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Reactive power control using dynamic Particle Swarm Optimization for real power loss minimization

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ABSTRACT

This paper presents Particle Swarm Optimization Algorithm, with dynamic weights, applied to reduce the real power loss in a system. Particle Swarm Optimization with detailed study on weights for particle movements is used. Generator bus voltages, transformer tap positions and switch-able shunt capacitor banks are used as variables to control the reactive power flow. Particle Swarm Optimization has been applied to IEEE 6 bus system to present the case. The proposed dynamic weights show better, fast and consistent results with higher rate of convergence.

1. Introduction

Reactive power flow optimization improves voltage profile and also minimizes the active power loss. The flow of reactive power in a power system can be controlled through generator voltages, transformer taps and switch-able VAR sources.

A certain combination of these generator voltages, transformer tap positions and reactive power from capacitor banks result in optimized reactive power flow. The reactive power optimization problem is thus a nonlinear combinatorial optimization problem. The search space is multidimensional due to large number of control variables. The complexity of reactive power optimization increases with increase in the size of power system.

Earlier, conventional methods were used for solving of reactive power flow optimization. These methods usually operate with single solution which is then optimized. The conventional methods have a major drawback of leading towards local minima. Also the conventional methods do not efficiently work for combination of variables. Time consumption of these methods is also very high. To overcome these drawbacks artificial intelligence methods such as genetic algorithm [6], simulated annealing, tabu search [5], Particle Swarm Optimization [7–10,14], and colony optimization methods have been used to solve reactive power optimization problem.

Mamandur and Chenoweth [1] have used optimization for voltage security and reactive power optimization, applied to different percentage of loads. Vaisakh and Kanta Rao [3] use differential evolution to find the optimized solution. Heuristic and evolutionary approach are implemented by Bhattacharya and Goswami [4] to find the optimal power flow solution.

Particle Swarm Optimization has been applied for reactive power optimization by Yoshida et al. [2], Hazra and Sinha [8] and, Mantawy and Al Ghamdi [14]. Hybrid PSO having some additional features of other search methods [10] or some unique features applied to PSO [9] have also been applied.

PSO search technique has been studied separately to predict the optimized weights and factors for the search method [11–13]. Peram et al. [11] uses fitness ratio to calculate the weights for particle movement in search space.

The approach proposed in this paper uses Particle Swarm Optimization (PSO) technique with dynamic weights. The dynamic weights are so called, because their values change in each iteration as detailed in Section 3.4. A case is presented on IEEE 6 bus system and the final optimal variable values are shown.

2. Power flow equations

The power flow equations describe the constraints governing the flow of power in the power system. These equations or constraints can be classified into equality and inequality constraints. The equality constraints are automatically satisfied through the load flow calculations. For inequality constraints to be satisfied, the program coding of Particle Swarm Optimization (PSO) Algorithm is used. The inequality constraints are checked for violations during the execution of the program.

Main objective equation:

$$F = \min P_{loss}$$

where P_{loss}: System loss.

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2.1. Constraints

2.1.1. Equality constraints

2.1.1.1. Real power constraint

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

$i \in n$: numbers of buses, except swing bus.
P_{Gi}: real power generated at bus i.
P_{Di}: real power load at bus i.
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.

2.1.1.2. Reactive power constraint

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

$i \in n$: numbers of buses, except swing bus.
Q_{Gi}: reactive power generated at bus i.
Q_{Di}: reactive power load at bus i.

2.1.2. Inequality constraints

2.1.2.1 Bus voltage magnitude constraint

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

$i \in N$: total number of buses.
$V_{i-\min}$, $V_{i-\max}$: voltage limits at bus i.
V_i: voltage magnitude of bus i.

2.1.2.2. Generator bus reactive power constraint

$$Q_{Gi-\min} \leqslant Q_{Gi} \leqslant Q_{Gi-\max} \quad i \in \{N_{pv}, N_o\}$$

$Q_{Gi-\min}$, $Q_{Gi-\max}$: reactive power limits of generator at bus i.
N_{pv}: Number of PV buses.
N_o: Swing bus.

2.1.2.3. Reactive power source capacity constraint

$$Q_{ci-\min} \leqslant q_{ci} \leqslant q_{ci-\max} \quad i \in N_c$$

q_{ci}: reactive power source at bus i.
$q_{c-\min}$, $q_{c-\max}$: reactive power source limits.
N_c: Numbers of reactive power sources.

2.1.2.4. Transformer tap position constraint

$$T_{i-\min} \leqslant T_i \leqslant T_{i-\max} \quad i \in N_T$$

T_i: tap position at transformer 'i'.
$T_{i-\min}$, $T_{i-\max}$: tap position limits.
N_T: Numbers of tap setting transformers.

