Diminution of Real Power Loss by Hybridization of Particle Swarm Optimization with Extremal Optimization

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Abstract

This paper presents an algorithm for solving the multi-objective reactive power dispatch problem in a power system. Modal analysis of the system is used for static voltage stability assessment. Loss minimization and maximization of voltage stability margin are taken as the objectives. Generator terminal voltages, reactive power generation of the capacitor banks and tap changing transformer setting are taken as the optimization variables. Particle swarm optimization (PSO) has received increasing interest from the optimization community due to its simplicity in implementation and its inexpensive computational overhead. However, PSO has premature convergence, especially in complex multimodal functions. Extremal Optimization (EO) is a recently developed local-search heuristic method and has been successfully applied to a wide variety of hard optimization problems. To overcome the limitation of PSO, this paper proposes a novel hybrid algorithm, called hybrid PSO-EO algorithm, through introducing EO to PSO. The hybrid approach elegantly combines the exploration ability of PSO with the exploitation ability of EO. The proposed approach is shown to have superior performance and great capability of preventing pre- mature convergence across it comparing favourably with the other algorithms. We demonstrated that our proposed HPSOEO (hybrid particle swarm optimization – Extremal optimization) presents a better performance when compared to the other algorithms. In order to evaluate the proposed algorithm, it has been tested on IEEE 30 bus system and compared to other algorithms reported those before in literature. Results show that HPSOEO is more efficient than others for solution of single-objective Optimal Reactive Power Dispatch problem.

Keywords: Modal analysis, optimal reactive power, Transmission loss, particle swarm, Particle swarm optimization, Extremal optimization, Numerical optimization, Metaheuristic.

1. Introduction

Optimal reactive power dispatch (ORPD) problem is one of the difficult optimization problems in power systems. The sources of the reactive power are the generators, synchronous condensers, capacitors, static compensators and tap changing transformers. The problem that has to be solved in a reactive power optimization is to determine the required reactive generation at various locations so as to optimize the objective function. Here the reactive power dispatch problem involves best utilization of the existing generator bus voltage magnitudes, transformer tap setting and the output of reactive power sources so as to minimize the loss and to enhance the voltage stability of the system. It involves a non linear optimization problem. Various mathematical techniques have been adopted to solve this optimal reactive power dispatch problem. These include the gradient method (O.Alsac et al.1973; Lee K Yet al.1985), Newton method (A.Monticelli et al.1987) and linear programming (Deeb Net al.1990; E. Hobson1980; K.Y Lee et al.1985; M.K. Mangoli 1993) .The gradient and Newton methods suffer from the difficulty in handling inequality constraints. To apply linear programming, the input-output function is to be expressed as a set of linear functions which may lead to loss of accuracy. Recently Global Optimization techniques such as genetic algorithms have been proposed to solve the reactive power flow problem (S.R.Paranjothi et al 2002;D. Devaraj et al 2005). In recent years, the problem of voltage stability and voltage collapse has become a major concern in power system planning and operation. To enhance the voltage stability, voltage magnitudes alone will not be a reliable indicator of how far an operating point is from the collapse point (C.A. Canizareset al.1996). The reactive power support and voltage problems are intrinsically related. Hence, this paper formulates the reactive power dispatch as a multi-objective optimization problem with loss minimization and maximization of static voltage stability margin (SVSM) as the objectives. Voltage stability evaluation using modal analysis is used as the indicator of voltage stability. Particle Swarm

Optimization (PSO) algorithm is a recent addition to the list of global search methods. This derivative-free method is particularly suited to continuous variable problems and has received increasing attention in the optimization community. PSO is originally developed by Kennedy and Eberhart et al 1993 and inspired by the paradigm of birds flocking. PSO consists of a swarm of particles and each particle flies through the multi-dimensional search space with a velocity, which is constantly updated by the particle's previous best performance and by the previous best performance of the particle's neighbours. EO is based on the Bak-Sneppen (BS) model (Bak et al 1993) which shows the emergence of self-organized criticality (SOC) in ecosystems. The evolution in this model is driven by a process where the weakest species in the population, together with its nearest neighbours, is always forced to mutate. Large fluctuations ensure, which enable the search to effectively scaling barriers to explore local optima in distant neighbourhoods of the configuration space (Boettcher et al 2006). This co-evolution activity leads to chain reactions called avalanches which are one of the keys especially relevant for optimizing highly disordered systems. To avoid premature convergence of PSO, an idea of combining PSO with EO is addressed in this paper (Min-Rong Chen et al 2006). Such a hybrid approach expects to enjoy the merits of PSO with those of EO. In other words, PSO contributes to the hybrid approach in a way to ensure that the search converges faster, while the EO makes the search to jump out of local optima due to its strong local-search ability. In this work, we develop a novel hybrid optimization method, called hybrid PSO-EO algorithm, to solve the optimal power dispatch problem. The proposed approach is shown to have better performance and strong capability of escaping from local optima. Hence, the hybrid PSO-EO algorithm may be a good alternative to deal with complex numerical optimization problems.The performance of HPSOEO has been evaluated in standard IEEE 30 bus test system and the results analysis shows that our proposed approach outperforms all approaches investigated in this paper.

