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Optimal Power Flow Using Particle Swarm Optimization

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Abstract:
The Optimal Power Flow (OPF) is an important criterion in today's power system operation and control due to scarcity of energy resources, increasing power generation cost and ever growing demand for electric energy. As the size of the power system increases, load may be varying. The generators should share the total demand plus losses among themselves. The sharing should be based on the fuel cost of the total generation with respect to some security constraints. Conventional optimization methods that make use of derivatives and gradients are, in general, not able to locate or identify the global optimum.

Heuristic algorithms such as genetic algorithms (GA) and evolutionary programming have been recently proposed for solving the OPF problem. Unfortunately, recent research has identified some deficiencies in GA performance. Recently, a new evolutionary computation technique, called Particle Swarm Optimization (PSO), has been proposed and introduced. This technique combines social psychology principles in socio-cognition human agents and evolutionary computations. In this paper, a novel PSO based approach is presented to solve Optimal Power Flow problem.

Key Words: Particle Swarm Optimization, Optimal Power Flow, Soft Computing Techniques, Evolutionary Computation Techniques

I Introduction

The fundamental mission of a power system is to provide consumers with sustained, reliable and cost-efficient electrical energy. In order to achieve this goal, system operators need to constantly adjust various controls such as generation outputs, transformer tap ratios, etc., to assure the continuous economic and secure system operations. This is a difficult task that relies highly on optimal power flow (OPF) function at power system control centers, the OPF procedure consists of using mathematical methodology to find the optimal operation of a power system under feasibility and security constraints. It has been consider as basic tool for determining secure and economic operating conditions of power systems.

The optimal power flow problem can be traced back early as early as 1920's when economic allocation of generation was the only concern. The economic operation of power system was achieved by dividing loads among available generator units such that their incremental generation costs are equal. This was a rather simple problem where only operating limits on real power generation were considered and the effect of system losses was either neglected or approximated by penalty factors calculated from loss formula or load flow Jacobian matrix.

As power system became increasingly large and complex, the security became an important issue, which requires more detailed system models. On the other hand, the evolution of digital computers made such detailed modeling become possible. In 1962, Carpentier for the first time established the Optimal Power Flow (OPF) problem on a rigorous mathematical base. He formulated it as a constrained nonlinear programming problem and derived its optimality conditions using Kuhn-Tucker theorem. In his formulation, the OPF problem is expressed in terms of all control and state variables, with

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both network and security constraints. The objective function can be total generation cost or transmission losses, depending on a specific application.

II Literature Survey

The first known Interior Point (IP) is usually attributed to Frisch in 1955, which is a logarithmic barrier method that was later extensively studied by Fiacco and McCormick to solve nonlinearly inequality constrained problem in 1960. In 1979 Khachiyan presented an ellipsoid method that would solve an LP problem in polynomial time. The greatest breakthrough in the Interior point method research field took place in 1984 by Karmarkar's method. After 1984, several variants of Karmarkar's Interior Point (IP) method have been proposed and implemented. Natural creatures sometimes behave as a swarm. One of the main streams of artificial life research is to examine how natural creatures behave as a swarm and reconfigure the swarm models inside a computer. Reynolds developed boid as a swarm model with simple rules and generated complicated swarm behavior by computer graphic animation [1]. Boyd and Richerson examined the decision process of human beings and developed the concept of individual learning and cultural transmission [2]. According to their examination, human beings make decisions using their own experiences and other persons' experiences.

A new 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, metaphor [3]. 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 [4]. Each individual exchanges previous experiences in PSO. These research efforts are called swarm intelligence [5, 6]. This paper focuses on PSO as one of the swarm intelligence techniques.

Other evolutionary computation (EC) techniques such as genetic algorithms (GAs), utilize multiple searching points in the solution space like PSO. Whereas GAs can treat combinatorial optimization problems, PSO was aimed to treat nonlinear optimization problems with continuous variables originally. Moreover, PSO has been expanded to handle combinatorial optimization problems and both discrete and continuous variables as well.

Efficient treatment of mixed-integer nonlinear optimization problems (MINLPs) is one of the most difficult problems in practical optimization. Moreover, unlike other EC techniques, PSO can be realized with only a small program; namely, PSO can handle MINLPs with only a small program. This feature of PSO is one of its advantages compared with other optimization techniques.

III Basic Particle Swarm Optimization

Swarm behavior can be modeled with a few simple rules. Schools of fishes and swarms of birds can be modeled with such simple models. Namely, even if the behavior rules of each individual (agent) are simple, the behavior of the swarm can be complicated. Reynolds utilized the following three vectors as simple rules in the researches on boid.

- Step away from the nearest agent
- Go toward the destination
- Go to the center of the swarm

The behavior of each agent inside the swarm can be modeled with simple vectors. The research results are one of the basic backgrounds of PSO.

Boyd and Richardson examined the decision process of humans and developed the concept of individual learning and cultural transmission [2]. According to their examination, people utilize two important kinds of information in decision process. The first one is their own experience; that is, they have tried the choices and know which state has been better so far, and they know how good it was. The second one is other people's experiences, i.e., they have knowledge of how the other agents around them have performed. Namely, they know

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which choices their neighbors have found most positive so far and how positive the best pattern of choices was.

Each agent decides its decision using its own experiences and the experiences of others. The research results are also one of the basic background elements of PSO.

According to the above background of PSO, Kennedy and Eberhart developed PSO through simulation of bird flocking in a two-dimensional space. The position of each agent is represented by its x, y axis position and also its velocity is expressed by vx (the velocity of x axis) and vy (the velocity of y axis). Modification of the agent position is realized by the position and velocity information.

