# OPTIMAL REACTIVE POWER DISPATCH USING PARTICLE SWARM OPTIMIZATION ALGORITHM

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Abstract: Reactive power dispatch plays a major role in order to present good facility secure and profitable operation. Optimal reactive power dispatch is useful to improve the voltage profile, to reduce losses, to improve voltage stability etc. This paper presents a Particle Swarm optimization (PSO) based approach for solving optimal Reactive Power Dispatch (ORPD) in power system. The proposed algorithm has been applied to the IEEE 30-bus system to find the optimal reactive power control variables, while keeping the system under safe found to be more effective for this task.

**Key words:** Optimal Reactive Power Dispatch (ORPD), Particle Swarm Optimization (PSO), Optimal Power Flow (OPF)

## 1. Introduction

Optimal power flow (OPF) is a main concern in the power system. Currently, planner and operator often use Optimal Reactive Power Flow (ORPF) as a powerful assistant tool in both planning and operating stage [1]. During the decades, study on reactive power has been available on. The problem of reactive power dispatch for improving economic operation and control of power system has arrived much more attention [2]. To regulate the power system voltage stability, voltage profile and to reduce the power loss appropriate reactive power and voltage are required [3, 4]. Several approaches are used to optimize the control variables of ORPD like generator voltage magnitude, the tap ratios of transformer, static VAR sources etc with the constraints of voltage limits of buses, tap ratio limits, VAR voltage limit of generators.

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Dynamic programming has successfully proved its capabilities in this field [5]. However, ORPF problem is not an exactly convex problem; as a result, most of the classical optimization techniques might converge to a local optimum instead of at the global optimum. Moreover, these classical techniques cannot solve the complex objective functions which are not differentiable. Due to major development in computers, capability of evolutionary algorithms (EAs), such as genetic algorithm (GA) [6-10] based optimization methods have been proposed which also suffer to get the best optimal results.

Hence, Particle Swarm Optimization (PSO) method is effectively used to solve the OPF problem. The global and local study capabilities of PSO are used to search for optimal settings of the control variables. The PSO algorithm is demonstrated with different power system objectives. An improved PSO algorithm is used to solve the ORPF problem with IEEE 30-bus system. Yoshida et al. [11] applied PSO for reactive power and voltage control with voltage security assessment. In [12] an adaptive PSO reactive power optimization is developed. Multi-agent-based PSO method is proposed in paper [13] to solve reactive power dispatch problem. A hybrid PSO with mutation operator to minimize the active power loss is presented in paper [14]. Kumari et al. [15] solved optimal reactive power control problem using an improved version of PSO. To find the optimal solution for the design of active filter using PSO algorithm is explained is

paper [16]. The Capability of the PSO method is investigated through the optimization and control of SFIG (Self Excited Induction Generator) is presented in paper [17]. For control of reactive power and voltage, Vlachogiannis et al. [18] proposed new PSO algorithms. Cai et al. [19] presented a modified version of PSO method for solution of optimal reactive power dispatch problems along with improvement in voltage stability margin. The additions of new features to low value solutions improve the value of solutions. Minimization of active power loss as the objective function using PSO is applied to solve the reactive power dispatch problem. The IEEE 30-bus system is employed to carry out the simulations and the results obtained using the PSO-based approaches are found to be better than the results obtained using the conventional method.

This paper is concerned with the application of PSO for optimal reactive power dispatch with line flow and voltage stability constraints. The L-index defined in the work [20] is used in this paper to compute the voltage stability level of the method. This index uses in turn from a regular power flow and is in the range of zero to one. In the current work, some limits are applied on the maximum value of Lindex in the normal operating condition so that even if a contingency occurs on the system the L-index value does not reach a disturbing level. Thus, voltage stability constrained reactive power dispatch problem is solved in this paper using the PSO algorithm. IEEE 30-bus test system has been used to carry out the simulation study.

Section II of the paper provides a brief description and mathematical formulation of optimal reactive power flow (ORPF) problems. The original PSO approach is described in Section III along with a short description of the algorithm. The simulation studies are discussed in Section IV. The conclusion is tried in Section V

## 2. Problem Formulation

The RPD problem aims at minimizing the real power loss in a power system while satisfying the unit and system constraints. This objective is achieved by proper alteration [2123] of reactive power variables like generator voltage magnitudes  $(V_{gi})$ , reactive power generation of capacitor banks  $(Q_{ci})$  and transformer tap settings  $(t_{\nu})$ .

