Swarm Intelligence Approach to Minimize the Transmission Line Losses

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Abstract— the real power transfers by maintaining voltage stability and system reliability. It is a critical element for a transmission operator to ensure the reliability of an electric system while minimizing the cost associated with it. Optimum scheduling of reactive power reduces the active power losses in the transmission system.This paper presents a Particle Swarm Optimization algorithm for Reactive Power Optimization problem. In this paper, reactive power optimization function is taken to minimize the real power losses. This paper covers the reactive power optimization problems, different optimization techniques, the basic concept of Particle Swarm Optimization and its algorithm for this problem and results obtained for 6-bus test system and IEEE 30-bus test system for PSO and Newton method.

Key words: Reactive Power Optimization, Particle Swarm Optimization, Minimize Real Power Losses, MATLAB

I. INTRODUCTION

During the steady state operation of an AC power system the active power production must match the consumption plus the losses, otherwise the frequency will change. There is an equally strong relationship between the reactive power balance of a power system and the voltages. In itself, a reactive power balance will always inherently be present, but with an unacceptable voltages if the balance is not appropriate. An excess of reactive power in an area means high voltages and a deficit means low voltages. The reactive power balance of a power system also influences the active losses of the network, the heating of components and in some cases, the power system stability.

Reactive power optimization is a sub-problem of the optimal power-flow (OPF) calculation, which determines all kinds of controllable variables, such as reactive power outputs of generators, tap ratios of transformers, outputs of shunt capacitors/reactors, etc., and minimizes transmission losses or other appropriate objective functions, while satisfying a given set of physical and operating constraints.

II. REACTIVE POWER OPTIMIZATION

A definition of optimization is given by, “A broad set of interrelated decisions on obtaining, operating and maintaining physical and human resources for electricity generation, transmission, and distribution that minimize the total cost of providing electric power to all classes of consumers.”

Optimization is the process of adjusting the inputs to or characteristics of a device, mathematical process or experiment to find the minimum or maximum output or result.

The objectives of reactive power (VAR) optimization are to improve the voltage profile, to minimize system active power losses and to determine optimal VAR compensation placement under various operating conditions. To achieve these objectives, power system operators utilize control options such as adjusting generator excitation, transformer tap changing, shunt capacitors and SVC.

III. OPTIMIZATION TECHNIQUES

The optimization techniques can be classified mainly in to two categories: Deterministic methods and Heuristic methods. They can be further classified in to following categories:

1) Deterministic Methods:
- Gradient Methods
- Newton's Method
- Simplex Method
- Sequential Linear Programming
- Sequential Quadratic Programming
- Interior Point Methods

2) Heuristic Methods:
- Ant Colony Optimization
- Artificial Neural Network
- Evolutionary Algorithms
- Particle Swarm Optimization
- Simulated Annealing
- Tabu Search

A. *Deterministic Methods:*

Quadratic Programming (QP) is a special form of nonlinear programming whose objective function is quadratic and constraints are linear. In Newton-Raphson (N-R) Method, the Jacobian matrix and the B-coefficients have been developed in terms of the generalized generation shift distribution factor. So the penalty factor and the incremental losses are easily obtained. Execution time is lesser than that of the conventional one. The Interior Point (IP) method finds improved search directions strictly in the interior of the feasible space.

B. *Heuristic Methods:*

Artificial Neural Network (ANN) is an interconnected group of artificial neurons that uses a mathematical model or computational model for information processing based on a connectionist approach to computation. Fuzzy Logic (FL) method is derived from fuzzy set theory dealing with reasoning that is approximate rather than exactly assumed from classical predicate logic. Genetic Algorithm (GA) method belongs to the category of random search algorithms which simulate the evolution process based on the theory of survival of the fittest. Ant Colony Optimization (ACO) is based on the idea of ant searching by pheromone communication to make path. As the ants are finding minimum path to reach the food source, the particles also try to obtain the best value to get optimum solution. Particle Swarm Optimization (PSO) is based on the ideas of social behavior of organisms such as bird flocking and fish schooling. The basic idea is nearly similar to that of Ant Colony Optimization.

C. Advantages of Heuristic Methods over Deterministic Methods:

Deterministic methods use single path search methods while heuristic methods use population-based search techniques to search the solution hyperspace.

