HYBRID PARTICLE SWARM OPTIMIZATION BASED REACTIVE POWER OPTIMIZATION

[1]Vivek Kumar Jain, [2]Himmant Singh
[1, 2] Department of Electrical Engineering, Madhav Institute of Technology and Science, Gwalior (M.P.), India

Abstract— in this paper, a solution to reactive power optimization problem with a Hybrid particle swarm optimization (PSO) approach. The algorithm changed the stochastic initialization and adopted a principle of particle searching by itself. Several particles in feasible solutions were used to lead swarms motion and update the performance of the proposed hybrid approach is demonstrated with the IEEE-30and IEEE-57 bus systems and also the performance of this hybrid PSO is compared with that of particle swarm optimization, genetic algorithm and evolutionary programming. The performance of the proposed method is compared with the previous approaches reported in the iterative. The performance of hybrid PSO seems to be better in terms of solution quality and computational times.

Keywords— reactive power optimization, particle swarm optimization, evolutionary programming, and hybrid approach and loss minimization.

I. INTRODUCTION

The problem of reactive power optimization is directly concerned not only with service quality and reliability of supply, but also with economy and security of the power systems. Therefore, the power system reactive power optimization problem result directly influences the power system stability and power quality. [2] The reactive power can be controlled in order to improve the voltage profile and minimize the system loss. Generally, some load bus voltage might violate their upper or lower limits during system operation due to disturbances and/or system configuration changes. The power system operator can alleviate this situation and voltages can be maintained within their permissible limits by reallocating reactive power generation in the system. This means by adjusting generator voltages, transformer taps and switch-able VAR sources (capacitors/reactors). [1] Generally, HPSO has a more global searching ability at the start of the run and a local search near the end of the run. Therefore, while solving problems with more limited optima, there are more possibilities for the PSO to discover local optima at the end of run. However, the reactive power optimization problem does have these properties itself. For these reasons, a reliable global approach to power system optimization problems would be of considerable value to power engineering society. Moreover, they did not consider the cost aspect of the problem. Only the sensitivity to voltage has been used for solving the difficulty [3].The purpose of reactive power optimization is to minimize the system loss or other optimum performance indices, subjecting to security and operation constraints. There are many solutions for it, such as linear programming, nonlinear programming, secondary programming, sensitive analysis, and mixed integer planning [10-7]. These methods are generally based on some presumptions and have some defects. With the development of artificial intelligent optimization technologies, the stochastic methods of global searching and optimization have attracted many interests, and have been applied in power system reactive power optimization. In [5], methods based on PSO, GA, Tabu search and fuzzy control, expert system, and neural network, are proposed with demonstration of good results. This paper proposes a hybrid approach to the reactive power optimization (RPO) problem. Particle Swarm Optimization (PSO) is one of the evolutionary computation (EC) technique based on swarm intelligence. It is sensitive to the tuning of its parameters and has a flexible mechanism to explore a global optimum point within a short calculation time [8]. By employing the PSO initially the solution quality improves rapidly; later on obtaining the further improvement is very difficult and most of the computation time is spend over obtaining small improvements. The hybrid Particle swarm optimization (PSO) [4-6] methods both under the category of Evolutionary Algorithms have been implemented independently as optimization techniques in the present paper, the authors propose a very new come near for the solution of the reactive power optimization (RPO) problem based on hybrid Particle swarm optimization (PSO) on an IEEE 30-bus power system and a practical 57- bus power system. Simulation results show that the proposed hybrid approach converges to better solutions much faster than the previous reported approaches.

II. PROBLEM FORMULATION

The reason of the RPO is to reduce the system real power Losses. The general RPO with standard power system circumstance can be formulated [12] as follows: The objective function is represented as:

$$P_L = \sum_{i=1}^{nl} loss\ k \qquad (1)$$

Where,

$P_L = network\ real\ power\ loss$

nl = number of line

The reactive power optimization (RPO) problem is subjected to the following constraints

(A)The Power constraint equations:

The power loss is a non-linear function of bus voltages, which are functions of control variables. The minimization predicament is subject to operating constraints [12], which are limits on various control variables (the inequality constraints) and power flow constraints (the equality constraints).