This is mathematically stated as;

Minimize 
$$P_{loss} = \sum_{K \in N_i} g_k \left( V_i + V_j - 2V_i V_j \cos \theta_{ij} \right)$$
 (1)

The real power loss given by (1) is a nonlinear function of bus voltages and phase angles which are a function of control variables. The minimization trouble is subjected to the following equality and inequality constraints:

i. Load flow constraints:

$$P_i - V_i \sum_{j=1}^{N_B} V_j (G_{ij} Cos\theta_{ij} + B_{ij} Sin\theta_{ij}) = 0, \quad i = 1, 2, \dots, N_B - 1$$
 (2)

$$Q_{i} - V_{i} \sum_{j=1}^{N_{B}} V_{j} \left( G_{ij} Sin\theta_{ij} - B_{ij} Cos\theta_{ij} \right) = 0, \quad i = 1, 2, \dots, N_{PQ}$$
(3)

ii. Voltage constraints:

$$V_i^{\min} \le V_i \le V_i^{\max}; \quad i \in N_B$$
 (4)

iii. Generator reactive power capability limit:

$$Qg_i^{\min} \le Qg_i \le Qg_i^{\max}; \quad i \in N_g \quad (5)$$

iv. Reactive power generation limit of capacitor banks:

$$Qc_i^{\min} \le Qc_i \le Qg_i^{\max}; i \in N_c$$

v. Transformer tap setting limit:

$$t_k^{\text{min}} \le t_k \le t_k^{\text{max}}; \quad k \in N_T$$
 (7)

vi. Transmission line flow limit:

$$S_l \leq S_l^{\text{max}}; \quad l \in N_l$$
 (8)

Vii. Voltage stability constraint

$$L^{\max} \le L^{\min} \tag{9}$$

The voltage stability index given in Equation (9) is evaluated as follows:

First, the L-indices [9] of all the load buses in the system are computed using the expression:

$$L_{j} = \left| 1 - \sum_{i=1}^{N_{g}} F_{ij} \frac{Vi}{Vj} \angle (\theta_{ji} + \delta_{i} + \delta_{j}) \right|$$
(10)

The values of  $F_{ji}$  are obtained from the matrix  $F_{LG}$ 

where, 
$$F_{LG} = -[F_{LL}]^{-1}[F_{LG}]$$
 (11)

The maximum of the L indices ( $L^{\max}$ ) gives the proximity of the system to voltage collapse. The bus with the maximum L index value determination is the most vulnerable bus in the system which needs critical reactive power support.

The equality constraints given by Equations (2) and (3) are satisfied by running the Newton Raphson Power flow algorithm. Generator bus terminal voltages transformer tap settings  $(t_k)$  and the reactive power generation of capacitor bank  $(Q_{ci})$  are the optimization variables and are self-restricted between the minimum and maximum value by the optimization algorithm. The limits on active control generation on the slack bus  $(V_{gs})$ , load bus voltages  $(V_{load})$  and reactive power generation  $(Q_{gi})$ , line flow  $(S_1)$  and voltage stability level ( $L^{\text{max}}$ ) are state variables which are satisfied by adding a penalty function to the objective function and minimizing the combined function.

## 3. Particle Swarm Optimization

Particle swarm optimization is one of the most recent developments in the category of combinatorial metaheuristic optimizations. This technique has been developed below the scope of artificial life where PSO is inspired by the natural phenomenon of fish schooling or bird The Flowchart of Particle Swarm Optimization as shown in fig1. PSO is mainly based on the fact that in quest of reaching the optimum solution in a multi-dimensional space, a population of particle is formed whose present coordinate determines the cost function to be minimized. After each iteration, the original velocity and hence the new position of each particle is updated on the basis of a summated influence of each particle's current velocity. distance of the unit from its own best performance, achieved so far

Let x and v denote a particle position and its corresponding velocity in an explore space, correspondingly. Therefore, the  $i^{th}$  particle is represented as  $X_i = (X_{i1}, X_{i2}, ..... X_{id})$ 

in the 'd' dimensional space. The best previous position of the  $i^{th}$  particles recorded and represented as  $pbest_i = (pbest_{i1}, pbest_{i2}, ..., pbest_{id})$ . The index of the best particle among all the particles in the group is represented by the gbestd. The rate of the velocity for the particle i is represented as  $v_i = (v_{i1}, v_{i2}, ..., v_{id})$ .

