at 9 buses.

The limits for the generator voltages are (0.9-1.1) p.u, tap settings are (0.9-1.1) p.u and shunt capacitors are (0-10) MVARs.

The test is performed with 50 agents and maximum number of iterations is set to 500. The initial value settings are listed below in Table 1.

Case 1:

The values obtained for the first objective function without penalty are tabulated below and hybrid PSOGSA shows the best optimal solution. Hence, in this case it is proved from Table 2 that the values obtained from hybrid PSOGSA have best results when compared to GSA and PSO.

Table 1. Initial parameter settings

S.NO	Control variables	Initial value
1.	V_{G1}	1.05
2.	V_{G2}	1.04
3.	V_{G5}	1.01
4.	V_{G8}	1.01
5.	V_{G11}	1.05
6.	V_{G13}	1.05
7.	T_{6-9}	1.078
8.	T_{6-10}	1.069
9.	T_{4-12}	1.032
10.	T_{27-28}	1.068
11.	Q_{10}	0
12.	Q_{12}	0
13.	Q_{15}	0
14.	Q_{17}	0
15.	Q_{20}	0
16.	Q_{21}	0
17.	Q_{23}	0
18.	Q_{24}	0
19.	Q_{29}	0

Table 2. Comparative results for case without penalty

S.No	Control Variables	PSO	GSA	Hybrid PSOGSA
1.	V_{G1}	1.1	1.0570	1.0999
2.	V_{G2}	1.0910	1.0472	1.0913
3.	V_{G5}	1.0677	1.0221	1.0702
4.	V_{G8}	1.0711	1.0251	1.0710
5.	V_{G11}	1.0066	1.0094	0.9857
6.	V_{G13}	1.0179	1.0206	0.9911
7.	T_{6-9}	0.9357	1.0108	1.0796
8.	T_{6-10}	1.0793	0.9918	1.1
9.	T_{4-12}	1.0218	1.0029	1.0982
10.	T_{27-28}	1.0027	0.9987	1.0072
11.	Q_{10}	2.2556	5.0833	6.5196
12.	Q_{12}	5.7689	4.8118	6.4311
13.	Q_{15}	9.5019	5.0365	6.5253
14.	Q_{17}	5.6934	5.2110	6.2971
15.	Q_{20}	3.5625	5.4531	6.5411
16.	Q_{21}	5.8536	5.7189	6.5429
17.	Q_{23}	10	6.2464	6.3899
18.	Q_{24}	5.9098	4.7719	6.5348
19.	Q_{29}	3.1201	6.1475	6.4935
20.	Fitness	3.6903	3.6451	3.3786
21.	Power loss	4.9826	5.2073	4.8260
22.	VD	0.67504	4.48e-07	0.0014
23.	Time	8.39	490	335

The below graph in Figure 4 shows the convergence of the fitness values with respect to number of iterations. The hybrid PSOGSA has the best convergence criteria.

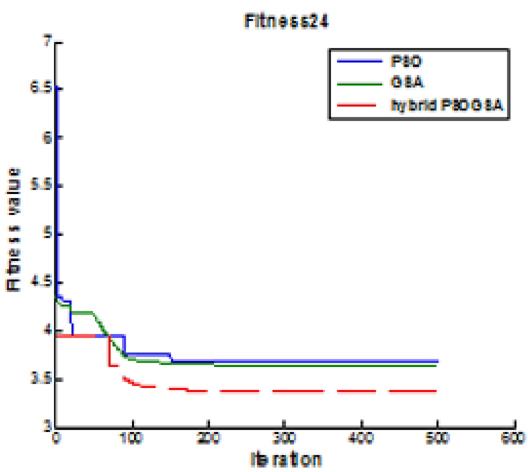

Figure 4. Fitness value convergence characteristics.

The real power loss for the given case is shown in the below graph Figure 5. It also proves that the hybrid PSOGSA algorithm converges at lower real power loss providing reactive power optimization.

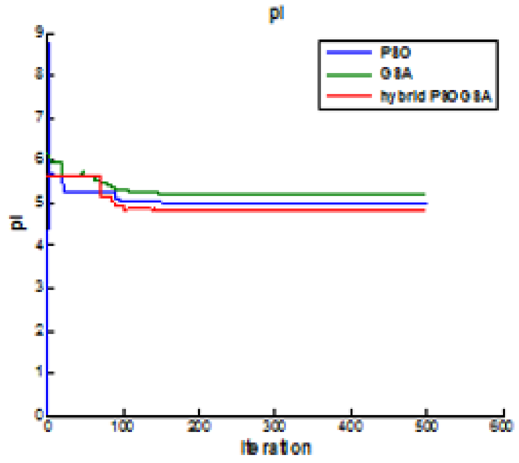

Figure 5. Real power loss characteristics.

The voltage deviation seems to be reduced for the hybrid algorithm and provides a good voltage profile in all load buses.

Figure 6 shows the voltage deviation characteristics of all three algorithms.

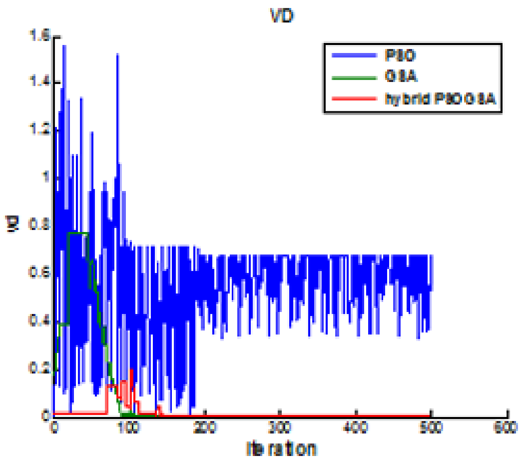

Figure 6. Voltage deviation characteristics.