Equality constraints:

$$P_i - V_i \sum_{i=1}^{N_B} V_j \left(G_{ij} \cos\theta_{ij} - B_{ij} \sin\theta_{ij}\right) = 0, \quad i \,\varepsilon\, N_{B-1} \tag{2}$$

$$Q_i - V_i \sum_{i=1}^{N_B} V_j \left(G_{ij} \sin\theta_{ij} - B_{ij} \cos\theta_{ij}\right) = 0 \quad i \,\varepsilon\, N_{PQ} \tag{3}$$

Where,

V_i = Voltage magnitude at bus I

V_j = Voltage magnitude at bus j

P_i, Q_i = Real and reactive powers injected into network at bus i

G_{ij}, B_{ij} = Mutual conductance and susceptance between bus i and bus j

Q_{gi} = Reactive power generation at bus i

$N_B - 1$ = Total number of buses excluding slack bus

N_{PQ} =Number of PQ buses

θ_{ij} = Voltage angle difference between bus i and bus j

Inequality Constraints:

In the control variables, the generator bus voltages (AVR operating values) are taken as continuous variable; the transformer tap settings are taken as discrete variable and shunt susceptance values are taken as binary variable. The load bus voltages and reactive power generation Q_g are taken as state variables.

Continuous control variable:

$$V_i^{min} \le V_i \le V_i^{max} \quad ; \quad i \varepsilon N_B \tag{4}$$

Discrete Control variable:

$$t_k^{min} \le t_k \le t_k^{max} \quad ; \quad i \varepsilon N_T \tag{5}$$

State Variables:

$$Q_{ci}^{min} \le Q_{ci} \le Q_{ci}^{max} \;\; ; \;\; i \,\varepsilon\, N_c \tag{6}$$

$$Q_{gi}^{min} \le Q_{gi} \le Q_{gi}^{max} \quad ; \quad i \,\varepsilon\, N_g$$

$$|s_1| \;\le\; |s_1^{max}| \tag{7}$$

$$S_l \le S_l^{max} \quad ; \quad l \varepsilon N_l \tag{8}$$

Where,

t_k= Tap setting of transformer at branch k

Q_{Ci}= Reactive power generated by i^{th} capacitor bank

Q_{gi} = Reactive power generation at bus i

S_l = Apparent power flow through the i^{th} branch

N_B = Total number of buses

N_T= Number of tap-setting transformer branches

N_c = Number of capacitor banks

N_g = Number of generator buses

State variable are restricted by adding them as a quadratic consequence terms to the objective function. Therefore the equation (1) is changed to the following form:

$$Min. F_T = f + K_v \sum_{i=1}^{N_{pq}} (V_i - V_i^{lim})^2 + K_q \sum_{i=1}^{N_g} (Q_{gi} - Q_{gi}^{lim})^2 + K_f \sum_{i=1}^{N_b} (S_l - S_l^{lim})^2 \quad (9)$$

Where K_v , K_q and K_f are the penalty factors for the bus voltage limit violations, generator reactive power limit violations and line flow violations respectively.

$$X_i^{lim} = X_i^{max} \text{ if } X_i > X_i^{max}$$

$$X_i^{lim} = X_i^{min} \text{ if } X_i < X_i^{min}$$

$$F = \frac{K}{F_T} \quad (10)$$

Where k is a large constant this is used to amplify $1/F_T$ the value of which is usually small, so that the fitness value of the chromosome will span a wider range. The objective function of the target power system is calculated using load flow calculation with the above mentioned equality and inequality constraint.

III. PARTICLE SWARM OPTIMIZATION APPROACH

PSO algorithm, originally introduced by Kennedy and Eberhart (1995). Similar to evolutionary algorithm, the PSO technique conducts searches using a population of particles, corresponding to individuals. Each particle represents a candidate solution to the reactive power optimization (RPO) problem. In a HPSO system, particles change their positions by flying around in a multidimensional search space until a relatively unchanged position has been encountered, or until computational boundaries are exceeded. In social science context, a PSO system combines a social –only model and a cognition-only model. The social-only component suggests that individuals ignore their own experience and adjust their behavior according to the successful beliefs of the individual in the neighborhood. On the other hand, the cognition-only component treats individuals as isolated beings. A particle changes its position using these models. [1-3] The PSO system simulates the knowledge evolvement of a Social organism, in which *N* individuals, a potential Solution to a problem is represented as a particle flying in D-dimensional search space, with the position vector $X_i = (X_{i1}, X_{i2}, X_{i3}, \dots \dots . X_{iD})$ and velocity $V_i = (V_{i1}, V_{i2}, V_{i3}, \dots \dots . V_{iD})$Each particle records its best previous position (the position giving the best fitness value) as $P_{besti} = P_{besti_1}, P_{besti_2}, \dots\dots P_{best_{id}}$ called personal best position. The global version of the PSO keeps track of the overall best value (g^{best}), and its location, obtained thus far by any particle in the population. At each iteration, each particle competes with the others in the neighborhood or in the whole population for the best particle (with best fitness value among neighborhood or the population) with best position $g_{besti} = g_{best\,i_1}, g_{besti_2} \dots \dots g_{best_{id}}$ called global best position. Then utilize those reminiscences to regulate their own velocity and position of each particle can be calculated as shown in the following formulas:

$$V_{id} = w_i v_{id}^k + C_1 rand_1 + C_2 rand_2 (g_{bestid} - X_{id}^k) \quad (11)$$

$$X_{id} = X_{id} + V_{id} \quad (12)$$

where i is the number of iteration; C1and C2are the cognitive and social components that are the acceleration constants responsible for varying the particle velocity towardsp_{best} andg_{best}, respectively; rand and Rand are two random numbers within (0, 1); and the parameter W is the inertia weight introduced to accelerate the convergent speed of the PSO [4].The particle swarm optimization algorithm is simple in concept easy to implement and computational efficient.

The weighting function is usually utilized in the above equation (11):

$$w_i = w_{max} - \frac{w_{max} - w_{min}}{iter_{max}} \times iter \quad (13)$$

Where,

w_{max} =initial weight

w_{min} = final weight

I_{ter} = current iteration

$Iter_{max}$ = maximum iteration

Using the above equation (13), a certain velocity which gradually gets close to p_{best} and g_{best} can be calculated. The current position can be modified by equation (12). The right hand side of Equation (11) consists of three terms. The first term is the previous velocity of the agent. The second term and third terms are utilized to change the velocity of agent. Without second third terms, the agent will keep on flying in the same direction until it hits the boundary. It's to explore new areas and, therefore, first term corresponds to diversification in the search procedure. On other hand, without the first term, velocity of the flying agent is only determined by using its current position and best position in history. It keeps track of its coordinates in hyperspace which are associated with its previous best fitness solution, and also of its counterpart corresponding to the overall best value acquired thus far by any other particle in the population. Vectors are taken as presentation of particles since most optimization problems are convenient for such variable presentations. In fact, the fundamental principles of swarm intelligence are adaptability, diverse response, proximity, quality, and stability. It is adaptive corresponding to the change of the best group value [6, 13]. The allocation of responses between the individual and group values ensures a diversity of response. The agents will try to converge to their p_{best} and g_{best} therefore, the terms correspond to intensification in the search procedure.

IV. HPSO ALGORITHM PROCEDURE

Step 1: Initialization of the parameters
Step 2: arbitrarily set the velocity and location of each and every one particles.
Step 3: calculate the robustness of the preliminary particles by conducting Newton-Raphson power flow analysis results. Pbest of e ach particle is set to preliminary position. The preliminary best evaluation value among the particles is set to gbest.
Step 4: revolutionize the velocity and position of the particle according to the equations (11) to (13).
Step 5: Select the best particles come into mutation operation according to (14).
Step 6: If the location of the particle violates the limit of variable, set it to the limit value.