2. Voltage Stability Evaluation

2.1 Modal analysis for voltage stability evaluation

Modal analysis is one of the methods for voltage stability enhancement in power systems. In this method, voltage stability analysis is done by computing Eigen values and right and left Eigen vectors of a jacobian matrix. It identifies the critical areas of voltage stability and provides information about the best actions to be taken for the improvement of system stability enhancements. The linearized steady state system power flow equations are given by.

$$\begin{bmatrix}\Delta P\\ \Delta Q\end{bmatrix} = \begin{bmatrix} J_{p\theta} & J_{pv} \\ J_{q\theta} & J_{QV} \end{bmatrix} \quad (1)$$

Where

ΔP = Incremental change in bus real power.

ΔQ = Incremental change in bus reactive

Power injection

$\Delta\theta$ = incremental change in bus voltage angle.

ΔV = Incremental change in bus voltage

Magnitude

$J_{p\theta}$, J_{PV} , $J_{Q\theta}$, J_{QV} jacobian matrix are the sub-matrixes of the System voltage stability is affected by both P and Q. However at each operating point we keep P constant and evaluate voltage stability by considering incremental relationship between Q and V.

To reduce (1), let $\Delta P = 0$, then.

$$\Delta Q = [J_{QV} - J_{Q\theta} J_{P\theta^{-1}} J_{PV}]\Delta V = J_R \Delta V \quad (2)$$

$$\Delta V = J^{-1} - \Delta Q \quad (3)$$

Where

$$J_R = (J_{QV} - J_{Q\theta} J_{P\theta^{-1}} JPV) \quad (4)$$

J_R is called the reduced Jacobian matrix of the system.

2.2 Modes of Voltage instability:

Voltage Stability characteristics of the system can be identified by computing the eigen values and eigen vectors

Let

$J_R = \xi \wedge \eta$ (5)

Where,

ξ = right eigenvector matrix of J_R

η = left eigenvector matrix of J_R

$\wedge$ = diagonal eigenvalue matrix of J_R and

$J_{R^{-1}} = \xi \wedge^{-1} \eta$ (6)

From (3) and (6), we have

$\Delta V = \xi \wedge^{-1} \eta \Delta Q$ (7)

or

$\Delta V = \sum_I \frac{\xi_i \eta_i}{\lambda_i} \Delta Q$ (8)

Where ξ_i is the ith column right eigenvector and η the ith row left eigenvector of J_R.

λ_i is the ith eigen value of J_R.

The ith modal reactive power variation is,

$\Delta Q_{mi} = K_i \xi_i$ (9)

where,

$K_i = \sum_j \xi_{ij^2} - 1$ (10)

Where

ξ_{ji} is the jth element of ξ_i

The corresponding ith modal voltage variation is

$\Delta V_{mi} = [1/\lambda_i] \Delta Q_{mi}$ (11)

It is seen that, when the reactive power variation is along the direction of ξ_i the corresponding voltage variation is also along the same direction and magnitude is amplified by a factor which is equal to the magnitude of the inverse of the ith eigenvalue. In this sense, the magnitude of each eigenvalue λ_i determines the weakness of the corresponding modal voltage. The smaller the magnitude of λ_i, the weaker will be the corresponding modal voltage. If $| \lambda_i | = 0$ the ith modal voltage will collapse because any change in that modal reactive power will cause infinite modal voltage variation.

