Optimal Reactive Power Dispatch Using Efficient Particle Swarm Optimization Algorithm

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Abstract*-This paper presents an efficient particle swarm optimization (EPSO) algorithm for the solution of the optimal reactive power flow (ORPF). The objective is to minimize the total active power loss with optimal setting of control variables without violating inequality constraints and satisfying equality constraint. Control variables are both continuous and discrete. The continuous control variables are generator bus voltage magnitudes, while the discrete variables are transformer tap settings and reactive power of shunt compensators. The PSO algorithm solution has been tested on the standard IEEE 30-Bus test system with both continuous and discrete control variable. The results have been compared to genetic algorithm method.*

Key words*- active power Loss minimization, particle swarm Optimization (PSO), load flow (Lf)*

I-Introduction

The main objective of optimal reactive power dispatch (ORPD) of electric power system is to minimize an active power loss via the optimal adjustment of the power system control variables, while at the same time satisfying various equality and inequality constraints. The equality constraints are the power flow balance equations, while the inequality constraints are the limits on the control variables and the operating limits of the power system dependent variables. The problem control variables include the generator bus voltages, the transformer tap settings, and the reactive power of shunt compensator, while the problem dependent variables include the load bus voltages, the generator reactive powers, and the power line flows. Generally, the ORPD problem is a large-scale highly constrained nonlinear non convex and multimodal optimization problem.

To solve the ORPD problems, the optimization methods are classified into classical and heuristic optimization methods.

Classical optimization methods, such as gradient based optimization algorithm [1,2], quadratic programming, interior point method [3], non linear programming[5]. Recently, due to the basic efficiency of interior point method, witch offer fast convergence and convenience in handling inequality constraints in comparison with other methods, interior point method has been widely used to solve the ORPD problem of large scale power systems. It converts the inequality constraints to equalities by the introduction of nonnegative slack variables. A logarithmic barrier function of the slack variables is then added to the objective function and multiplied by a barrier parameter, which is gradually reduced to zero during the solution process. Linear programming methods are fast and reliable but their main disadvantage is associated with the piecewise linear approximation. Nonlinear programming method is known to suffer from the complex algorithms.

Most of these methods are based on the combination of the objective function and the constraints by Lagrange formulation, Kuhn Tucker condition, and applying sensitivity analysis and gradient-based optimization algorithm [4].

Heuristic methods such as genetic algorithm (GA), evolutionary programming algorithm, and particle swarm optimization (PSO) have been recently proposed for solving the ORPD problem. These algorithms have recently found extensive applications in solving global optimization searching problems, when the closed-form optimization technique cannot be applied. GA is parallel and global search technique emulating natural genetic operators such as, selection, crossover and mutation. A GA based optimization method is more likely to converge toward the global solution because it, simultaneously, evaluates many points in the parameter space. It does not need to assume that the search space is differentiable or continuous. The PSO algorithm is also a global search method which explores search space to get to the global optimum. The PSO is a stochastic, population-based computer algorithm modeled on swarm intelligence. PSO finds the global minimum of a

multidimensional, multimodal function with best optimum. In reference [8], a standard genetic algorithm method has been proposed to minimize the total active power loss.
In the present paper an efficient PSO algorithm method is used to improve the quality of solution, leading to the near global optimum, and gets the best solution with both continuous and discrete control variables.
The continuous control variables are generator bus voltage magnitudes, while the discrete variables are transformer tap settings and reactive power of shunt compensators.
This method has been tested on the IEEE 30-bus standard system with two cases, one problem contains two VAR shunt compensators; the other contains three VAR shunt compensators. The results are compared with the standard GA.