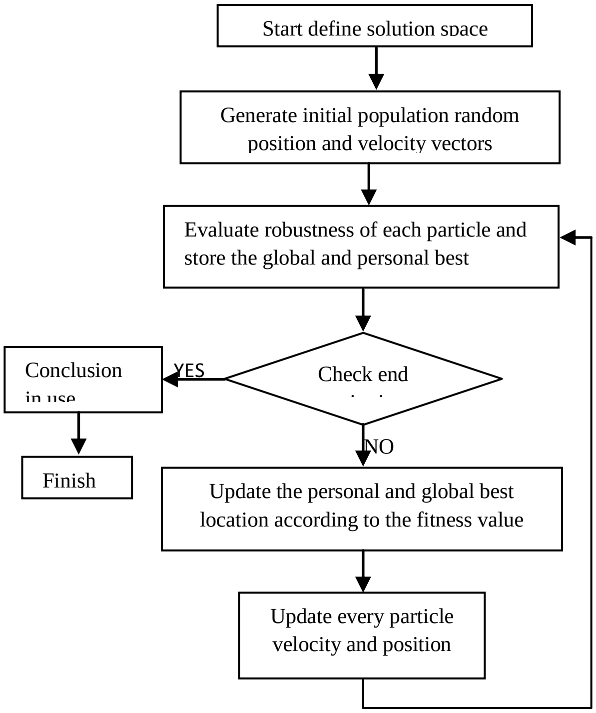

Fig-1 Flow Chart for PSO

Step 7: Compute the fitness of new particles. If the fitness of each character is better than the previous pbest the current value is set to pbest value. If the best pbest is better than gbest, the value is set to be gbest.
Step 8: The algorithm repeats step 4 to step 7 awaiting the meeting criteria is met, usually a satisfactorily good fitness or a greatest quantity of iterations.

The advantages of PSO more than other established optimization techniques can be summarized as follows:

(1) PSO uses probabilistic evolution system and not deterministic regulations. Hence, PSO is a kind of stochastic optimization algorithm that can search a complicated and unsure area. This makes PSO more bendable and roust than predictable methods.

(2) PSO uses payoff (presentation guide or purpose function) in sequence to guide the search in the difficulty breathing space. Therefore, PSO can without difficulty arrangement with non-differentiable objective functions. Moreover, this property relieves PSO of assumptions and approximations, which are often necessary by fixed optimization models.

(3) Separate Genetic Algorithm (GA) and other heuristic algorithms, PSO has the elasticity to control the balance between the global and local examination of the explore space. This single characteristic of a PSO overcomes the rash meeting difficulty and enhances the explore ability.

(4) PSO is a population-based search algorithm this property ensures PSO to be a lesser amount of subject to receiving gripped on limited minima and different the established methods, the solution excellence of the future advance don't rely on the initial people. Preparatory wherever in the search space, the algorithm ensures the meeting to the most favorable explanation [14, 15].

V. Test Results And Analysis

The process described above was implemented using the FORTRAN language and the residential software Program was executed on a 450 MHz Pentium III PC. The Hybrid particle swarm optimization based reactive power optimization problem was implemented using MATLAB code was executed on a PC. The proposed algorithm was run minimization of real power loss as the objective function [3]. The IEEE 30-bus system has 6 generator buses, 24 loads buses and 41 transmission lines of which four branches are (6-9), (6-10) , (4-12) and (28-27) - are through the tap setting transformers. The IEEE 57-bus system has 7 generator buses, 50 load buses and 80 transmission lines of which 17 branches are with tap setting transformers. The real power settings are taken from [1]. 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, 0.05 p.u. for the PQ buses and the reference bus for IEEE 30-bus and IEEE 57-bus system. To obtain the most favorable values of the control variables, the HPSO based algorithm was run Maximum no. of generations: 50

PSO based parameters

Maximum no. of generations	:	60
Population size	:	30
W_{max}	:	0.9
W_{min}	:	0.4
C_1	:	2
C_2	:	2

The effectiveness of the PSO algorithm has been demonstrated through solution of reactive power optimization problem in, IEEE 30-bus test system and IEEE 57-bus system.

TABLE 1. Comparison of simulation results of RPO with Other methods for IEEE-30 bus systems

	PSO	GA	EP	**HPSO**
$P_{loss\,(MW)}$	4.52	4.71	4.92	4.472

TABLE 2. Comparison of results of reactive power Optimization for IEEE30 and IEEE-57 bus systems

Compared item	IEEE-30 bus	IEEE-57 bus
best	4.4240	26.5731
worst	4.4769	26.6754
average	4.6497	26.6132

TABLE 3: comparison of best and worst results in IEEE30, 57 and IEEE 118- bus systems

Loss(MW)	**IEEE-30 bus**	**IEEE-57 bus**	**IEEE-118 bus**
best	4.32	26.5760	135.51
worst	4.46	26.6390	137.17
average	4.37	26.6128	136.42