In (8), let $\Delta Q = e_k$ where e_k has all its elements zero except the kth one being 1. Then,

$$\Delta V = \sum_i \frac{\eta_{1k}\ \xi_1}{\lambda_1} \quad (12)$$

η_{1k} k th element of η_1

V –Q sensitivity at bus k

$$\frac{\partial V_K}{\partial Q_K} = \sum_i \frac{\eta_{1k}\ \xi_1}{\lambda_1} = \sum_i \frac{P_{ki}}{\lambda_1} \quad (13)$$

3.Problem Formulation

The objectives of the reactive power dispatch problem considered here is to minimize the system real power loss and maximize the static voltage stability margins (SVSM).

3.1 Minimization of Real Power Loss

It is aimed in this objective that minimizing of the real power loss (Ploss) in transmission lines of a power system. This is mathematically stated as follows.

$$P_{loss} = \sum^{n}_{\substack{k=1 \\ k=(i,j)}} g_{k(V_i^2 + V_j^2 - 2V_i V_j \cos\theta_{ij})} \quad (14)$$

Where n is the number of transmission lines, g_k is the conductance of branch k, V_i and V_j are voltage magnitude at bus i and bus j, and θij is the voltage angle difference between bus i and bus j.

3.2 Minimization of Voltage Deviation

It is aimed in this objective that minimizing of the Deviations in voltage magnitudes (VD) at load buses. This is mathematically stated as follows.

Minimize $\mathrm{VD} = \sum_{k=1}^{nl} |V_k - 1.0|$ (15)

Where nl is the number of load busses and V_k is the voltage magnitude at bus k.

3.3 System Constraints

In the minimization process of objective functions, some problem constraints which one is equality and others are inequality had to be met. Objective functions are subjected to these constraints shown below.

Load flow equality constraints:

$$P_{Gi} - P_{Di} - V_{i\sum_{j=1}^{nb} V_j} \begin{bmatrix} G_{ij} & \cos\theta_{ij} \\ +B_{ij} & \sin\theta_{ij} \end{bmatrix} = 0, i = 1,2 \ldots., nb \quad (16)$$

$$Q_{Gi} - Q_{Di} V_{i\sum_{j=1}^{nb} V_j} \begin{bmatrix} G_{ij} & \cos\theta_{ij} \\ +B_{ij} & \sin\theta_{ij} \end{bmatrix} = 0, i = 1,2 \ldots., nb \quad (17)$$

where, *nb* is the number of buses, P_G and Q_G are the real and reactive power of the generator, P_D and Q_D are the real and reactive load of the generator, and G_{ij} and B_{ij} are the mutual conductance and susceptance between bus *i* and bus *j*.

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

$$V_{Gi}^{min} \leq V_{Gi} \leq V_{Gi}^{max}, i \in ng \quad (18)$$

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

$$V_{Li}^{min} \leq V_{Li} \leq V_{Li}^{max}, i \in nl \quad (19)$$

Switchable reactive power compensations (Q_{Ci}) inequality constraint:

$$Q_{Ci}^{min} \leq Q_{Ci} \leq Q_{Ci}^{max}, i \in nc \quad (20)$$

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

$$Q_{Gi}^{min} \leq Q_{Gi} \leq Q_{Gi}^{max}, i \in ng \quad (21)$$

Transformers tap setting (T_i) inequality constraint:

$$T_i^{min} \leq T_i \leq T_i^{max}, i \in nt \quad (22)$$

Transmission line flow (S_{Li}) inequality constraint:

$$S_{Li}^{min} \leq S_{Li}^{max}, i \in nl \quad (23)$$

Where, nc, ng and nt are numbers of the switchable reactive power sources, generators and transformers. During the simulation process, all constraints satisfied as explained below .

4.Particle Swarm Optimization (PSO)

PSO is a population based optimization tool, where the system is initialized with a population of random particles and the algorithm searches for optima by updating generations. Suppose that the search space is *D*-dimensional. The position of the *i*-th particle can be represented by a *D*-dimensional vector $X_i = (x_{i1}, x_{i2}, .., x_{iD})$ and the velocity of this particle is $V_i = (v_{i1}, v_{i2}, .., v_{iD})$.The best previously visited position of the *i*-th particle is represented by $P_i = (p_{i1}, p_{i2}, .., p_{iD})$ and the global best position of the swarm found so far is denoted by $P_g = (p_{g1}, p_{g2}, .., p_{gD})$. The fitness of each particle can be evaluated through putting its position into a designated objective function. The particle's velocity and its new position are updated as follows:

$$v_{id}^{t+1} = \omega^t v_{id}^t + c_1 r_1^t (p_{id}^t - x_{id}^t) + c_2 r_2^t (p_{gd}^t - x_{id}^t) \quad (24)$$

$$x_{id}^{t+1} = x_{id}^t + v_{id}^{t+1} \quad (25)$$

Where $d \in \{1,2,..,D\}, i \in \{1,2,..,N\}$ N is the population size, the superscript t denotes the iteration number, ω is the inertia weight, r_1 and r_2 are two random values in the range [0,1], c_1 and c_2 are the cognitive and social scaling parameters which are positive constants.