3. Particle Swarm Optimization

3.1. Introduction

PSO search method is a non-conventional search technique. In PSO, a number of control variable combinations are randomly created. Each such solution is called as a particle. A particle represents a probable solution. The collection of such particles is known as a population. The population of particles is used to conduct searches through multidimensional search space. The particles belonging to a population, moving in such a way, so as to converge to a common optimal solution is called as a Swarm.

In PSO technique, the particles change their positions after every iteration. The change in position depends on: previous position, best individual position, best global position and a random velocity. The individual best position is the position that a particle currently or previously represented and which resulted in minimum objective function value for that particle. The global best position is the position which gives minimum active power loss from the group of individual best positions of all the particles. The individual best position, of each particle, as well as, the global best position needs to be updated in every iteration. Since PSO caters to a multidimensional search, more than one control variable in a particle may be changed simultaneously, in between iterations.

A random velocity element is also used for changing the position of a particle. The term maintains the randomness in the search process. The random velocity element can be created before the beginning of PSO iterations or can be generated during the iterations. This paper generates the random velocity for each particle at real time, which enhances the random behavior of the search.

The terms, Individual Best, Global Best and Random Velocity, responsible for change in particle position during iterations are associated with values called as inertia weights. These weights decide the influence of each term for change in particle positions. They are normally decided through a number of executions. In this paper, weights are calculated at real time and are referred as 'dynamic weights'. This method of calculation of weights has been found to guide the particles towards convergence.

The search method of PSO is terminated if the stopping criteria are satisfied. The stopping criteria can be: number of iterations, convergence of particles to a common solution or maximum number of iterations for which the optimal solution does not change. This paper uses maximum number of iterations for termination of the search process. After the termination of the search process if convergence is not achieved, the global best position shall represent the optimal solution.

3.2. Advantages and disadvantages

PSO is a non-conventional optimization technique used for searching nonlinear multidimensional search spaces. The following are some of the advantages of using PSO:

(a) PSO's search includes multiple particles which reduces the chances of getting trapped in local minima.
(b) It is a stochastic search technique, which makes it suitable for searching vast unknown solution spaces.
(c) The problems faced by search techniques for non-differentiable objective equations are also overcome in PSO.
(d) PSO technique rules for changing particle position depends on individual as well as global best. Thus, the method normally does not get prematurely converged.
(e) PSO maintains the randomness in search during initialization of particle positions and also for change in particle position through random velocity.

Even though PSO has multiple advantages, it also has some inherent drawbacks.

(a) The initialization of particles in PSO is done randomly. If the particles initialized, are located in a local space, then the chances of getting trapped in local minima is increased.
(b) The speed of search depends on the separation of particles.

3.3. Algorithm and flowchart

The algorithm of PSO used for searching an optimal solution for reactive power dispatch is given in Fig. 1.

(i) Minimum and maximum values for control and state variables are set. Transformer tap positions are initiated. Random particles are generated.
(ii) The counter is initialized to 1 and it measures each iteration.
(iii) Load flow constraints are verified.
(iv) Load flow is executed for each and every particle using fast decoupled method. This gives the active power loss, i.e., the value of objective function or the fitness value for each particle.
(v) The individual best is updated for better fitness value of a particle.
(vi) After updating all individual best, the global best is also updated.
(vii) Based on the values of individual best, global best and random velocities, each particle is assigned a new position.
(viii) Stopping criteria is checked, if satisfied the search process stops and displays the result, else proceeds for the next iteration.

3.4. Dynamic weights

The particles in PSO change their positions in every iteration based on individual best, global best and a random velocity. The new position of the particle is also dependent on the weights attached with these quantities. These weights can be static or dynamic. The static weights are determined by repeated execution of the algorithm and set before execution of the program. The dynamic weights change for each iteration of PSO. The weights introduced by Peram et al. [11], make use of fitness ratio. The ratio is calculated separately for each control variable and the fitness values are taken from different particles. A novel concept is introduced here. The dynamic weights, used in this paper, change in every iteration, depending on the difference in fitness values of the particle and the referred best positions.

The new position of a particle is calculated as:

new position = old position + (difference between individual best position and current position)
∗ (difference in losses of individual best position and current position)
∗ scale value + (difference between global best position and current position)
∗ (difference in losses of global best position and current position)
∗ scale value + random value ∗ signis()
∗ scale value

where scale value: to scale the calculated value in variable range.

signis : function which generates random positive or negative value.

Thus, more a particle is away from the global or individual best; the more it will be driven towards these positions. The introduction of dynamic weights makes the search converge faster. This method of calculation of weights was not found in the references mentioned.