II-Problem Formulation

The OPF problem is considered as a general minimization problem with constraints, and can be written in the following form:

$$\text{Minimize} \quad f(x,u) \tag{1}$$

$$\text{subject to} \quad g(x,u)=0 \tag{2}$$

$$\text{and:}\ h(x,u)\le 0 \tag{3}$$

Where $f(x,u)$ is the objective function, $g(x,u)$ and $h(x,u)$ are respectively the set of equality and inequality constraints. x is the vector of state variables, and u is the vector of control variables.
The state variables are the load buses voltages, angles, the generator reactive powers and the slack active generator power:

$$x^T=(P_{g1},\theta_2,..\theta_N,V_{L1},..V_{LNL},Q_{g1},..Q_{gng})^T \tag{4}$$

The control variables are the generator bus voltages, the shunt capacitors/reactors and the transformers tap-settings:

$$U=(V_g,T,Q_c)^T \tag{5}$$

or :

$$U=(V_{g1},......V_{gng},T_1,....T_{Nt},Q_{c1},..Q_{cNC})^T \tag{6}$$

Where Ng, NT, NC are the number of generators, number of tap transformers and the number of shunt compensators respectively.

A-Objective Function

The objective of the reactive power dispatch is to minimize the active power loss in the transmission network, which can be described as follows:

$$F=\sum_{k\in Nbr} g_k(V_i^2+V_j^2-2V_iV_j\cos\theta_{ij}) \tag{7}$$

or

$$F=\sum_{i\in Ng}P_{gi}-P_d=P_{gslack}+\sum_{i\ne slack}^{Ng}P_{gi}-P_d \tag{8}$$

Where g_k is the conductance of branch between nodes i and j , Nbr is the number of transmission lines.
P_d is the total active power demand, P_{gi} is is the generator active power of unit i, and P_{gsalck} is the generator active power of slack bus.

B-Equality Constraint

The equality constraint *g(x,u)* of the ORPD problem is represented by the power balance equation, where the total power generation must cover the total power demand and the power losses:

$$P_G=P_D+P_L \tag{9}$$

This equation is solved by running Newton Raphson load flow method, by calculating the active power of slack bus to determine active power loss.

C-Inequality Constraints

The inequality constraints h(x,u) reflect the limits on physical devices in the power system as well as the limits created to ensure system security:
Upper and lower bounds on the active power of slack bus, and reactive power of generators:

$$P_{gslack}^{\min}\le P_{gslack}\le P_{gslack}^{\max} \tag{10}$$

$$Q_{g\min}\le Q_{gi}\le Q_{g\max},\ i\in N_g \tag{11}$$

Upper and lower bounds on the bus voltage magnitudes:

$$V_{i\min} \le V_i \le V_{i\max} \quad i \in N \tag{12}$$

Upper and lower bounds on the transformers tap ratios:

$$T_{i\min} \le T_i \le T_{i\max} \quad i \in N_T \tag{13}$$

Upper and lower bounds on the compensators reactive powers:

$$Q_{c\min} \le Q_c \le Q_{c\max} \quad i \in N_c \tag{14}$$

Where N is the number of buses, N_T is the number of Transformers, N_c is the number of shunt reactive compensators,

In PSO search algorithm all control variables stand in there limits except active power in slack bus

By adding the inequality constraints to the objective function, the augmented fitness function to be minimized becomes:

$$F_T = F + \lambda_V \sum_{i:=1}^{NL} (V_i - V_i^{\lim})^2 + \lambda_S \left(P_{gsalack} - P_{gslack}^{\lim}\right)^2 \tag{15}$$

Where λ_V and λ_s are the penalty factors, and both penalty factors are large positive constants; *NL* is a number of load buses (PQ buses).

F is the total active power loss given by (8).

$V_i^{\lim}$ and $P_{gslack}^{\lim}$ are defined as:

$$V_i^{\lim} = \begin{cases} V_i^{\min} \text{ if } V_i < V_i^{\min} \\ V_i^{\max} \text{ if } V_i > V_i^{\max} \end{cases} \tag{16}$$

$$P_{gslack}^{\lim} = \begin{cases} P_{gslack}^{\min} \text{ if } P_{gslack} < P_{gslack}^{\min} \\ P_{gslack}^{\max} \text{ if } P_{gslack} > P_{gslack}^{\max} \end{cases} \tag{17}$$

The equality constraint and generators reactive power inequality constraints are handling by Newton Raphson load flow calculation method.