5.Extremal Optimization (EO)

EO is inspired by recent progress in understanding far-from-equilibrium phenomena in terms of self-organized criticality, a concept introduced to describe emergent complexity in physical systems. EO successively updates extremely undesirable variables of a single sub-optimal solution, assigning them new, and random values. Moreover, any change in the fitness value of a variable engenders a change in the fitness values of its neighbouring variable. Large fluctuations emerge dynamically, efficiently exploring many local optima (S. Boettcher et al 2001). Thus, EO has strong local-search ability. Procedure of EO algorithm.

1. Randomly generate algorithm$X = (x_1, x_2, ., x_D)$. Set the optimal solution $X_{best} = X$ and the minimum cost function $C(X_{best}) = C(X)$.
2. For the current solution X ,
   a. Evaluate the fitness λ_i for each variable x_i, $i \in \{1,2, .. D\}$,
   b. Rank all the fitness and find the variablex_j, with lowest fitness i.e.$\lambda_j \leq \lambda_i$for all i.
   c. Choose one solution X' in the neighbourhood X, such that j-th variable must change its state.
   d. Accept $X=X'$ unconditionally
   e. If $C(X) < C(X_{best})$ then set $X_{best} = X$ and $C(X_{best}) = C(X)$.
3. Repeat set 2 as long as desired
4. Return X_{best} and$C(X_{best})$.

Note that in the EO algorithm, each variable in the current solution *X* is considered “species”. In this study, we adopt the term “component” to represent “species” which is usually used in biology. For example, if $X = (x_1, x_2, x_3)$, then x_1, x_2 and x_3 are called “components” of *X*. From the EO algorithm, it can be seen that unlike genetic algorithms which work with a population of candidate solutions, EO evolves a single sub-optimal solution *X* and makes local modification to the worst component of *X*. A fitness value j is required for each variable *xi* in the problem, in each iteration variables are ranked according to the value of their fitness. This differs from holistic approaches such as evolutionary algorithms that assign equal-fitness to all components of a solution based on their collective evaluation against an objective function.

6.Hybrid PSO-EO Algorithm

Note that PSO has great global-search ability, while EO has strong local-search capability. In this work, we propose a novel hybrid PSO-EO algorithm which combines the merits of PSO and EO. This hybrid approach makes full use of the exploration ability of PSO and the exploitation ability of EO. Consequently, through introducing EO to PSO, the proposed approach may overcome the limitation of PSO and have capability of escaping from local optima. However, if EO is introduced to PSO each iteration, the computational cost will increase sharply. And at the same time, the fast convergence ability of PSO may be weakened. In order to perfectly integrate PSO with EO, EO is introduced to PSO at *INV* -iteration intervals (here we use a parameter *INV* to represent the frequency of introducing EO to PSO). For instance, *INV* = 10 means that EO is introduced to PSO every 10 iterations. Therefore, the hybrid PSO-EO approach is able to keep fast convergence in most of the time under the help of PSO, and capable of escaping from a local optimum with the aid of EO. The value of parameter *INV* is predefined by the user. Usually, according to our experimental experience, the value of *INV* can be set to 50~100. As a consequence, PSO will play a key role in this case. When the test function is multimodal with many local optima, the value of *INV* can be set to 1~50 and thus EO can help PSO to jump out of local optima. In the main procedure of PSO-EO algorithm, the fitness of each particle is evaluated through putting its position into the objective function. However, in the EO procedure, in order to find out the worst component, each component of a solution should be assigned a fitness value. We defined the fitness of each component of a solution for an unconstrained minimization problem as follows. For the *i*-th particle, the fitness $\lambda_{ik}$of the *k*-th component is defined as the mutation cost, i.e. $OBJ(X_{ik})$ - $OBJ(P_g)$, where X_{ik} is the new position of the *i*-th particle obtained by performing mutation only on the *k*-th component and leaving all other components fixed, $OBJ(X_{ik})$ is the objective value of X_{ik}, and $OBJ(P_g)$ is the objective value of the best position in the swarm found so far.

