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Hybrid Quantum Genetic Particle Swarm Optimization Algorithm For Solving Optimal Reactive Power Dispatch Problem

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Abstract: **This paper presents hybrid particle swarm algorithm for solving the multi-objective reactive power dispatch problem. 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. Evolutionary algorithm and Swarm Intelligence algorithm (EA, SI), a part of Bio inspired optimization algorithm, have been widely used to solve numerous optimization problem in various science and engineering domains. In this paper, a framework of hybrid particle swarm optimization algorithm, called Hybrid quantum genetic particle swarm optimization (HQGPSO), is proposed by reasonably combining the Q-bit evolutionary search of quantum particle swarm optimization (QPSO) algorithm and binary bit evolutionary search of genetic particle swarm optimization (GPSO) in order to achieve better optimization performances. The proposed HQGPSO also can be viewed as a kind of hybridization of micro-space based search and macro-space based search, which enriches the searching behavior to enhance and balance the exploration and exploitation abilities in the whole searching space. In order to evaluate the proposed algorithm, it has been tested on IEEE 30 bus system and compared to other algorithms.**

Keywords: **quantum particle swarm optimization, genetic particle swarm optimization, hybrid algorithm Optimization, Swarm Intelligence, optimal reactive power, Transmission loss.**

I. INTRODUCTION

Optimal reactive power dispatch 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 [1, 2], Newton method [3] and linear programming [4-7].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 [8.9]. 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 [10]. 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 [10] is used as the indicator of voltage stability. The PSO is inspired by observing the bird flocking or fish school [15]. A large number of birds/fishes flock synchronously, change direction suddenly, and scatter and regroup together. Each individual, called a particle, benefits from the experience of its own and that of the other members of the swarm during the search for food. Comparing with genetic algorithm, the advantages of PSO lie on its simple concept, easy implementation and quick convergence. The PSO has been applied successfully to continuous nonlinear function [15], neural network [16], nonlinear constrained optimization problems [17], etc.

Most of the applications have been concentrated on solving continuous optimization problems [18]. To solve discrete (combinatorial) optimization problems, Kennedy and Eberhart [19] also developed a discrete version of PSO (DPSO), which however has seldom been utilized. DPSO essentially differs from the original (or continuous) PSO in two characteristics. First, the particle is composed of the binary variable. Second, the velocity must be transformed into the change of probability, which is the chance of the binary variable taking the value one. Furthermore, the relationships between the DPSO parameters differ from normal continuous PSO algorithms [20] [21]. Though it has been proved the DPSO can also be used in discrete optimization as a common optimization method, it is not as effective as in continuous optimization. When dealing with integer variables, DPSO sometimes are easily trapped into local minima [19]. Therefore, Yang et al. [22] proposed a quantum particle swarm optimization (QPSO) for discrete optimization in 2004. Their simulation results showed that the performance of the QPSO was better than DPSO and genetic algorithm. Recently, Yin [23] proposed a genetic particle swarm optimization (GPSO) with genetic reproduction mechanisms, namely crossover and mutation to facilitate the applicability of PSO to combinatorial optimization problem, and the results showed that the GPSO outperformed the DPSO for combinatorial optimization problems. QPSO uses a Q-bit, defined as the smallest unit of information, for the probabilistic representation and a Q-bit individual as a string of Q-bits. The Q-bit individual has the advantage that it can represent a linear superposition of states (binary solutions) in search space probabilistically [22] [24]. Thus the Q-bit representation has a better characteristic of population diversity than other representations. However, the performance of simple quantum-inspired PSO is often not satisfactory and is easy to be trapped in local optima so as to be premature convergence. In the binary genetic particle swarm optimization, genetic reproduction, in particular, crossover and mutation, have been combined to form a discrete version particle swarm optimization, is suitable for solving combinatorial optimization problems. In QPSO, the representation of population is Q-bit and evolutionary search is in micro-space (Q-bit based representation space). Differently, in GPSO the representation is binary number and evolutionary search is in macro-space (binary space). It is quite different between QPSO and GPSO in terms of representation and evolution operators.