Generally, for the reactive optimization problem, the range of variations of P_{gslack} is small then we set $\lambda_s = 0$.

III- Overview of PSO

Particle Swarm Optimization was introduced by R, Eberhart and J, Kennedy in 1995 [10], inspired by social behavior of bird flocking or fish schooling. It is a part of modern heuristic optimization algorithm, it work on population or group in witch individuals called particles move to reach the optimal solution in the multidimensional search space. It works with direct real - valued numbers, which eliminates the need to do binary conversion of a classical canonical genetic algorithm. The number of particles in the group is Np. The initial population of a PSO algorithm is randomly generated within the control variables bounds. Each particle adjusts its position through its present velocity, previous positions and the positions of its neighbors.

In **d** dimensional search space the position and velocity of particle **i** are represented as the vectors:

$X_i = (x_{i1},....,x_{id})$ and $Vt_i = (vt_{i1},....vt_{id})$ respectively where $i \in Np$**,** and d is the number of elements in the particle. It represents in general the number of control variables in the objective function .

Let $Xpbest_i = (x_{i1}^{best},...x_{id}^{best})$ the best previous position of particle i, and $Xgbest = (x_1^{gbest},....x_d^{gbest})$ the best particle among all the particles in the swarm. The updated velocity of particle ***i*** is modified under the following equation:

$$vt_i^{k+1} = \omega vt_i^k + c_1 rand_1 \times (Xpbest_i^k - X_i^k) + c_2 rand_2 (Xgbest^K - X_i^K) \tag{18}$$

where

Vt_i^K : velocity of particle *i* at iteration k;

ω : inertia weight factor ;

c_1, c_2 : acceleration constant;

k : current iteration;

$\text{rand}_1, \text{rand}_2$: random numbers between 0 and 1;

$Xpbest_i^k$:best position of particle *i* until iteration k;

$Xgbest^k$: best position of the swarm until iteration k;

Each particle changes its current position to the new position by adding the modified velocity (18) using the following equation:

$$X_i^{k+1} = X_i^k + Vt_i^{K+1}, i = 1,2,..Np \tag{19}$$

In general inertia weight factor ω decreases linearly from $\omega_{\max}$ to $\omega_{\min}$ according to the following equation**:**

$$\omega = \omega_{\max} - \frac{\omega_{\max} - \omega_{\min}}{k_{\max}} \times k \tag{20}$$

where $k_{\max}$ is the maximum number of iterations.

IV- implementation of the ORPD PSO algorithm

IV-1 Initialization

Initial value of each particle is generated randomly between $[u_{\min}, u_{\max}]$ $X_i^0 = (x_{i,1}^0, \ldots, x_{i,j}^0)$ then $x_{i,j}^0 = random(u_j^{\min}, u_j^{\max})$.

Also initials values of velocity of each particle is generated randomly between $[Vt_{\min}, Vt_{\max}]$

$vt_{i,j}^0 = random(vt_{i,j}^{\min}, vt_{i,j}^{\max})$

$vt_{i,j}^{\max} = -Vt_{i,j}^{\min} = (u_j^{\max} - u_j^{\max})/Nv$ Where Nv is an integer value, representing the number of intervals.

Where $i = 1,..N_P, j = 1,..d$ and $u_j^{\max}, u_j^{\min}$ are maximum and minimum values of control variables respectively.

IV-2 Algorithm OF ORPD-EPSO

Step 1: give the PSO parameters Np; $\omega_{\min}$, $\omega_{\max}$, $k_{\max}$, c1,c2, d=dimension of vector of control Variables U, set k=1.

Step 2: Initialize at random Np particles within their limits.

Step 3: Calculate fitness function of each initial particle X_i^0 using objective function F_T (15).

