Paper accepted for presentation at 2003 IEEE Bologna PowerTech Conference, June 23-26, Bologna, Italy

A New Reactive Power Optimization Algorithm

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Abstract: This paper presents a new algorithm for optimizing reactive power using Particle Swarm Algorithm. A new implementation for the particle swarm algorithm has been applied. The objective function of the proposed algorithm is to minimize the system active power loss. The control variables are generator bus voltages, transformer tap positions and switch-able shunt capacitor banks. The proposed algorithm has been applied to practical IEEE 6-bus system. The proposed algorithm shows better results as compared to previous work.

Keywords: Particle Swarm Algorithm, Reactive Power Optimization, and Loss Minimization

I. INTRODUCTION

The problem of optimal reactive power dispatch 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. [6] 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). [7]

Generally, the optimal VAR dispatch problem has many objectives such as: reducing the fuel costs: ameliorating the supply quality and reliability by improving the voltage profile over the system; and enhancing the system security by uploading the system equipment. The reactive power optimization problem is a nonlinear combinatorial optimization problem. During the last two decades much effort has been devoted to the development of the mathematical methods for solving reactive power optimization (VAR dispatch) problem, the complexity of which is based upon the following factors [9]:

- Large and complex network configuration
- Nonlinear relationship between voltage levels and reactive power injected
- Nonlinear loads characteristics
- Discrete nature of rated capacity of compensators
- Constant components factor in compensator costs
- Requirement for reactive power adjustable corresponding to system load change.

Conventional optimization methods, which have been used for solving the reactive power optimization, are Linear Programming, Nonlinear programming, mixed integer programming, decomposition method, etc. [6] However, these conventional methods can only be lead to a local minimum and most of them cannot deal with integer problem. In recent years, some artificial intelligence methods such as expert system, neural network, simulated annealing and genetic algorithm have been used to solve reactive power optimization problem.

In this paper, a proposed approach employs particle-swarm-optimization (PSO) technique to search for optimal settings of Reactive Power Problem. Finally, case will be presented and the final optimal settings for the entire of the network will be shown.

II. PROBLEM FORMULATION

The main objective function is to minimize the system active power loss. The control variables are generators bus voltages, transformer tap positions and switch-able shunt capacitor banks. [7] The equality constraints are power/reactive power equalities, the inequality constraints include bus voltage constraints, generator reactive power constraints, reactive source reactive power capacity constraints and the transformer tap position constraints, etc. The equality constraints can be automatically satisfied by load flow calculation, while the lower/upper limit of control variables corresponds to the coding on the Particle Swarm Optimization (PSO) Algorithm, so the inequality constraints of the control variables are satisfied.

Objective Function:

$F = \min P_{loss}$

Constraints:

1. Real Power Constraints:

$$P_{Gi} - P_{Di} - V_i \sum_{j \neq i} V_j (G_{ij} \sin\theta_{ij} + B_{ij} \sin\theta_{ij}) = 0 \qquad (1)$$

$i \in n$, where set of numbers of buses except the swing bus

2. Reactive Power Constraints:

$$Q_{Gi} - Q_{Di} - V_i \sum_{j \neq i} V_j (G_{ij} \sin\theta_{ij} - B_{ij} \sin\theta_{ij}) = 0 \quad (2)$$

$i \in n$, where set of numbers of buses except the swing bus.

3. Bus Voltage magnitude constraints:

$$V_{i-\min} \le V_i \le V_{i-\max}$$

(3) $i \in N$: Set of total buses

4. Generator bus reactive power constraints:

$$Q_{Gi-\min} \le Q_{Gi} \le Q_{Gi-\max} \qquad i \in \{N_{pv}, N_0\} \qquad (4)$$

5. Reactive power source capacity constraints:

$$q_{ci-\min} \le q_{ci} \le q_{ci-\max} \qquad i \in N_c$$

(5) $q_{ci} = q_{ci-\min} + N_{ci} * \Delta q_{ci}$

6. Transformer Tap position constraints:

$$T_{i-\min} \le T_i \le T_{i-\max} \qquad i \in N_T \qquad (6)$$

$$T_i = T_{i-\min} + N_{Ti} * \Delta Ti$$

Where:

P_{loss} : System loss

N_b : Set of numbers of total buses

N_t : Set of numbers of tap-setting transformer branches

N_c : Set of numbers of possible reactive power source installation buses

N_{pv} : Set of numbers of PV buses

N_0 : the swing bus

P_{Gi} : bus i real power supply

Q_{Gi} : bus i reactive power supply

P_{Di} : bus i real power load

Q_{Di} : bus i reactive power load

V_i : bus i voltage magnitude

θ_i : bus i voltage phase angle

θ_{ij} : Phase angle difference between bus i and j

G_{ij} : mutual conductance between bus i and j

B_{ij} : mutual susceptance between bus i and j

G_{ii} : self conductance of bus i

B_{ii} : self susceptance of bus i

q_{ci} : reactive power source i installation

T_K : transformer k tap

$V_{i\ min}$, $V_{i\ max}$: bus i voltage limit

$Q_{Gi\ min}$, $Q_{Gi\ max}$: reactive source i reactive power limit

$T_{K\ min}$, $T_{K\ max}$: transformer k tap position limit

$q_{C\ min}$, $q_{C\ max}$: reactive power source installation capacity limit

III. PARTICLE SWARM OPTIMIZATION

A. Overview

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 problem. In a PSO system, particles change their positions by flying a round in a multidimensional search space until a relatively unchanged position has been encountered, or until computational limitations 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 advantages of PSO over other traditional optimization techniques can be summarized as follows:

a) PSO is a population-based search algorithm (i.e., PSO has implicit parallelism). This property ensures PSO to be less susceptible to getting trapped on local minima.

b) PSO uses payoff (performance index or objective function) information to guide the search in the problem space. Therefore, PSO can easily deal with non-differentiable objective functions. Additionally, this property relieves PSO of assumptions and approximations, which are often required by traditional optimization models.

c) PSO uses probabilistic transition rules and not deterministic rules. Hence, PSO is a kind of stochastic optimization algorithm that can search a complicated and uncertain area. This makes PSO more flexible and roust than conventional methods.

d) Unlike Genetic Algorithm (GA) and other heuristic algorithms, PSO has the flexibility to control the balance between the global and local exploration of the search space. This unique feature of a PSO overcomes the premature convergence problem and enhances the search capability.

e) Unlike the traditional methods, the solution quality of the proposed approach doesn't rely on the initial population. Starting anywhere in the search space, the algorithm ensures the convergence to the optimal solution.

B. PSO Algorithm:

The basic elements of the PSO techniques are briefly stated and defined as follows:

1. **Particle X (t)**: It is a candidate solution represented by a k-dimensional real-valued vector, where k is the number of optimized parameters. At time t, the i^{th} particle Xi(t) can be described as Xi(t)=[$x_{i,1}(t)$; $x_{i,2}(t)$; ……;$x_{i,k}(t)$].

2. **Population**: it is a set of n particles at time t.

3. **Swarm**: it is an apparently disorganized population of moving particles that tend to cluster together while each particle seems to be moving in a random direction.

4. **Particle velocity V (t)**: It is the velocity of the moving particles represented by a k-dimensional real-valued vector. At time t, the i^{th} particle Vi (t) can be described as Vi (t)=[$v_{i,1}(t)$; $v_{i,2}(t)$; ……;$v_{i,k}(t)$].

5. **Inertia weight w(t)**: it is a control parameter that is used to control the impact of the previous velocity on the current velocity. All the control variables transformer tap positions and switch-able shunt capacitor banks are integer variables and not continuous variables. Therefore, the value of the inertia weight is considered to be 1 in this study.

6. **Individual best X^* (t)**: As the particle moves through the search space, it compares its fitness value at the current position to the best fitness value it has ever attained at any time up to the current time. The best position that is associated with the best fitness encountered so far is called the individual best X^* (t). For each particle in the swarm, X^* (t) can be determined and updated during the search.

7. **Global best X^{**} (t)**: It is the best position among all of the individual best positions achieved so far.

8. **Stopping criteria**: These are the conditions under which the search process will terminate. In this study, the search will terminate if one of following criteria is satisfied:
   - The number of the iterations since the last change of the best solution is greater than a pre-specified number.
   - The number of iterations reaches the maximum allowable number.

In a PSO algorithm, the population has n particles that represent candidate solutions. Each particle is a k-dimensional real-valued vector, where k is the number of the optimized parameters. Therefore, each optimized parameter represents a dimension of the problem space. The modified PSO technique for integer problem can be described in the following steps.

