Global Journal of Researches in Engineering: F
Electrical and Electronics Engineering
Volume 14 Issue 3 Version 1.0 Year 2014
Type: Double Blind Peer Reviewed International Research Journal
Publisher: Global Journals Inc. (USA)
Online ISSN: 2249-4596 & Print ISSN: 0975-5861

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GJRE-F Classification : FOR Code: 090607

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I. Introduction

In recent years the optimal reactive power dispatch (ORPD) problem has received great attention as a result of the improvement on economy and security of power system operation. Solutions of ORPD problem aim to minimize object functions such as fuel cost, power system loses, etc. while satisfying a number of constraints like limits of bus voltages, tap settings of transformers, reactive and active power of power resources and transmission lines and a number of controllable Variables [1, 2]. In the literature, many methods for solving the ORPD problem have been done up to now. At the beginning, several classical methods such as gradient based [3], interior point [4], linear programming [5] and quadratic programming [6] have been successfully used in order to solve the ORPD problem. However, these methods have some disadvantages in the Process of solving the complex ORPD problem. Drawbacks of these algorithms can be declared insecure convergence properties, long execution time, and algorithmic complexity. Besides, the solution can be trapped in local minima [1, 7]. In order to overcome these disadvantages, researches have successfully applied evolutionary and heuristic algorithms such as Genetic Algorithm (GA) [2], Differential Evolution (DE) [8], Particle Swarm Optimization (PSO) [9] and harmony search algorithms [10-11].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 [12] is used as the indicator of voltage stability. Function optimization has received extensive research attention, and several optimization algorithm such as neural networks [13], evolutionary algorithms [14], genetic algorithms [15] and swarm intelligence-based algorithms [16-17] have been developed and applied successfully to solve a wide range of complex optimization problems. Most stochastic optimization algorithms including particle swarm optimizer (PSO) [18, 19] and genetic algorithm (GA) [15] have shown inadequate to complex optimization problems, as they rapidly push an artificial population toward convergence. That is, all individuals in the population soon become nearly identical. To improve PSO performance, several methods have been proposed. Many of these methods concerned predefining numerical coefficients, consisting of the maximum velocity, inertia weight, social factor and individual factor, which can affect various characteristics of the algorithm, such as convergence rate or the ability of global optimization. Recently, some hybrid implementations of PSO algorithm with other search

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methods. NM-PSO (Nelder- Mead-PSO) [20] comprises NM method at the top of level, and PSO at the lower level. CPSO (Chaotic PSO) [21] applies PSO to perform global exploration and chaotic local search to perform local search on the solutions produced in the global exploration process. These methods can equip PSO with extra facilities. In this paper, an improved PSO (IPSO) based of harmony search (HS) [22, 23] is proposed to solve complex optimizations. The PSO algorithm includes some tuning parameters that greatly influence the algorithm performance, often stated as the exploration-exploitation trade off: Exploration is the ability to test various regions in the problem space in order to locate a good optimum, hopefully the global one. Exploitation is the ability to concentrate the search around a promising candidate solution in order to locate the optimum precisely. Facing complicated optimizations, it's difficult to explore every possible region of the search space. Recently, harmony search (HS) algorithm imitates the improvisation process of music players and had been very successful in a wide variety of optimization problems [24-25], presenting several advantages with respect to traditional optimization techniques such as the following [24]:(a) HS algorithm imposes fewer mathematical requirements and does not require initial value settings of the decision variables. (b) As the HS algorithm uses stochastic random searches, derivative information is also unnecessary. (c) The HS algorithm generates a new vector, after considering all of the existing vectors, whereas the genetic algorithm (GA) only considers the two parent vectors. These features increase the flexibility of the HS algorithm and produce better solutions. In this study, one of the ways of integrating the concepts of these two optimization algorithms for solving complex optimization problems is explored. The performance of IHPSO 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 Evaluatio

a) *Modal analysis for voltage stability evaluation*

The linearized steady state system power flow equations are given by.