Step 4: set $Xpbest_i = X_i^0$ as a previous Xi and $Xgbest$ to the best particle have the best fitness among all particles $Xpbest_i$

Step 5: set iteration K=1;

Step 6: update velocity of each particle using equation (18), If $vt_{i,j} < vt_{i,j}^{\min}$ then $vt_{i,j} = vt_{i,j}^{\min}$, or if $vt_{i,j} > vt_{i,j}^{\max}$ then $vt_{i,j} = vt_{i,j}^{\min}$

Step 7: adjusts the position of each particle using equation (19) if the element of vector of particle *Xi* exceeds its limits, enforce it within its limits.

Step 8: calculate new fitness function of each particles X_i using objective function F_T (15).

Step 9: if the fitness value of each particle is better than previous $Xpbest_i$, the current is set to be $Xpbest_i$ if the best particle of all $Xpbest_i$ is better than $Xgbest$, the current is set to $Xgbest$.

Step 10: if $k < Kmax$ set $K=K+1$ and go to step 5, otherwise go to step 11.

Step 11: take $U^{best} = Xgbest$ and running load flow to calculate real slack power, active power loss, and other elements of state variables.

To calculate the fitness function of each particle X_i set the vector of control variables $U = X_i$, and running load flow to calculate real slack power, active power loss using(8), and fitness function using (15).

IV-3- Handling of discrete Variables

The discrete control variables are adjusting by 0.01 step size. Then each transformer tap setting is rounded to its nearest decimal integer value of 0.01, by utilizing the rounding operator. The same principle applies to the discrete reactive power injection of shunt compensators. The rounding operator is only performed in evaluating the fitness function.

V- Numerical Results

The PSO algorithm has been tested on the IEEE 30-bus, 41 branch system [6]. It has a total of 13 control variables as follows: 6 generator-bus voltage magnitudes, 4 transformer-tap settings, and 3 bus shunt reactive compensators.

The considered security constraints are the voltage magnitudes of all buses, the reactive power limits of the shunt VAR compensators and the transformers tap settings limits. The variables limits are listed in Table1. The transformer taps and the reactive power source installation are discrete with the changes step of 0.01.

TABLE 1
VARIABLES LIMITS IN PU

V_g^{min}	V_g^{max}	V_L^{min}	V_L^{max}	T^{min}	T^{max}
0.9	1.1	0.95	1.05	0.95	1.05

SHUNT VAR COMPENSATOR LIMITS IN PU

Q_c^{min}	Q_c^{max}
-0.12	0.36

The power limits generators buses are represented in Table2. Generators buses are: PV buses 2,5,8,11,13 and slack bus is 1.the others are PQ-buses.

The total power demand is 283.4 Mw.

The PSO population size is taken equal to 30. The maximum number of generations is 100, acceleration factors $C_1=C_2=2$, maximum and, minimum inertia factors are $\omega_{max}=0.9$,$\omega_{min}=0.1$, the penalty factor in (15) is chosen as $\lambda_v = 500$.

The complete algorithm has been implemented in Delphi oriented object programming. 20 runs have been performed for two cases of VAR shunt compensators, and the results which follow are the best solution of these 20 runs.

TABLE 2
Generators power Limits in Mw and Mvar

Bus N°	P_g^0	P_{gmin}	P_{gmax}	Q_{gmin}	Q_{gmax}
1	99.22	50	200	-20	200
2	80	20	80	-20	100
5	50	15	50	-15	80
8	20	10	35	-15	60
11	20	10	30	-10	50
13	20	12	40	-15	60

Case1: Two VAR shunt compensators

In this case1 reactive power of shunt compensator at bus 3 is equal to zero. The optimal settings of the control variables are given in table 3 case1 of PSO. The total active power loss was initially 5.822 Mw and, it has been reduced by the proposed PSO to 4.9273 Mw.
This solution is improved than the optimal active power loss obtained by the other heuristic method reported in the literature with both continuous and discrete control variables such as standard genetic algorithm SGA[8] with 4.98 Mw.
The real power of slack bus is 98.32729Mw.

Case2: Three VAR shunt compensators

In The case 2, reactive power of shunt compensator at bus 3 is considered, the optimal settings of the control variables are given in table 3 case2 of PSO. The total active power loss has been reduced by the proposed PSO to 4.91948Mw.
This solution is improved than the optimal active power loss of case 1.
The real power of slack bus is 98.31947Mw.