Step 1:
(Initialization): Set t=I=0 and generate random n particles, {Xj(0), j=1,2,..n}. Each article is considered to be solution for the problem and it can be described as Xj(0)=[$x_{i,1}(0)$; $x_{i,2}(0)$; ……;$x_{i,k}(0)$]. Each control variable will have a range [xmin,xmax]. Each particle in the initial population is evaluated using the objective function f. In this study, the objective function is the power loss in the network, which will be calculated after running the power flow and meeting all our constraints.

Step 2:
Counter Updating: update the counter i= i +1

Step 3:
Velocity updating: Using the global best and individual best, the jth particle velocity in the kth dimension in this study (integer problem) is updated according to the following equation:

$$v(k,j,i+1)=v(k,j,i)+1*rand*(pbestx(j,k)-x(k,j,i)) + 1*rand*(gbestx(k)-x(k,j,i)) \quad (7)$$

From the previous equation i is the iteration number, j is the particle number and k is the kth control variable. Then, check the velocity limits. If the velocity violated its limit, set it at its proper limit. The second term of the above equation represents the cognitive part of the PSO where the particle changes its velocity based on its own thinking and memory. The third term represents the social part of PSO where the particle changes its velocity based on the social-psychological adaptation of knowledge.

Step 4:
Position updating: Based on the updated velocity, each particle changes its position according to the following equation:

$$x(k,j,i+1) = x(k,j-1,i) + v(k,j,i) \quad (8)$$

Step 5:

Individual best updating: each particle is evaluated and updated according to the update position.

Step 6:
Search for the minimum value in the individual best and its solution has ever been reached so far, and consider it to be the minimum.

Step 7:
Stopping criteria: if one of the stopping criteria is satisfied, then stop otherwise go to step-2.
Figure-1 shows PSO Algorithm.

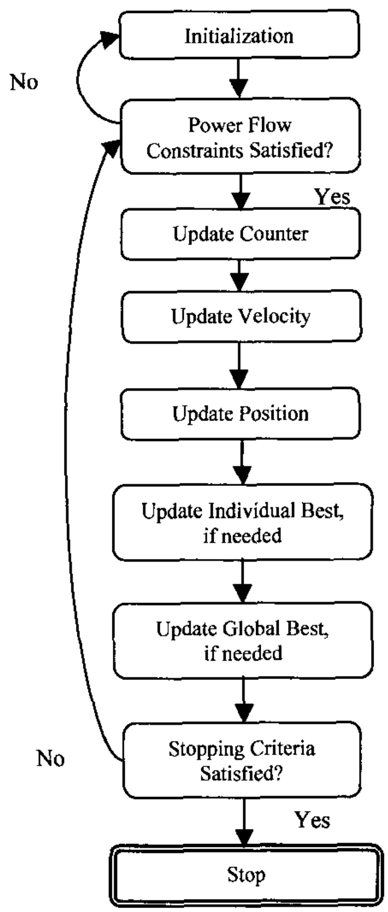

Figure 1. PSO Algorithm

III. TEST RESULTS

The IEEE 6-bus system is used to show the practicability of the proposed algorithm and to find the optimal settings for generator voltages, transformer taps and switch-able VAR sources while maintain the allowable limit for previously mentioned constraints.

The IEEE 6-bus system is shown in Figure 2. Bus 1 is the swing bus, bus 2 is a PV bus, while Bus 3 and 6 are reactive power installation buses. The two branches with tap-setting transformer are branch 1-4 and 6-5. The line data, the control variables constraints, and the state variable constrains for the IEEE 6-Bus system are shown in Tables 1,2 and 3. Table 4 presents the system initial status. Tables 5 and 6 present the simulation results of the tested system.

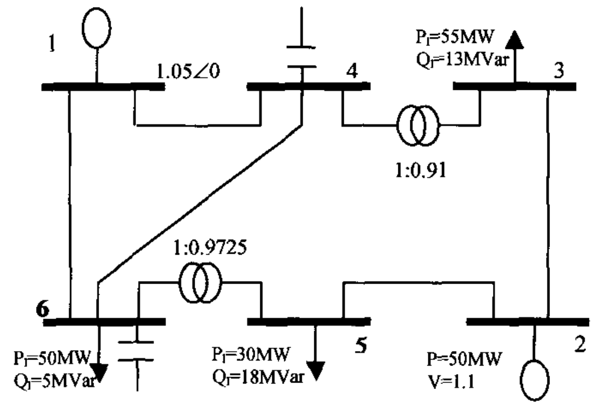

Figure 2. IEEE 6-Bus System

Table 1: IEEE 6-BUS SYSTEM DATA (p.u.)