VI. CONCLUSIONS

The performance of the expectations method recognized through its estimation on the IEEE 30-bus and IEEE 57- bus power system shows that HPSO is able to undertake global search with a fast convergence rate and a characteristic of robust computation. From the reproduction learning, it has been found that HPSO converges to the global optimum. The optimization strategy is all-purpose and can be used to other power system optimization problems as well. Table(2,3)gives the best and the worst solutions obtained using particle swarm optimization(PSO) and genetic algorithm(GA) .reproduction consequences shows that the particle swarm optimization(PSO) and genetic algorithm(GA) based reactive power optimization (RPO)algorithm is able to improve profile along with minimization in power scheme. This new strategy can adequately utilize the historical in sequence in PSO algorithm. In addition, to intensify the refined search ability in restricted region, local search procedure is employed and hybridized with PSO algorithm. Based on the above constraints management procedure and restricted explore method, the HPSO algorithm model is proposed for reactive power optimization (RPO) difficulty. The computational results verify its good presentation in terms of solution excellence, computational cost as well as the meeting stability.

Acknowledgement

The authors are thankful to Director, Madhav Institute of Technology and Science, Gwalior (M.P.) India for providing support and facilities to carry out this research work.

References

[1] Haibo Zhang, Lizi Zhang, Fanling Meng, “Reactive Power Optimization Based on Genetic Algorithm”, Proceedings of International Conference on Power System Technology, POWERCON '98. 1998, Vol. 2, pp. 1448 –1453

[2] W.N.W Abdullah, H. Saibon A.AM Zain, “Genetic Algorithm for Optimal Reactive Power Dispatch”, Proceedings of International Conference on Energy Management and Power Delivery, 1998. Vol. 1, 3-5 Mar 1998, pp. 160-164.

[3] Luss, R. and Jaakola, T.H.I. 1973 Optimization by direct search and systematic reduction of the size of the search region American Institute of Chemical Engineering Journal, (1973)760-766.

[4] A. I.Selvakumar and K. Thanuskodi,“Anti predatory particle swarm optimization solutionto non convex economic dispatch problems”, Electric Power System Research, Vol. 78, No. 1, Jan. 2008, pp. 2 -10.

[5] Venkatesh, B.; Sasadivam, G.; Abdullah Khan [M]. “Towards on-line optimal reactive power scheduling using ANN memory model based method”, Power Engineering Society 1999 Winter Meeting, IEEE, Volume 2, 31 Jan-4 Feb 1999 Page(s):844 - 848 vol.2

[6] J. Kennedy and R.C. Eberhart, “Particle swarm optimization”, IEEE Int. Conf. Neural Networks, Perth, Australia, 1995

[7] DAS D B, PATVARDHAN C. “Reactive Power Dispatch with a Hybrid Stochastic Search Techniques”, Electric Power Energy System, 2002, 24(9): 731-736

[8] Liang, J.J., Qin, A.K Suganthan P.N. and Baskar S.,2004 Particle swarm optimization algorithms with novel learning strategies IEEE International Conference on. Systems, Man and Cybernetics, (2004) 3659-3664

[9] Shonkwiler, R., Mendivil, F. and Deliu, A. “Genetic Algorithms for the I-D Fractal Inverse Problem”. Proceedings of the 4th International Conference on Genetic Algorithms and Their Applications, pp: 495-501. University of California, San Diego, 1991

[10] Bjelogrlic M, Calovic M S, Ristanovic P, et al. Application of Newton’s optimal power flow in voltage/reactive power control [J]. IEEE Trans on power system, 1990, 5(4): 1447-1454.

[11] B. Bhattacharyya and S.K. Goswami, “SA based genetic algorithm for reactive power optimization”, The Journal of CPRI, Vol. 3, No. 1, pp. 59-64, Sept. 2006.

[12] Abdul Rahaman, K.H. Shahidehpour, S.M.1993 A fuzzy based optimal reactive power control IEEE Transactions on power System, 8(1993) 662-670.

[13] H.D. Chiang, J.C. Wang, O. Cockings, and H.D. Shin,“Optimal capacitor placements in distribution systems: part 2: solution algorithms and numerical results”, IEEE Trans. Power Delivery, Vol. 5, No. 2, pp. 634-641, April 1990.

[14] Golhdberg, D.G. “Genetic Algorithm in search optimization and machine learning” , Addison Wesley: reading, M.A. 1989.

[15] K.-P. Wang, L. Huang, C.-g. Zhou, and W. Pang, “Particle Swarm Optimization for Traveling Salesman Problem,” In Proceedings of the Second International Conference on Machine Learning and Cybernetics. Vol. 5, pp. 1583-1585, 2003.