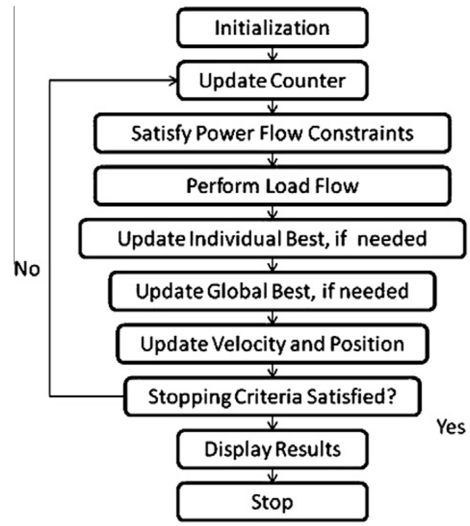

Fig. 1. PSO algorithm.

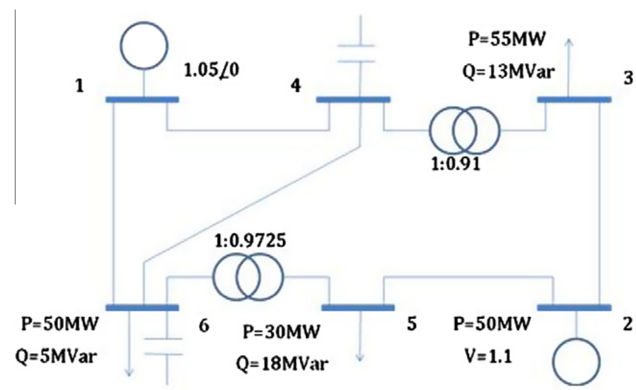

Fig. 2. IEEE 6 bus system.

Table 1
IEEE 6 bus system data.

Start bus	End bus	Branch impedance	Transformer tap
1	6	0.23 + j0.518	
1	4	0.080 + j0.370	
4	6	0.097 + j0.407	
5	2	0.282 + j0.640	
2	3	0.723 + j1.050	
6	5	0.000 + j0.300	1.025
4	3	0.000 + j0.133	1.1

Table 2
Control variable constraints.

	Transformer tap	Generator bus voltage		VAR installation (MVAR)	
	T_{65}, T_{43}	V_1	V_2	Q_4	Q_6
Lower limit	0.910	1.0	1.1	0.0	0.0
Upper limit	1.110	1.1	1.15	5.0	5.5
Discrete value	0.91 + 16 ∗ 1.25%			10 ∗ 0.5	10 ∗ 0.5

4. Results

The IEEE 6-bus system [1] (Fig. 2) was implemented using MATLAB. Bus 1 is a swing bus; bus 2 is a PV bus whereas the buses 3, 5,

Table 3
State variable constraints.

	PQ bus voltage	PY bus reactive power (MYAR)
Lower limit	0.9	−20
Upper limit	1.1	100

Table 4
Initial state.

Bus	Voltage (pu)		Load (pu)		Power supply (pu)	
	V	θ	P_1	Q_1	P_G,	Q_G
1	1.05	0	0	0	0.966	0.381
2	1.100	−6.139	0	0	0.500	0.348
3	0.855	−13.83	0.55	0.13	0	0
4	0.953	−9.92	0	0	0	0
5	0.901	−13.42	0.3	0.18	0	0
6	0.933	−12.65	0.5	0.05	0	0

System total loss = 11.61 MW.

Table 5
Control variables (initial state).

V_1	V_2	Q_4	Q_6	T_{43}	T_{65}
1.05	1.1	0	0	1.1	1.025

Table 6
Final state.

Bus	Voltage (pu)		Load (pu)		Power supply (pu)	
	V	θ	P_1	Q_1	P_G	Q_G
1	1.100	0	0	0	0.937	0.419
2	1.150	−2.676	0	0	0.500	0.137
3	1.034	−11.44	0.55	0.13	0	0
4	0.998	−8.737	0	0	0	0.05
5	1.014	−10.98	0.3	0.18	0	0
6	0.98	−10.86	05	0.05	0	0.055

System total loss = 8.7036 MW.

Table 7
Control variables (final state).

V_1	V_2	Q_4	Q_6	T_{43}	T_{65}
1.1	1.15	5	5.5	0.9475	0.935

and 6 are load buses. The switchable shunt capacitor banks are connected on buses 4 and 6. The transformers are connected between buses 3–4 and 5–6. The load at each bus is also specified.

The line data, the control variable constraints, and state variable constraints for the system are shown in Tables 1–3 respectively. Tables 4 and 5 presents the initial state of the system and control variable values in initial state. Tables 6 and 7 present the simulation results after using PSO, with dynamic weights, on the system.

It is noted that all the state variables and control variables are in their specified limits. The voltage profile of the system has also improved. The active power loss has reduced from 11.61 MW to 8.7036 MW, which is a 25% reduction in total active power losses.

5. Conclusion

Reactive power flow optimization is a complex combinatorial problem. Particle Swarm Optimization Algorithm with dynamic weights has been successfully used to minimize the active power losses in the system, while satisfying all power system constraints. The proposed algorithm was found to be better at reducing losses and convergence when compared to existing [14] methods. The PSO Algorithm has been coded using MATLAB.

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