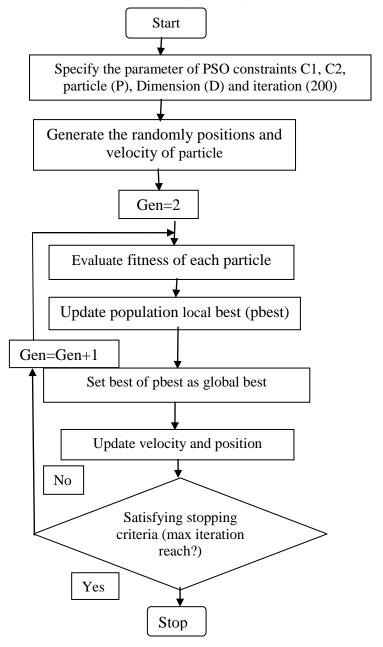


Fig.1. Flow Chart of PSO

The modified velocity and position of each particle can be calculated using the current velocity and the distance from  $pbest_{id}$  to  $gbest_{id}$  as shown in the following formulae:

$$V_{id}^{k+1} = W * V_{id}^{k} + C_{1} * rand() * (pbest - X_{id}^{k}) + C_{2} * rand() * (gbest_{d} - X_{id}^{k})$$

$$X_{id}^{k+1} = X_{id}^{k} + V_{id}^{k+1}$$

$$i = 1, 2, \dots, N_{p}, d = 1, 2, \dots, N_{g}$$
(12)

where,  $N_{\scriptscriptstyle p}$  is the number of particles in a group,  $N_{g}$  the number of members in a particle, k the pointer of iterations, w the inertia weight factor, C1, C2 the acceleration constant, rand ( ) the uniform random value in the range  $[0, 1], V_i^k$ the velocity of a particle i at iteration k,  $V_d^{\min} \le V_{id}^{k} \le V_d^{\max}$  and  $X_i^{k}$  is the current position of a particle i at iteration k. In the above procedures, the parameter determined the resolution, with which region is to be searched between the present position and the target position. If  $V^{\text{max}}$  is too high, articles might fly past good solutions. If  $V^{\max}$  is too small, particles may not explore sufficiently beyond local solution. The constants C1 and C2 stand for the weighting of the stochastic acceleration terms that pull each particle toward  $P_{best}$  and  $g_{best}$  positions. Low values allow particle to roam far from the target regions before creature tug back. On the other hand, high value results in abrupt movement near or past, objective region. Hence, the acceleration constants C1 and C2 were regularly set to be 3.0 according to precedent experiences. Suitable selection of inertia weight 'w' provides a balance between global and local explorations, thus requires fewer iteration on average to find a sufficiently optimal solution. Originally developed 'w' often decreases linearly from about 0.3 to -0.2 during a run. In general, the inertia weight w is put according to the follow equation:

$$W = W_{\text{max}} - \frac{W_{\text{max}} - W_{\text{min}}}{iter_{\text{max}}} X iter$$
 (14)

Where  $iter_{max}$  is the maximum quantity of iterations and 'iter' is the current number of iterations.

## 4. Computational Algorithm

In this section, an algorithm based on particle Swarm Optimization for solving the dynamic economic load dispatch problem is described as follows:

Let

 $P_k = [P_{11}, P_{21}, P_{i1}, \dots, P_{N1}), \dots, (P_{1m}, P_{2m}, \dots, P_{im}, \dots, P_{Nm}) \dots]$  be the trial vector designating  $K^{th}$  particle of the population and  $K = 1, 2, 3, \dots, N_p$ . The elements

of vector are  $P_k$  real power outputs of N generating units over m time sub –internals.

**Step 1**: Read the method contribution data which is consisting of fuel cost curve coefficient, power generation limits, ramp rate limits of all generators, load demands, transmission losses co-efficient, number of sub-intervals and duration of sub-intervals.

**Step 2**: Initialize the particles of the population in a random manner according to the limits of each unit counting character dimensions (i.e.) generator reactive limit, transformer tap limit, search point and velocity. These initial particles must be feasible candidate solutions that satisfy the practical operating constraints.