It also improves the convergence for heuristic methods and makes it less dependent on the initial solution points. Being derivative-free, modern methods are applicable to any optimization problem regardless of the linearity or non-linearity of its objective function and constraints.

IV. OPTIMAL POWER FLOW PROBLEM

A. Problem Formulation:

The optimal power flow problem is a nonlinear optimization problem. It consists of a nonlinear objective function defined with nonlinear constraints. The optimal power flow problem requires the solution of nonlinear equations, describing optimal and/or secure operation of power systems. The general optimal power flow problem can be expressed as a constrained optimization problem as follows:

Minimize *f(x)*

Subject to $g(x) = 0$, equality constraints

$h(x) \leq 0$, inequality constraints

B. Objective Function:

The main objective function is to minimize the system active power loss. The control variables are generators bus voltages, transformer tap positions and switchable shunt capacitor banks. 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.

1) Objective Function:

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

The different operating constraints are as follows:

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 ∈ n, where set of numbers of buses except the swing bus

2) Reactive Power Constraints:

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

i ∈ n, where set of numbers of buses except the swing bus

3) Bus Voltage magnitude constraints:

$$T_i = T_{i-\min} + N_{Ti} * \Delta T_i \;,\; V_{i-\min} \leq V_i \leq V_{i-\max} \qquad (3)$$

i ∈ n, set of total buses

4) Generator bus reactive power constraints:

$$Q_{Gi-\min} \leq Q_{Gi} \leq Q_{Gi-\max} \qquad (4)$$

i ∈ {N_{pv}, No}

5) Reactive power source capacity constraints:

$$q_{ci-\min} \leq q_{ci} \leq q_{ci-\max} \qquad (5)$$

$$q_{ci} = q_{ci-\min} + N_{ci} * \Delta q_{ci} \quad , i \in N_c$$

6) Transformer Tap position constraints:

$$T_{i-\min} \leq T_i \leq T_{i-\max} \qquad (6)$$

$$T_i = T_{i-\min} + N_{Ti} * \Delta T_i \;, i \in N_T$$

where,

- P_{loss} : System loss
- N_b : Set of number of total buses
- N_t : Set of number of tap-setting transformer branches
- N_c : Set of number of possible reactive power source installation buses
- N_{pv} : Set of number 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

V. PARTICLE SWARM OPTIMIZATION

A. Introduction:

An optimization technique using an analogy of swarm behavior of natural creatures was started in the beginning of the 1990s. Dorigo developed Ant Colony Optimization (ACO) based mainly on the social insect, especially ant. Each individual exchanges information through pheromones implicitly in ACO. Eberhart and Kennedy developed Particle Swarm Optimization (PSO) based on the analogy of swarms of birds and fish schooling. Each individual exchanges previous experiences in PSO. These research efforts are called swarm intelligence.

Particle swarm optimization simulates the behavior of bird flocking. Imagine a group of birds, which are randomly searching food in an area. There is only one piece of food in the area being searched. All the birds do not know where that food is. But they know how far the food is in each iteration. So what’s the best strategy to find the food? The effective one is to follow the bird, which is nearest to the food.

B. Concept of PSO:

In PSO, each single solution is a "bird" in the search space. Here it is called as "particle". All of particles have fitness values, which are evaluated by the fitness function to be optimized, and have velocities, which direct the flying of the particles.

PSO is initialized with a group of random particles (solutions) and then searches for optima by updating generations. In every iteration, each particle is updated by following two "best" values. The first one is the best solution (fitness) it has achieved so far. (The fitness value is also stored.) This value is called Pbest. Another "best" value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the population. This best value is a global best and called Gbest.

After finding the two best values, the particle updates its velocity and positions with following eq. (1) and (2),

$$V_{id} = V_{id} + c_1 * rand() * (P_{id} - X_{id}) + c_2 * rand() * (P_{gd} - X_{id}) \quad (7)$$

$$X_{id} = X_{id} + V_{id} \quad (8)$$

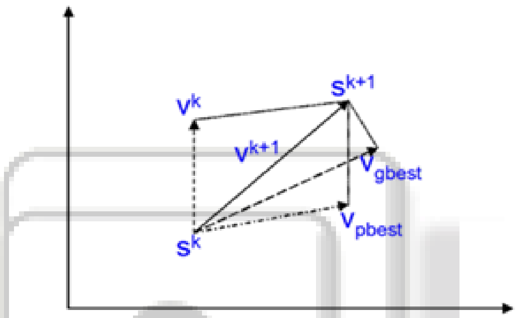

Fig. 1: Concept of modification of searching point

Where, S^K: Current searching point

– S^{K+1}: Modified searching point
– V^K: Current velocity
– V^{K+1}: Modified velocity
– V_{pbest}: Velocity based on Pbest
– V_{gbest}: Velocity based on Gbest