It is clear that all control variables are within their boundary limits.
System of voltage profile of case1 and case 2 for all buses is shown in Figure 1. All voltage magnitudes of buses are within their limits, in PQ buses (load buses) voltage magnitude does not exceed its limits (1.05 and 0.95) except voltage magnitude at bus 3 of case 1 is 1.05006 pu. It is reduced in case 2 to 1.04997pu.
The proposed approach succeeds in keeping the dependent variables within their limits.
By adding the VAR shunt compensator at bus 3, active power loss is reduced.
Table 3 summarizes the results of the optimal settings of control variables obtained by PSO and GA methods. These results show that the optimal dispatch solution determined by the PSO lead to lower active power loss than that found by GA method; witch confirms that PSO is well capable of determining the global or near global optimum dispatch solution.

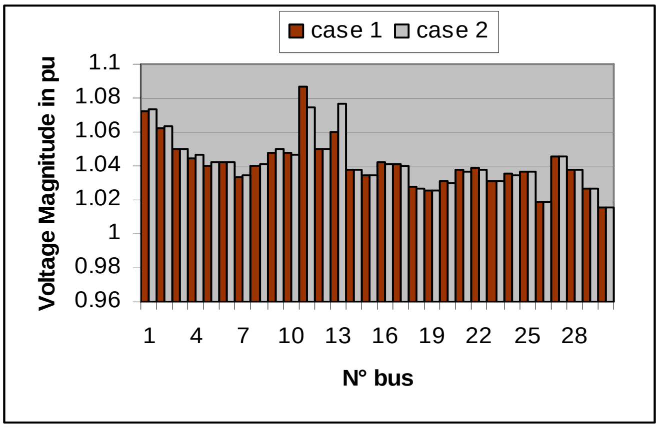

Figure1: Voltage Profile Diagram

TABLE 3
VALUES OF CONTROL VARIABLES AFTER OPTIMIZATION AND ACTIVE LOSS

Variables in p.u	Initial	PSO case1	PSO case2	SGA
V_1	1.05	1.0719	1.0738	1.0751
V_2	1.04	1.0625	1.0636	1.0646
V_5	1.01	1.0400	1.0422	1.0422
V_8	1.01	1.0402	1.0406	1.0454
V_{11}	1.05	1.0864	1.0749	1.0337
V_{13}	1.05	1.0599	1.0770	1.0548
$T_{4,12}$	1.032	0.98	1.01	1.04
$T_{6,9}$	1.078	1.03	1.01	0.94
$T_{6,10}$	1.069	0.95	0.97	1.04
$T_{28,27}$	1.068	0.97	0.97	1.02
Q_3	0.00	0.00	-0.08	0.00
Q_{10}	0.00	0.15	0.15	0.37
Q_{24}	0.00	0.11	0.11	0.06
Loss (Mw)	5.822	4.9273	4.91948	4.98

Generator reactive powers are given in table 4. These values are within their limits.

TABLE 4
Generator Reactive
Powers IN Mvar

	Case1	*Case2*
Q_{g1}	*-2.293*	*0.343*
Q_{g2}	*11.307*	*8.758*
Q_{g5}	*22.096*	*23.483*
Q_{g8}	*27.81*	*27.264*
Q_{g11}	*20.442*	*13.466*
Q_{g13}	*7.813*	*21.061*

VI- Conclusion

In this paper, a PSO solution to the OPF problem has been presented for determination of the global or near-global optimum solution for optimal reactive power dispatch. The main advantages of the PSO to the ORPD problem are optimization of convex or non-convex objective function, real coded of both continuous and discrete control variables, and easily handling nonlinear constraints. The proposed algorithm has been tested on the IEEE 30-bus system to minimize the active power loss. The optimal setting of control variables are obtained in both continuous and discrete value.
The results were compared with the other heuristic method such as SGA algorithm reported in the literature and demonstrated its effectiveness and robustness.

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