EO algorithm for the RPO problem

1. Set the index of the current particle i =1.
2. for the position $X_i = (x_{i1}, x_{i2}, .., x_{iD})$ of the i-th particle
   a. perform mutation on each component ofX_i
   One by one, while keeping other components fixed. Then D new positions $x_{ik}(k = 1, .., D)$ can be obtained;
   b. evaluate the fitness $\lambda_{ik} =$ $OBJ(X_{ik})$ - $OBJ(P_g)$ of each component X_{ik} , $k \in \{1, .., D\}$.

c. compare all the components according to their fitness values and find out the worst adapted component x_{iw} ,and then x_{iw} is the new position corresponding to x_{iw} ,$w \in \{1, .., D\}$.
d. if OBJ(x_{iw})< OBJ(x_i) then set X_i=X_{iw} , and OBJ(x_i) = OBJ(x_{iw})continue the next step. Otherwise, X_i keeps unchanged and go to Step 3;
e.update p_i and p_g
3. If i equals to the population size N , return the results; otherwise, set i = i +1 and go to Step 2.

Algorithm of PSO-EO for solving reactive power dispatch problem.

1. Initialize a swarm of particles with random positions and velocities N on D dimensions.
Set iteration = 0 .
2. Evaluate the fitness value of each particle, and update $P_i = (i = 1, .., N)$and P_g.
3. Update the velocity and position of each particle using Eq.24 and Eq.25, respectively.
4. Evaluate the fitness value of each particle, and update$P_i = (i = 1, .., N)$and P_g.
5. If (iteration mod INV) =0, the EO procedure is introduced. Otherwise, continue the next step.
6. If the terminal condition is satisfied, go to the next step; otherwise, set iteration = iteration +1, and go to Step 3.
7. Output the optimal solution and the optimal objective function value.

6.1Mutation Operator

Since there is merely mutation operator in EO, the mutation plays a key role in EO search. This mutation method mixes Gaussian mutation and Cauchy mutation. The mechanisms of Gaussian and Cauchy mutation operations have been studied by Yao et al 1999. They pointed out that Cauchy mutation is better at coarse-grained search while Gaussian mutation is better at fine-grained search. In the hybrid *GC* mutation, the Cauchy mutation is first used. It means that the large step size will be taken first at each mutation. If the new generated variable after mutation goes beyond the range of variable, the Cauchy mutation will be used repeatedly for some times (*TC*), until the new generated offspring falls into the range. Otherwise, Gaussian mutation will be carried out repeatedly for another sometimes (*TG*), until the offspring satisfies the requirement. That is, the step size will become smaller than before. If the new generated variable after mutation still goes beyond the range of variable, then the upper or lower bound of the decision variable will be chosen as the new generated variable. Thus, the hybrid *GC* mutation combines the advantages of coarse-grained search and fine-grained search. Unlike some switching algorithms which have to decide when to switch between different mutations during search, the hybrid *GC* mutation does not need to make such decisions. In the hybrid *GC* mutation, the values of parameters *TC* and *TG* are set by the user beforehand. The value of *TC* decides the coarse-grained searching time, while the value of *TG* has an effect on the fine-grained searching time. Therefore, both values of the two parameters cannot be large because it will prolong the search process and hence increase the computational overhead. According to the literature, the moderate values of *TC* and *TG* can be set to 2∼4.

7. Simulation Results

The validity of the proposed technique HPSOEO is demonstrated by simulating it on IEEE-30 bus system. The IEEE-30 bus system has 6 generator buses, 24 load buses and 41 transmission lines of which four branches are (6-9), (6-10) , (4-12) and (28-27) - are with the tap setting transformers. The lower voltage magnitude limits at all buses are 0.95 p.u. and the upper limits are 1.1 for all the PV buses and 1.05 p.u. for all the PQ buses and the reference bus. The simulation results has been presented in Tables 1, 2, 3 &4. And in the table 5 shows clearly that proposed algorithm powerfully reduces the real power losses when compared to other given algorithms. The optimal values of the control variables along with the minimum loss obtained are given in Table 1. Corresponding to this control variable setting, it was found that there are no limit violations in any of the state variables.