Start Bus	End Bus	Branch Impedance	Transformer Tap
6	3	0.123+0.518j	
6	4	0.080+0.370j	
4	3	0.097+0.407j	
5	2	0.282+0.640j	
2	1	0.723+1.050j	
6	5	0.000+0.300j	0.9725
4	3	0.000+0.133j	0.9100

Table 2: CONTROL VARIABLE CONSTRAINTS

	Transformer Tap	Generator Bus Voltage		VAR Installation (MVAR)	
	T_{65}, T_{43}	V_1	V_2	Q_6	Q_4
Lower Limit	0.910	1.0	1.1	0.0	0.0
Upper Limit	1.110	1.1	1.15	5.0	5.0
Discrete Value	0.91+16*1.25%			10*0.5	10*0.5

Table 3: STATE VARIABLE CONSTRAINTS

	PQ Bus Voltage	PV Bus Reactive Power (MVAR)
Lower Limit	0.9	-20
Upper Limit	1.1	100

Table 4: SYSTEM INITIAL STATUS (S_B = 100 MVA) BEFORE OPTIMIZATION

	Voltage (p.u.)		Load (p.u.)		Power Supply (p.u.)	
Bus	V	θ (degree)	P_l	Q_l	P_G	Q_G
1	1.0500	0	0	0	0.9662	0.3792
2	1.1000	-6.1494	0	0	0.5000	0.3499
3	0.8563	-13.8236	0.55	0.13	0	0
4	0.9528	-9.9245	0	0	0	0
5	0.8992	-13.4205	0.3	0.18	0	0
6	0.9338	-12.6485	0.5	0.05	0	0
System Total Loss = 11.62 MW						

Table 5: CONTROL VARIABLE VALUE AFTER OPTIMIZATION

Control Variable	T_{65}	T_{43}	V_1	V_2	Q_3	Q_4
Optimal Variable	1.0725	1.06	1.1000	1.1500	0.05	0.05

Table 6: SYSTEM STATUS AFTER OPTIMIZATION (S_B= 100 MVA)

	Voltage (p.u.)		Load (p.u.)		Power Supply (p.u.)	
Bus	V	θ (degree)	P_l	Q_l	P_G	Q_G
1	1.1000	0	0	0	0.9372	0.4277
2	1.1500	-2.6290	0	0	0.5000	0.1345
3	1.0366	-11.4258	0.55	0.13	0	0
4	0.9964	-8.73710	0	0	0	0.05
5	1.0147	-10.9578	0.3	0.18	0	0
6	0.9775	-10.8484	0.5	0.05	0	0.05
System Total Loss = 8.72 MW						

Table 5 shows the obtained optimal values of control variables for the tested system. The optimal values of status variables are shown in Table 6. It can be noticed that all the state variable values are adjusted, all bus voltages are in their permissible limits, and system loss decreases from 11.62 MW to 8.72 MW. Table 7 shows a comparison between our results and the reported results in the literature [6,16,17,18 and 19]. It is obvious that the obtained results using the proposed PSO algorithm are better than that given in the literature.

Table 7: RESULT COMPARISONS BETWEEN DIEFFERENT METHODS FOR IEEE 6-BUS SYSTEM

Literature	Method	Minimal Loss (MW)
6	Genetic Algorithm	8.77
16	Non-linear programming	8.84
17	Simplex linear programming with upper limit	8.865
18	Improved linear programming	8.89
19	Dual-simplex linear programming	8.93
This paper	Particle Swarm Algorithm	**8.72**

IV. CONCLUSION

Reactive power optimization is a complex combinational optimization problem. A new improved integer coding Particle Swarm Algorithm is presented to solve this problem. The main objective is to minimize the active power loss in the network, while satisfying all the power system operation constraints. The particle swarm algorithm has been coded as well as the power flow fast-decoupled method using MATLAB. The proposed algorithm has been successfully applied to the IEEE 6-bus system. The simulation results show that PSO algorithm always lead to a satisfactory result. The obtained results are superior compared to previously reported work in the literature.

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VI. ACKNOWLEDGMENT

The authors acknowledge the support of King Fahd University of Petroleum and Minerals for this work.

VII. BIOGRAPHIES

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