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

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.

$$\Delta Q = \left[J_{QV} - J_{Q\theta} J_{P\theta^{-1}} J_{PV}\right]\Delta V = J_R \Delta V \tag{2}$$

$$\Delta V = J^{-1} - \Delta Q \tag{3}$$

Where

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

J_R is called the reduced Jacobian matrix of the system.

a) *Modes of Voltage instability*

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

Let

$$J_R = \xi \wedge \eta \tag{5}$$

Where,

ξ = right eigenvector matrix of J_R

η = left eigenvector matrix of J_R

$\wedge$ = diagonal eigenvalue matrix of J_R and

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

From (3) and (6), we have

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

or

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

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,

$$\Delta Q_{mi} = K_i \xi_i \tag{9}$$

where,

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

Where

ξ_{ji} is the jth element of ξ_i

The corresponding ith modal voltage variation is

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

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*

Minimization of the real power loss (Ploss) in transmission lines of a power system 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 θij is the voltage angle difference between bus i and bus j.

b) *Minimization of Voltage Deviation*

Minimization of the Deviations in voltage magnitudes (VD) at load buses 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. Standard PSO

PSO is a population-based, co-operative search meta-heuristic introduced by Kennedy and Eberhart. The fundament for the development of PSO is hypothesis that a potential solution to an optimization problem is treated as a bird without quality and volume, which is called a particle, coexisting and evolving simultaneously based on knowledge sharing with neighbouring particles. While flying through the problem search space, each particle modifies its velocity to find a better solution (position) by applying its own flying experience (i.e. memory having best position found in the earlier flights) and experience of neighbouring particles (i.e. best-found solution of the population). Particles update their positions and velocities as shown below:

$$v_{t+1}^i = \omega_t . v_t^i + c_1 . R_1 . (p_t^i - x_t^i) + c_2 . R_2 . (p_t^g - x_t^i) \quad (24)$$

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

Where x_t^i represents the current position of particle i in solution space and subscript t indicates an iteration count; p_t^i is the best-found position of particle i up to iteration count t and represents the cognitive contribution to the search velocity v_t^i . Each component of v_t^i can be clamped to the range to control excessive roaming of particles outside the search space; p_t^g is the global best-found position among all particles in the swarm up to iteration count t and forms the social contribution to the velocity vector; r_1 and r_2 are random numbers uniformly distributed in the interval (0,1), where c_1 and c_2 are the cognitive and social scaling parameters, respectively; ω_t is the particle inertia, which is reduced dynamically to decrease the search area in a gradual fashion [25]. The variable ω_t is updated as

$$\omega_t = (\omega_{max} - \omega_{min}).\frac{(t_{max} - t)}{t_{max}} + \omega_{min} \quad (26)$$

Where ω_{max} and ω_{min} denote the maximum and minimum of ω_t respectively; t_{max} is a given number of maximum iterations. Particle i fly toward a new position according to Eq. (24) and (25). In this way, all particles of the swarm find their new positions and apply these new positions to update their individual best p_t^i points and global best p_t^g of the swarm. This process is repeated until termination conditions are met.