Case 2:

For the second case objective function with penalties considered the following Table 3 shows the same results proving that the hybrid algorithm is the best. Since it converges with minimum values of fitness value, power loss and voltage deviations. Zero penalty of the algorithm proves its reliability.

The following graph in Figure 7 is the fitness value convergence characteristics. Here the PSO algorithm has higher value of reactive power penalty and the other algorithms have less penalty or zero penalty.

Table 3. Comparative results for case with penalty

S. No	Control Variables	PSO	GSA	Hybrid PSOGSA
1.	V_{G1}	0.9286	1.0177	1.0999
2.	V_{G2}	0.9321	1.0106	1.0916
3.	V_{G5}	0.9655	0.9869	1.0701
4.	V_{G8}	0.9690	0.9967	1.0726
5.	V_{G11}	0.9942	1.0483	1.0337
6.	V_{G13}	1.0062	1.0434	1.0117
7.	T_{6-9}	1.0562	0.9874	1.1000
8.	T_{6-10}	0.9812	0.9824	1.0349
9.	T_{4-12}	1.0900	0.9925	1.0717
10.	T_{27-28}	0.972	0.9931	1.0086
11.	Q_{10}	1.0976	5.0724	3.8737
12.	Q_{12}	5.5107	4.7563	3.7027
13.	Q_{15}	9.2722	4.9747	2.5672
14.	Q_{17}	5.0225	5.1915	2.8844
15.	Q_{20}	3.6781	5.3688	3.5074
16.	Q_{21}	5.7617	5.6149	3.1194
17.	Q_{23}	9.6333	6.0501	3.4105
18.	Q_{24}	5.0896	4.7980	3.1937
19.	Q_{29}	2.3161	6.0772	3.6930
20.	Fitness	$9.5657e^{+03}$	3.9980	3.3798
21.	Power loss	8.2076	5.6565	4.8274
22.	VD	1.6613	0.1176	0.0022
23.	Time	6.6773	235.977	244.0864
24.	Penalty line	0	0	0
25.	Penalty volt	0.0275	$3.1446e^{-04}$	0
26.	Penalty reactive	955.9159	0	0
27.	Penalty slack	0	0	0

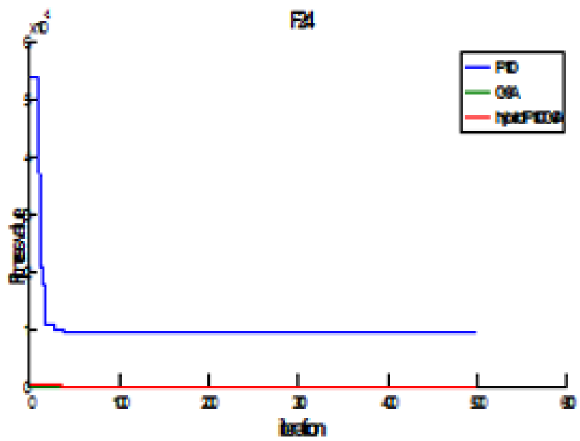

Figure 7. Fitness value convergence.

The power loss curves for the case is shown in Figure 8 and hybrid algorithm shows the best optimal results.

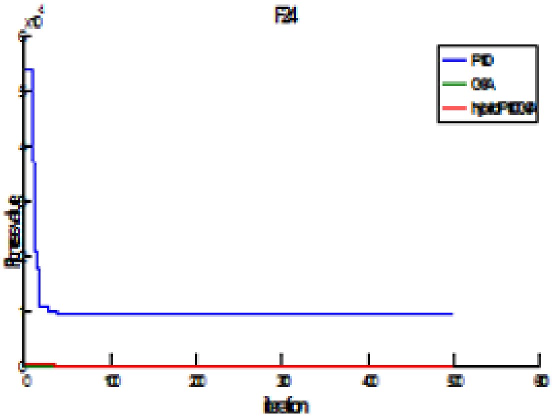

Figure 8. Power loss curves.

The voltage deviations for the case are also low for hybrid algorithm as shown in Figure 9.

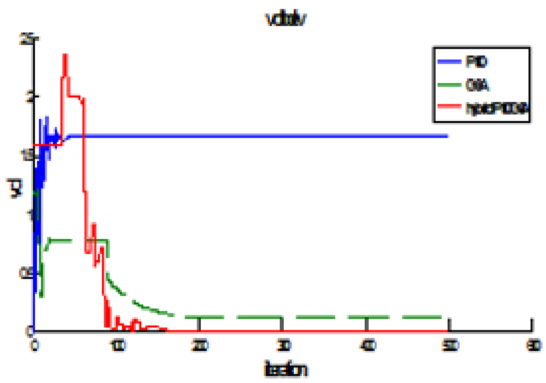

Figure 9. Voltage deviation characteristics.

The hybrid algorithm is the best for both the cases of the ORPD problems.

5. Conclusion

1. Hybrid PSOGSA algorithm has the best results than PSO and GSA algorithms. It also converges at a faster rate.
2. Globally best optimal values are obtained from the hybrid algorithm.
3. Real power losses are minimized to the maximum.
4. Voltage profile of the system is well maintained.
5. All the above results are proved using zero penalty values.

Hence, ORPD problem is best solved using Hybrid PSOGSA and reactive power optimization is achieved. Future works may include the implementation of the algorithm for several other test systems and problems.

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