V_{id} is the particle velocity and X_{id} is the current particle (solution). P_{id} and P_{gd} are Pbest and Gbest. Rand ( ) is a random number between (0, 1). cl and c2 are learning factors. Usually c1=c2=2.

Particle velocities on each dimension are clamped to a maximum velocity V_{max}, if the sum of accelerations would cause the velocity on that dimension to exceed V_{max} – which is a parameter specified by the user. Then the velocity on that dimension is limited to V_{max}.

C. Flow-Chart Of PSO:

The steps used in PSO algorithms are given below:

1) Initial searching points and velocities are randomly generated within their limits.
2) Pbest is set to each initial searching point. The best evaluated values among Pbest are set to Gbest.
3) Evaluate the fitness values for new searching point. If evaluated values of each agent is better than previous Pbest then set to Pbest. If the best Pbest is better than best Gbest then set to Gbest.
4) New velocities are calculated using the equation (7).
5) If the maximum iteration is reached stop the process otherwise go to step3.
6) The final values we get are the optimal solution of our problem.

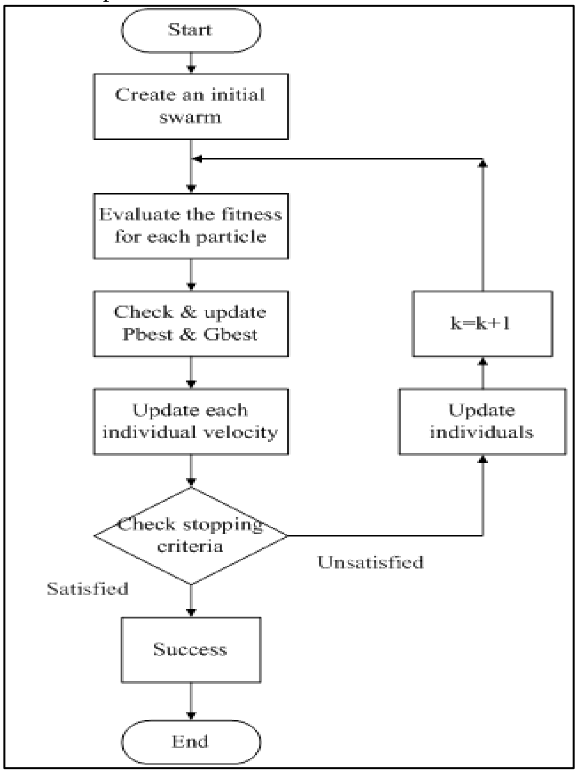

Fig. 2: Flow-chart of PSO

D. PSO Control Parameters:

1) Number of Particles:

The typical range is 20-40. Actually for most of the problems 30 particles is large enough to get good results. For some difficult or special problems, one can try 100 or 200 particles as well.

2) Vmax:

It determines the maximum change one particle can take during iteration. Usually the range of the particle is taken as the Vmax. For example, the particle (x1, x2, x3) x1 belongs [-5, 5], then Vmax=10.

3) Learning Factors:

c1 and c2 usually equal to 2. However, other settings were also used in different works. But usually c1 equals to c2 and ranges from [0, 4].

4) Stop Conditions:

The maximum number of iterations the PSO execute and the minimum error requirement. This stop condition depends on the problem to be optimized.

E. Merits and Demerits of PSO:

1) Merits:

1) Capable to solve large-scale non-convex optimization problems like OPF.
2) Simple concept, easy implementation, relative robustness to control parameters and computational efficiency.
3) Fast convergence
4) PSO can easily deal with non-differentiable and non-convex objective functions
5) PSO has the flexibility to control the balance between the global and local exploration of the search space

6) Every particle remembers its own previous best value as well as the neighborhood best; therefore, it has a more effective memory capability than the GA.