Step 3: Calculate the fitness function (1)  $C_{it}$  (

 $P_{\rm Git}$ ) for each individual  $P_{\rm K}$  in the population.

**Step 4**: Compare the loss of each particle with that of its  $P_{\text{best}}$ . If the new loss value for  $P_K$  is less than that obtained with  $P_{\text{best}K}$ , then replace the co-ordinates of P best K with the present co-ordinates of  $P_K$ .

**Step 5**: Compare the loss values of  $P_{bestK}$  of the particles to determine the best particle the store the co-ordinates of the best particle as  $g_{best}$ .

**Step 6**: Modify the associate velocity of every particle according to following equation.

$$V_{i}^{k+1} = \omega V_{i}^{k} + C_{1} rand_{1} \left( Pbest - S_{i}^{k} \right) + C_{2} rand_{2}$$
$$\left( gbest - S_{i}^{k} \right) + C_{3} rand_{2} \left( gbest - S_{i}^{k} \right) a$$

Where

$$\omega = \omega_{\text{max}} \left[ \frac{(\omega_{\text{max}} - \omega_{\text{min}})}{iter_{\text{max}}} \right]$$
 iter.

 $\omega_{\rm max}$  is the initial weigh

 $\omega_{\min}$  is the final weight

 $ter_{max}$  is the maximum iteration

number and

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**Step 6**: Modify the associate velocity of every particle according to following equation.

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Where

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 iter.

 $\omega_{\rm max}$  is the initial weigh

 $\omega_{\min}$  is the final weight

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number and

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number.

**Step 7**: Modify the member current position (Searching point) of each particle according to the following equation.

$$S_i^{K+1} = S_i^k + V_i^{K+1}$$

**Step 8**: If the number of iterations reaches the maximum, then go to step 9 other wise, go to Step 3.

**Step 9:** The particle that generates the latest best is the solution of the problem.

## 5. Simulation Result

This section presents the details of the simulation study carried out on IEEE 30-bus system using the proposed PSO-based method. IEEE 30-bus system consists of 6 generator buses, 24 load buses and 41transmission lines of which 4 branches (6-9), (6-10), (4-12) and (28-27) are with the tap location transformer.

Generator parameter is given in the Appendix. The transmission line parameter of this system and the base loads are given in [10]. For the RPD problem, the candidate buses for reactive power compensation are 10, 12, 15, 17, 20, 21, 23, 24 and 29. The PSO based RPD algorithm is implemented on MATLAB platform and is execute using three different case studies. In case1, RPD problem is solved using PSO with base load condition. In case 2, reactive power dispatch is done with 150% of the base load without considering the voltage stability level of the system. In case 3, voltage stability limit is integrated to improve the voltage stability in the contingency state. The results of these simulations are obtainable below.

## Case 1

In this case, the optimal reactive power dispatch problem is solved under base load condition using the PSO algorithm. The real power setting of the generator is taken from [2]. To obtain the optimal values of the control variables, the PSO based algorithm is run with different control parameter settings.

The optimal values of the control variables and power loss obtained using the above settings are presented in Table 1. To illustrate the convergence of the algorithm, the connection among the best fitness value of the population and the average fitness are plotted against the number of generations in Fig. 2. From the figure, it can be seen that the proposed algorithm converges rapidly towards the optimal solution. The minimum transmission loss obtained is **7.037 MW**.

In this method, the control variables are updated in the optimization process and the range of optimum step length is chosen to be very small, otherwise oscillations will occur and the algorithm will deviate. Table 2 gives the comparison between the results obtained using the proposed PSO approach. From this Table, it is found that the minimum loss obtained using the proposed PSO based advance. Notably, the loss obtained here is also less than the value reported in the literature [7-8] using the evolutionary computation techniques. This shows the efficiency of the proposed advance to solve the RPD problem.