Table 1. Results of HPSOEO – ORPD optimal control variables

Control variables	*Variable setting*
V1	1.041
V2	1.040
V5	1.039
V8	1.032
V11	1.010
V13	1.033
T11	1.03
T12	1.00
T15	1.0
T36	1.0
Qc10	3
Qc12	3
Qc15	4
Qc17	0
Qc20	1
Qc23	4
Qc24	3
Qc29	3
Real power loss	4.2375
SVSM	0.2375

ORPD including voltage stability constraint problem was handled in this case as a multi-objective optimization problem where both power loss and maximum voltage stability margin of the system were optimized concurrently. Table 2 indicates the optimal values of these control variables. Also it is found that there are no limit violations of the state variables. It indicates the voltage stability index has increased from 0.2375 to 0.2387, an advance in the system voltage stability. The Eigen values equivalents to the four critical contingencies are given in Table 3. From this result it is observed that the Eigen value has been improved considerably for all contingencies in the second case.

Table 2. Results of HPSOEO-Voltage Stability Control Reactive Power Dispatch Optimal Control Variables

Control Variables	*Variable Setting*
V1	1.043
V2	1.044
V5	1.041
V8	1.035
V11	1.003
V13	1.038
T11	0.090
T12	0.090
T15	0.090
T36	0.090
Qc10	3
Qc12	3
Qc15	4
Qc17	0
Qc20	3
Qc23	4
Qc24	3
Qc29	3
Real power loss	4.9869
SVSM	0.2387

Table 3. Voltage Stability under Contingency State

Sl.No	*Contigency*	*ORPD Setting*	*VSCRPD Setting*
1	28-27	0.1404	0.1440
2	4-12	0.1628	0.1651
3	1-3	0.1754	0.1743
4	2-4	0.2022	0.2021

Table 4. Limit Violation Checking Of State Variables

State variables	*limits*		*ORPD*	*VSCRPD*
	Lower	*upper*		
Q1	-20	152	1.3422	-1.3269
Q2	-20	61	8.9900	9.8232
Q5	-15	49.92	25.920	26.001
Q8	-10	63.52	38.8200	40.802
Q11	-15	42	2.9300	5.002
Q13	-15	48	8.1025	6.033
V3	0.95	1.05	1.0372	1.0392
V4	0.95	1.05	1.0307	1.0328
V6	0.95	1.05	1.0282	1.0298
V7	0.95	1.05	1.0101	1.0152
V9	0.95	1.05	1.0462	1.0412
V10	0.95	1.05	1.0482	1.0498
V12	0.95	1.05	1.0400	1.0466
V14	0.95	1.05	1.0474	1.0443
V15	0.95	1.05	1.0457	1.0413
V16	0.95	1.05	1.0426	1.0405
V17	0.95	1.05	1.0382	1.0396
V18	0.95	1.05	1.0392	1.0400
V19	0.95	1.05	1.0381	1.0394
V20	0.95	1.05	1.0112	1.0194
V21	0.95	1.05	1.0435	1.0243
V22	0.95	1.05	1.0448	1.0396
V23	0.95	1.05	1.0472	1.0372
V24	0.95	1.05	1.0484	1.0372
V25	0.95	1.05	1.0142	1.0192
V26	0.95	1.05	1.0494	1.0422
V27	0.95	1.05	1.0472	1.0452
V28	0.95	1.05	1.0243	1.0283
V29	0.95	1.05	1.0439	1.0419
V30	0.95	1.05	1.0418	1.0397

Table 5. Comparison of Real Power Loss

Method	*Minimum loss*
Evolutionary programming(Wu Q H et al 1995)	5.0159
Genetic algorithm (S.Durairaj et al 2006)	4.665
Real coded GA with Lindex as SVSM (D.Devaraj 2007)	4.568
Real coded genetic algorithm(P. Aruna Jeyanthy et al 2007)	4.5015
Proposed HPSOEO method	4.2375

8. Conclusion

In this paper a novel approach HPSOEO algorithm used to solve optimal reactive power dispatch problem, considering various generator constraints, has been successfully applied.The performance of the proposed algorithm demonstrated through its voltage stability assessment by modal analysis is effective at various instants following system contingencies. Also this method has a good performance for voltage stability Enhancement of large, complex power system networks. The effectiveness of the proposed method is demonstrated on IEEE 30-bus system.

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