However, as QPSO, the performance of GPSO is also often not satisfactory and is easy to be trapped in local optima so as to be premature convergence. In contrast to the continuous PSO algorithm that has been widely studied and improved by a large body of researchers, the discrete PSO and its application to combinatorial optimization problems has not been as popular or widely studied. Therefore, it is an important topic to develop a new or improved discrete particle swarm optimization algorithm with applications to combinatorial optimization problems. The performance of (HQGPSO) 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. The performance of (HQGPSO) 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.

II. Voltage Stability Evaluation

A. Modal analysis for voltage stability evaluation

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.

B. Modes of Voltage instability:

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

Let

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

Where,

ξ = right eigenvector matrix of J_R

η = left eigenvector matrix of J_R

$\wedge$ = diagonal eigenvalue matrix of J_R and

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

From (3) and (6), we have

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

or

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

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,

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

where,

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

Where

ξ_{ji} is the jth element of ξ_i

The corresponding ith modal voltage variation is

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

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

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

III. 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).

A. 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.

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

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 θ_{ij} is the voltage angle difference between bus i and bus j.

B. 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.

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

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

C. 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.

IV. Hybrid QGPSO

A. *Quantum Particle Swarm Optimization (QPSO)*

In the quantum theory, the minimum unit that carries information is a Q-bit, which can be in any superposition of state 0 and 1. Let $Qi(t) = (q_{i1}(t), q_{i2}(t),.., q_{iD}(t))$, $q_{id}(t) \in [0,1]$, be quantum particle *I* with *D* bits at iteration *t*, where $q_{id}(t)$ represents the probability of *d*-th bit of *i*-th particle being 0 at iteration *t*. Let $X_i(t) = (x_{i1}(t), x_{i2}(t),.., x_{iD}(t))$, $x_{id}(t) \in \{0,1\}$ be binary particle *i* with *D* bits at iteration *t*. $X_i(t)$ is the corresponding binary particle of the quantum particle $Q_i(t)$ and also can be treated as a potential solution. A binary particle $X_i(t)$ can be got from quantum particle $Q_i(t)$ by performing a random observation as following:

$$x_{id}(t) = \begin{cases} 1 & if\ rand() > q_{id}(t) \\ 0 & otherwise \end{cases} \quad (24)$$

Where rand () is a random number selected from a uniform distribution in [0,1]. Let $P_i(t) = (p_{i1}(t), p_{i2}(t),..., p_{iD}(t))$ be the best solution that binary particle $X_i(t)$ has obtained until iteration *t*, and $P_g(t) = (p_{g1}(t), p_{g2}(t),..., p_{gD}(t))$ be the best solution obtained from $P_i(t)$ in the whole swarm at iteration *t*. The QPSO algorithm can be described as [22]:

$$q_{localbest}(t) = \alpha \cdot P_{id}(t) + \beta \cdot (1 - P_{id}(t)) \quad (25)$$

$$q_{golbalbest}(t) = \alpha \cdot P_{id}(t) + \beta \cdot (1 - P_{id}(t)) \quad (26)$$

$$q_{id}(t+1) = c_1 \cdot q_{id}(t) + c_2 \cdot q_{localbest}(t) + c_3 \cdot q_{globalbest}(t) \quad (27)$$

Where $\alpha + \beta = 1$, $0 < \alpha, \beta < 1$ are control parameters. The smaller of α , the bigger of the appear probability of the desired item. $c_1 + c_2 + c_3 = 1$, $0 < c_1, c_2, c_3 < 1$ represent the degree of the belief on oneself, local best solution and global best solution, respectively. In order to keep the diversity in particle swarm and further improve QPSO performance, we incorporated a mutation operator into the QPSO. The mutation operator independently changes the Q-bit of an individual with a mutation probability p as following:

$$q_{id}(t) = 1 - q_{id}(t) \text{, if rand( )} < p \quad (28)$$

B. Genetic Particle Swarm Optimization (GPSO)

Denote by N the number of particles in the swarm. The GPSO with genetic recombination for the d-th bit of particle i is described as follows:

$$x_{id}(t+1) = w(0,w_1)rand(x_{id}(t)) + w(w_1,w_2)rand(p_{id}(t)) + w(w_2,1)rand(p_{gd}(t)) \quad (29)$$

where $0 < w_1 < w_2 < 1$, $w(\,)$ and rand() are a threshold function and a probabilistic bit flipping function, respectively, and they are defined as follows:

$$w(a,b) = \begin{cases} 1 \ if \ a \leq r_1 \leq P_m \\ 0 \ \ otherwise \end{cases} , \quad (30)$$

$$rand(y) = \begin{cases} 1 - y \ if \ r_2 \leq p_m \\ y \ \ \ otherwise \end{cases} \quad (31)$$

where r_1 and r_2 are the random numbers uniformly distributed in [0,1]. Thus, only one of the three terms on right hand side of Eq. (29) will remain dependent on the value r_1 , and rand(y) mutates the binary bit y with a small mutation probability pm . The updating rule of the genetic PSO is analogue to the genetic algorithm in two aspects. First, the particle derives its single bit from the particle x_{id} , p_{id} and p_{gd} . This operation corresponds to a 3-way uniform crossover among X_i , P_i and P_g , such that the particle can exchange building blocks (segments of ordering or partial selections of elements) with personal and global experiences. Second, each bit attained in this way will be flipped with a small probability p_m , corresponding to the binary mutation performed in genetic algorithms. As such, genetic reproduction, in particular, crossover and mutation, have been added to the particle swarm optimization. This new genetic version, named GPSO, is very likely more suitable for solving combinatorial optimization problems than the original one.

V. Procedure of HQGPSO

It is concluded from ‘‘No Free Lunch’’ theorem [25] that there is no any method can solve all the problems optimally, so that hybrid optimization algorithms have gained wide research in recent years [26] [27]. Based on the description of last section, it can be seen that it is quite different between QPSO and GPSO in terms of representation and evolution operators. In QPSO, the representation of population is Q-bit and evolutionary search is in micro-space (Q-bit based representation space). Differently, in GPSO the representation is binary number and evolutionary search is in macro-space (binary space). We consider the hybridization of QPSO and GPSO to develop hybrid QPSO characterized the principles of both quantum computing and evolutionary computing mechanisms.

Algorithm for solving reactive power dispatch problem.

1. Initialize.

1.1 Set $t = 0$, and initialize the $QP(t)$.

1.2 Make $BP(t)$ by observing the states of $QP(t)$.

1.3 Evaluate the $BP(t)$, and update the local best solutions and the global best solution.

1.4 Store $BP(t)$ into $Parent(t)$.

2. Repeat until a given maximal number of iterations (*MaxIter*) is achieved.
2.1 Set $t = t + 1$.
2.2 Update $QP(t)$ using QPSO.
2.3 Make $BP(t)$ by observing the states of $QP(t)$.
2.4 Evaluate the $BP(t)$.
2.5 Select better one between $BP(t)$ and $Parent(t\text{-}1)$ for each individual to update $BP(t)$.
2.6 Update the local best solutions and the global best solution.
2.7 Update $BP(t)$ using GPSO for a given maximal number of iteration (*gMaxIter*).
2.8 Evaluate the $BP(t)$, and update the local best solutions and the global best solution.