2) Demerits:

1) The candidate solutions in PSO are coded as a set of real numbers. But, most of the control variables such as transformer tap settings and switchable shunt capacitors change in discrete manner. Real coding of these variables represents a limitation of PSO methods as simple round-off calculations may lead to significant errors.
2) Slow convergence in refined search stage (weak local search ability).

VI. OPTIMIZATION RESULTS FOR PSO

The superiority of PSO is verified on 6-bus test system and IEEE 30-bus test system as shown. The results are obtained on MATLAB 7.9.0.529 (2009b) with computer configurations 3rd generation core-2-i3, 4 GB RAM, 2.50 GHz Processor and 64-bit operating system.

The tests were carried out by solving the optimal power flow problem of the power loss objective in which variable limits as given in Table-1 are used as system constraints. The results are verified with the results presented in paper [1].

Variable	**Limits**	
	Min	**Max**
V_1-V_6 (p.u.)	0.90	1.1
T_1-T_2 (p.u.)	0.90	1.1
Q_1,Q_2 (MVAR)	0	50
P_{G1}(MW)	60	120
P_{G2} (MW)	25	80

Table 1: Variable limits used for OPF

1	Population size	20
2	Acceleration constant (C1, C2)	2.1 and 2.0
3	Constriction factor(X)	0.621
4	Max. and Min. inertia weights	1 and 0.2
5	Max. and Min. velocity of particles	0.003 and -0.003
6	Convergence criterion	75 iterations

Table 2: selected parameters of PSO for 6-bus

	Real Power Losses	Reactive Power Losses
PSO	6.908 MW	21.21 MVAR
Newton Method	7.875 MW	24.17 MVAR

Table 3: Results obtained for 6-bus test system

1	Population size	50
2	Acceleration constant (C1, C2)	2.1 and 2.0
3	Constriction factor(X)	0.719
4	Max. and Min. inertia weights	1 and 0.2
5	Max. and Min. velocity of particles	0.003 and -0.003
6	Convergence criterion	111 iterations

Table 4: selected parameters of PSO for 30-bus

	Real Power Losses	**Reactive Power Losses**
PSO	15.6397 MW	61.48 MVAR
Newton Method	17.557 MW	67.69 MVAR

Table 5: Results obtained for IEEE 30-bus system

In fig.3, a graph of real power losses with respect to iteration numbers is shown. The real power losses are minimized as the number of iterations increases. The total numbers of iterations taken are 111.

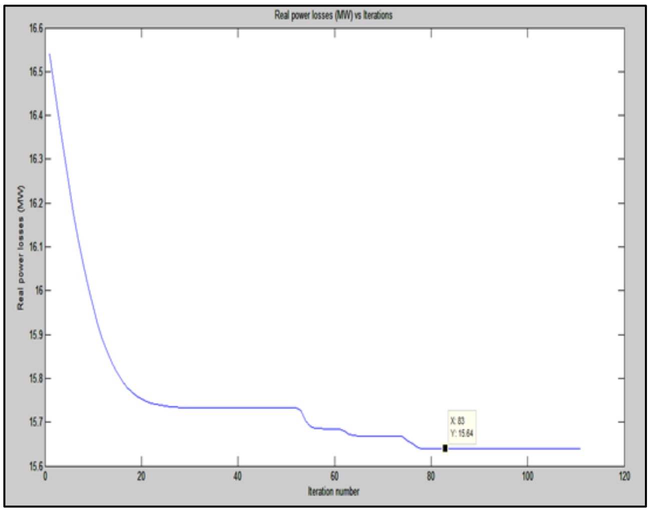

Fig. 3: Graph of real power losses for IEEE 30- bus test system using PSO

These results show that the PSO algorithm is better than the Newton method as real power losses are minimized up to 12.28% and reactive power losses are minimized up to 12.25% for 6-bus test system. While for IEEE 30-bus system, the real power losses are minimized up to 10.92% and reactive power losses are minimized up to 9.174%. The time taken by PSO to converge for IEEE 30-bus system is 145 sec.

VII. CONCLUSION

In this paper, the significance of reactive power optimization, various optimization techniques, optimal power flow problem, basic concept of particle swarm optimization, and results of 6-bus test system IEEE 30-bus test systems are obtained. The results are verified with paper [1]. As the results are obtained for test systems, the computation time is not a major issue. The main objective of this paper is to reduce the active power losses in the transmission system and it is achieved.

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