V. Harmony Search

Harmony search (HS) algorithm is based on natural musical performance processes that occur when a musician searches for a better state of harmony, such as during jazz improvisation. The engineers seek for a global solution as determined by an objective function, just like the musicians seek to find musically pleasing harmony as determined by an aesthetic [26]-[27]. In music improvisation, each player sounds any pitch within the possible range, together making one harmony vector. If all the pitches make a good solution, that experience is stored in each variable's memory, and the possibility to make a good solution is also increased next time. HS algorithm includes a number of optimization operators, such as the harmony memory (HM), the harmony memory size (HMS, number of solution vectors in harmony memory), the harmony memory considering rate (HMCR), and the pitch adjusting rate (PAR). In the HS algorithm, the harmony memory (HM) stores the feasible vectors, which are all in the feasible space. The harmony memory size determines how many vectors it stores. A new vector is generated by selecting the components of different vectors randomly in the harmony memory. For example, Consider a jazz trio composed of saxophone, double bass and guitar. There exist certain amount of preferable pitches in each musician's memory: saxophonist, {Do, Mi, Sol}; double bassist, {Si, Sol, Re}; and guitarist, {La, Fa, Do}. If saxophonist randomly plays {Sol} out of {Do, Mi, Sol}, double bassist {Si} out of {Si, Sol, Re}, and guitarist {Do} out of {La, Fa, Do}, that harmony (Sol, Si, Do) makes another harmony (musically C-7 chord). And if the New Harmony is better than existing worst harmony in the HM, the New Harmony is included in the HM and the worst harmony is excluded from the HM. This procedure is repeated until fantastic harmony is found. When a musician improvises one pitch, usually he (or she) follows any one of three rules: (a) playing any one pitch from his (or her) memory, (b) playing an adjacent pitch of one pitch from his (or her) memory, and (c) playing totally random pitch from the possible sound range. Similarly, when each decision variable chooses one value in the HS algorithm, it follows any one of three rules: (i) choosing any one value from HS memory (defined as memory considerations), (ii) choosing an adjacent value of one value from the HS memory (defined as pitch adjustments), and (iii) choosing totally random value from the possible value range (defined as randomization). The three rules in HS algorithm are effectively directed using two parameters, i.e., harmony memory considering rate (HMCR) and pitch adjusting rate (PAR).

The steps in the procedure of harmony search are as follows:

Step 1: Initialize the problem and algorithm parameters.

Step 2: Initialize the harmony memory (HM).

Step 3: Improvise a new harmony from the HM.

Step 4: Update the HM.

Step 5: Repeat Steps 3 and 4 until the termination criterion is satisfied.

VI. The Realization of ihpso based of hs

This section describes the implementation of proposed improvement in PSO using HS approach. The proposed method, called, IHPSO (improved hybrid particle swarm optimization) is based on the common characteristics of both PSO and HS algorithms. HS algorithm provides a new way to produce new particles. Different from PSO and GA, HS algorithm generates a new vector after considering all of the existing vectors. HS algorithm can produce new solution and the parameters of HMCR and PAR are introduced to allow the solution to escape from local optima and to improve the global optimum prediction of the algorithm. Enlightened by this, the HS realization concept has been used in the PSO in this paper to exploration the potential solution space. In summary, the realization of improved PSO algorithm for solving reactive power dispatch is described as follows:

Step 1: Initializing the parameters of PSO and HS;

Step 2: Initailizing the particles;

Step 3: Evaluating particles according to their fitness then descending sort them;

Step 4: Performing HS and generating a new solution;

Step 5: If the new solution is better than the worst particle then replacing it with the new one;

Step 6: Update the particles by using equation's (24) & (25)

Step 7: The program is finished if the terminations conditions are met otherwise go to step3.

Improvising a new harmony from the HM can be realized as follows:

A New Harmony vector $x' = \{x_1', x_2', \wedge, x_N'\}$ is generated from the HM based on memory considerations, pitch adjustments, and randomization. For instance, the value of for the new vector can be chosen from any value in the specified HM rang $(x_1^1 - x_1^{HMS})$. Values of the other design variables can be chosen in the same manner. Here, it's possible to choose the new value using the HMCR parameter, which varies between 0 and 1 as follows:

$$x_i' \leftarrow \begin{cases} x_i' \in \{x_i^1, x_i^2, \wedge, x_i^{HMS}\} \, with\, probability\, HMCR \\ x_i' \in X_i \, with\, probability\, 1 - HMCR \end{cases} \quad (27)$$