In the main loop the above procedure, firstly, quantum swarm is evolved by the evolution mechanism of the QPSO (Step 2.2). After one generation evolution of quantum swarm, a random observation is performed on quantum swarm (Step 2.3). Thus, binary swarm is made by the random observation and prepares to be evolved by the evolution mechanism of the GPSO in succession. Note that the individuals to perform GPSO are based on all the individuals resulted by QPSO in current generation and all the individuals resulted by GPSO in last generation (Step 2.5). That is, if a binary individual in the population resulted by QPSO in current generation is worse than the corresponding binary individual in the population resulted by GPSO in last generation, then the worse one is replaced by the better one. This selection process is something like the $(\mu + \lambda)$ selection in evolutionary algorithm [28]. The selection in the hybrid algorithm is helpful to reserve better solutions and speed up the evolution process. After the one or more generation GPSO evolution of binary swarm (Step 2.7), the best solutions that each particle has obtained and the best solution that obtained from the whole swarm are recorded and transferred to quantum swarm to guide a new generation evolution of quantum swarm (Step 2.8). In the hybrid algorithm, the best solutions that each binary particle has obtained and global best solution of whole swarm can also be considered as additional swarm individuals. They not only guide the evolution of quantum swarm, but also guide evolution of binary swarm observed from quantum swarm.

Therefore, quantum swarm co-evolves with binary swarm and the information of evolution is exchanged between them by the best solutions and global best solution. With the hybridization of different representation spaces and various particle swarm optimization operators, it can not only enrich the searching behaviour but also enhance and balance the exploration and exploitation abilities to avoid being trapped in local optima. Moreover, to balance the effort of QPSO and GPSO, different parameters can be used, such as population size. On the other hand, the initial inspiration for the PSO was the coordinated movement of swarms of animals in nature, for example schools of fish or flocks of birds. It reflects the cooperative relationship among the individuals within a swarm. However, in natural ecosystems, many species have developed cooperative interactions with other species to improve their survival. Such cooperative co-evolution is called symbiosis [29]. According to the different symbiotic interrelationships, symbiosis can be classified into three main categories: mutualism (both species benefit by the relationship), commensalism (one species benefits while the other species is not affected), and parasitism (one species benefits and the other is harmed) [30]. The co-evolution between quantum swarm and binary swarm in the proposed hybrid algorithm is similar to the mutualism model, where both swarms benefit from each other.

VI. Simulation Results

The soundness of the proposed HQGPSO Algorithm method is demonstrated 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 have been presented in Tables 1, 2, 3 &4. And in the Table 5 shows clearly that proposed algorithm powerfully reduce 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. Equivalent to this control variable setting, it was found that there are no limit violations in any of the state variables.

Table1. Results of HQGPSO – ORPD optimal control variables

Control variables	Variable setting
V1	1.044
V2	1.044
V5	1.04
V8	1.032
V11	1.012
V13	1.04
T11	1.09
T12	1.02
T15	1
T36	1
Qc10	3
Qc12	2
Qc15	4
Qc17	0
Qc20	3
Qc23	4
Qc24	3
Qc29	3
Real power loss	4.4345
SVSM	0.2471

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 0.2471 to 0.2486, an advance in the system voltage stability. To determine the voltage security of the system, contingency analysis was conducted using the control variable setting obtained in case 1 and case 2. 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 HQGPSO -Voltage Stability Control Reactive Power Dispatch Optimal Control Variables

Control Variables	Variable Setting
V1	1.045
V2	1.044
V5	1.041
V8	1.033
V11	1.009
V13	1.034
T11	0.09
T12	0.091
T15	0.092
T36	0.091
Qc10	4
Qc12	3
Qc15	2
Qc17	4

Qc20	0
Qc23	4
Qc24	4
Qc29	4
Real power loss	4.9799
SVSM	0.2486

Table 3. Voltage Stability under Contingency State

Sl. No	Contigency	ORPD Setting	VSCRPD Setting
1	28-27	0.1410	0.1435
2	4-12	0.1658	0.1669
3	1-3	0.1774	0.1779
4	2-4	0.2032	0.2049

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[11]	5.0159
Genetic algorithm[12]	4.665
Real coded GA with Lindex as SVSM[13]	4.568
Real coded genetic algorithm[14]	4.5015
Proposed HQGPSO method	4.4345

VII. CONCLUSION

In this paper a novel approach HQGPSO algorithm used to solve optimal reactive power dispatch problem. The effectiveness of the proposed method has been demonstrated by testing it on IEEE 30-bus system and simuation results reveals about the reduction of real power loss when compared with other standard algorithms in table 5 and also volatge profiles are within the limits .

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