Table 1 Optimal control variable

Control	Optimal control variable settings		
variables	Case1	Case 2	Case 3
	(Base case)	(150% load)	(with L constraint)
V <sub>1</sub>	1.0373	1.0341	1.0357
$V_{2}$	1.0310	1.0040	1.0103
V <sub>5</sub>	1.0119	0.9722	0.9738
$V_{_8}$	1.0143	0.9802	0.9754
V <sub>11</sub>	1.0071	1.0405	1.0468
V <sub>13</sub>	1.0262	1.0500	1.0484
t <sub>11</sub>	1.0500	1.0429	0.9000
t <sub>12</sub>	1.0750	1.0429	0.9000
t 15	1.1000	1.0143	0.9000
t 36	0.9250	0.9571	0.9857
Qc <sub>10</sub>	0	20	20
Qc <sub>12</sub>	0	17.1429	20
Qc <sub>15</sub>	2.8571	8.5714	11.4286
Qc <sub>17</sub>	2.8571	17.1429	20
Qc	2.8571	8.5714	11.4286
Qc	8.5714	20	2.8571
Qc <sub>23</sub>	2.8571	2.8571	14.2857
Qc <sub>24</sub>	0	17.1429	11.4286
Qc <sub>29</sub>	5.7143	5.7143	17.1429
$P_L(MW)$	4.6501	20.8074	21.4004
L <sub>max</sub> (Base case)	0.1828	0.2027	0.1702
L <sub>max</sub> (Contingency case)	0.2237	0.3319	0.2815

Table2 Comparison of Result

Parameter	Case 1	Case 2	Case 3
	PSO	PSO	PSO
P <sub>loss</sub> (MW)	7.037	24.323	24.488
Q <sub>gen</sub> (MVAR)	75.948	110.696	124.887
L-index(max)	0.0486	0.0695	0.0577
Total Q <sub>c</sub> (MVAR)	0.5366	0.3042	0.4748
Load bus voltage violations	No	No	No
Line flow violations	No	No	No

## Case 2

In this case, the load on each bus is uniformly increased to 150% of the base load state to study the voltage stability level of the system under strict conditions. Over again. generator bus voltage magnitudes, reactive power generation of capacitor bank and transformer taps position are taken as control variables. The optimal control variables are obtained by PSO based algorithm is listed in table 1.based on that the minimum loss of 24.245MW and maximum 1-index value of **0.0695** are obtained. In order to test the ability of the system to withstand the contingencies, the system response for the worst case contingency namely, line outage (4-12) is checked. In this case, it is created that the L-index value reached a maximum value of **0.3319.** To keep the Lindex value under suitable value even under contingency condition, it is decided to put some restriction on the L-index value in the normal condition. The simulation results of this case are presented next.

## Case 3

Again in this case, the same values of load condition and generator setting as in case 2 are followed. But an additional constraint in the form of limit on the maximum value of L-index under normal condition is included. This is done to limit the maximum value of L-index under contingency condition from reaching a seriously high value. For the similar contingency, namely line outage (4-12), with the inclusion of the voltage stability constraint the PSO based algorithm is applied to obtain the optimal values of the control variables under standard situation, the result of which is given in the fourth column of Table 1. From these optimal values of control variables when line (4-12) is removed, it is found that the maximum value of L-index reached by the system is 0.0577 only. This improvement in voltage stability is achieved because of the restriction put on the maximum L-index value in the base case condition. This shows the effectiveness of the proposed algorithm for voltage security enhancement.

The best solutions are shown in Table 2. The convergence characteristic of PSO algorithm is shown in Fig. 2. It can be seen that the proposed algorithm converges rapidly towards the optimal solution. The comparison of

objective function values as shown in Table 3.

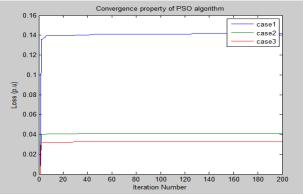


Fig.2. Convergence Property of PSO Algorithm

Table3 Comparison of objective function values

Objective function Minimum $P_{loss} = \sum_{K \in N_l} g_k (V_i + V_j - 2V_i V_j \cos \theta_{ij})$					
Value	Case 1	Case 2	Case 3		
gbest value	7.037	24.245	24.488		
Average	7.098	24.361	24.611		
value					
Bad value	7.124	24.399	24.809		

## 6. Conclusion

Voltage instability condition in a stressed power system could be improved by implementing an effective Reactive Power Dispatch (RPD) method. In this suggestion, Particle swarm optimization (PSO) solution to the ORPF problem has been presented for determination of the global or near-global optimum solution for optimal reactive power dispatch. The proposed algorithms have been experienced on the IEEE 30-bus test system to minimize the active power loss. The optimal setting of control variable is obtained in  $L_{\rm max}$  constraints. With the addition of voltage stability constraint, the algorithm has helped to improve the voltage security of the system.

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