The HMCR is the probability of choosing one value from the historic values stored in the HM, and (1-HMCR) is the probability of randomly choosing one feasible value not limited to those stored in the HM. For example, an HMCR of 0.95 indicates that the HS algorithm will choose the design variable value from historically stored values in the HM with a 95% probability and from the entire feasible range with a 5% probability. An HMCR value of 1.0 is not recommended because of the possibility that the solution may be improved by values not stored in the HM. This is similar to the reason why the genetic algorithm uses a mutation rate in the selection process. Every component of the New Harmony vector $x' = \{x_1', x_2', \wedge, x_N'\}$ is examined to determine whether it should be pitch-adjusted. This procedure uses the parameter that set the rate of adjustment for the pitch chosen from the HM as follows:
Pitch adjusting decision for

$$x_i' \leftarrow \begin{cases} Yes\, with\, probability\, PAR \\ No\, with\, probability\;\; 1 - PAR \end{cases} \quad (28)$$

The Pitch adjusting process is performed only after a value is chosen from the HM. The value (1-PAR) sets the rate of doing nothing. A PAR of 0.3 indicates that the algorithm will choose a neighbouring value with probability. If the pitch adjustment decision for x' is Yes, and x' is assumed to be $x_i(k)$ i.e., the kth element in X_i, the pitch-adjusted value of$x_i(k)$ is:

$$x' = x' + \alpha \quad (29)$$

Where $\alpha -$ the value of is $bw \,\mathrm{x}\, (1, -1)$, bw is an arbitrary distance bandwidth for the continuous design variable, and u (−1, 1) is a uniform distribution between -1 and 1. The HMCR and PAR parameters introduced in the harmony search help the algorithm escape from local optima and to improve the global optimum prediction of the HS algorithm. After improvising a new harmony, evaluating the new one and if it is better than the worst one in the HM in terms of the objective function value, the new one is included in the HM and the existing worst harmony is excluded from the HM. The HM is then sorted by the objective function value.

VII. Simulation Results

The accuracy of the proposed IHPSO Algorithm method is demonstrated by testing it on standard 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 the 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 IHPSO – ORPD Optimal Control Variables

Control variables	Variable setting
V1	1.040
V2	1.041
V5	1.040
V8	1.030
V11	1.003
V13	1.041
T11	1.01
T12	1.00
T15	1.0
T36	1.0
Qc10	3
Qc12	4
Qc15	4
Qc17	0
Qc20	3
Qc23	4
Qc24	3
Qc29	3
Real power loss	4.2985
SVSM	0.2482

ORPD together with 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 simultaneously. 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 0.2482 to 0.2498, 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 Ihpso -Voltage Stability Control Reactive Power Dispatch Optimal Control Variables

Control Variables	Variable Setting
V1	1.043
V2	1.044
V5	1.042
V8	1.031
V11	1.005
V13	1.035
T11	0.090
T12	0.090
T15	0.090
T36	0.090
Qc10	4
Qc12	4
Qc15	3
Qc17	4
Qc20	0
Qc23	3
Qc24	3
Qc29	4
Real power loss	4.9690
SVSM	0.2498

Table 3 : Voltage Stability Under Contingency State

Sl.No	Contigency	ORPD Setting	VSCRPD Setting
1	28-27	0.1410	0.1425
2	4-12	0.1658	0.1665
3	1-3	0.1774	0.1783
4	2-4	0.2032	0.2045

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[28]	5.0159
Genetic algorithm[29]	4.665
Real coded GA with Lindex as SVSM[30]	4.568
Real coded genetic algorithm[31]	4.5015
Proposed IHPSO method	4.2985

VIII. Conclusion

In this paper, one of the recently developed stochastic algorithms IHPSO has been demonstrated and applied to solve optimal reactive power dispatch problem. The problem has been formulated as a constrained optimization problem. Different objective functions have been considered to minimize real power loss, to enhance the voltage profile. The proposed approach is applied to optimal reactive power dispatch problem on the IEEE 30-bus power system. The simulation results indicate the effectiveness and robustness of the proposed algorithm to solve optimal reactive power dispatch problem in test system.

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