Bird flocking optimizes a certain objective function. Each agent knows its best value so far (pbest) and its x, y position. This information is an analogy of the personal experiences of each agent. Moreover, each agent knows the best value so far in the group (gbest) among pbests.

This information is an analogy of the knowledge of how the other agents around them have performed. Each agent tries to modify its position using the following information:

- The current positions (x, y),
- The current velocities (vx, vy),
- The distance between the current position and pbest
- The distance between the current position and gbest

This modification can be represented by the concept of velocity (modified value for the current positions).

Velocity of each agent can be modified by the following equation:

$$v_i^{k+1} = wv_i^k + c_1 rand_1 * (pbest_i - s_i^k) + c_2 rand_2 * (gbest - s_i^k) \quad (1)$$

where v_i^k is velocity of agent i at iteration k, w is weighting function, c_1 and c_2 are weighting factors, $rand_1$ and $rand_2$ are random numbers between 0 and 1, s_i^k is current position of agent i at iteration k, $pbest_i$ is the pbest of agent i, and gbest is gbest of the group. Namely, velocity of an agent can be changed using three vectors such like boid. The velocity is usually limited to a certain maximum value. PSO using eqn. (1) is called the Gbest model.

The following weighting function is usually utilized in eqn. (1):

$$w = w_{max} - ((w_{max} - w_{min}) / (iter_{max})) * iter \quad (2)$$

Where w_{max} is the initial weight, w_{min} is the final weight, $iter_{max}$ is maximum iteration number and iter is current iteration number.

The meanings of the right-hand side (RHS) of eqn. (1) can be explained as follows [7]. The RHS of eqn. (1) consists of three terms (vectors). The first term is the previous velocity of the agent. The second and third terms are utilized to change the velocity of the agent.

Without the second and third terms, the agent will keep on “flying” in the same direction until it hits the boundary. Namely, it tries to explore new areas and, therefore, the first term corresponds with diversification in the search procedure. On the other hand, without the first term, the velocity of the “flying” agent is only determined by using its current position and its best positions in history. Namely, the agents will try to converge to their pbests and/or gbest and, therefore, the terms correspond with intensification in the search procedure. As shown below, for example, w_{max} and w_{min} are set to 0.9 and 0.4. Therefore, at the beginning of the search procedure, diversification is heavily weighted, while intensification is heavily weighted at the end of the search procedure such like simulated annealing (SA).

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Namely, a certain velocity, which gradually gets close to pbests and gbest, can be calculated. PSO using eqns.(1) & (2) is called inertia weights approach (IWA).

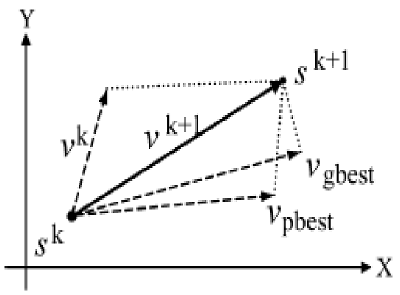

Figure 1: concept of modifications of a searching point by PSO

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

The current position (searching point in the solution space) can be modified by the following equation (3):

$$s_i^{k+1} = s_i^k + v_i^{k+1} \quad (3)$$

Figure 1 shows a concept of modification of a searching point by PSO, and it shows a searching concept with agents in a solution space. Each agent changes its current position using the integration of vectors as shown in Figure 1.

The features of the searching procedure of PSO can be summarized as follows:

- As shown in eqns. (1), (2), and (3), PSO can essentially handle continuous optimization problems.
- PSO utilizes several searching points, and the searching points gradually get close to the optimal point using their pbests and the gbest.
- The first term of the RHS of eqn. (1) corresponds with diversification in the search procedure. The second and third terms correspond with intensification in the search procedure. Namely, the method has a well-balanced mechanism to utilize diversification and intensification in the search procedure efficiently.
- The above concept is explained using only the x, y axis (two-dimensional space). However, the method can be easily applied to n-dimensional problems. Namely, PSO can handle continuous optimization problems with continuous state variables in an n-dimensional solution space.

Shi and Eberhart tried to examine the parameter selection of the above parameters [7, 8]. According to their examination, the following parameters are appropriate and the values do not depend on problems:

$$c_i = 2.0, \; w_{max} = 0.9, \quad w_{min} = 0.4,$$

The values are also proved to be appropriate for power system problems [9, 10]. The basic PSO has been applied to a learning problem of neural networks and Schaffer f6, a famous benchmark function for GA, and the efficiency of the method has been observed [4].

IV Mathematical formulation of optimal-power flow problem

The conventional formulation of the optimal-power-flow (OPF) problem determines the optimal settings of control variables such as real power generations, generator terminal voltages, transformer tap settings and phase-shifter angles while minimizing the objective function such as fuel cost as given in eqn.(4).

$$\text{Min (Fuel cost)} = \min \left(\sum_{i=1}^{NG} (a_i P_{Gi}^2 + b_i P_{Gi} + C_i)\right) \quad (4)$$

Where

NG: No. of Generators

P_{Gi}: Active Power produced by generator i.

a_i, b_i, c_i: Fuel cost coefficients of generator i.

The minimization problem of the objective function is subjected to the satisfaction of constraints from eqns. (5-9)

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Load-flow constraints:

$$P_i = V_i \sum_{j=1}^{N_b} V_j (G_{ij}\cos\theta_{ij} + B_{ij}\sin\theta_{ij})$$
$$i = 1,2,\ldots,N_b, i \neq s \quad (5)$$

$$Q_i = V_i \sum_{j=1}^{N_b} V_j (G_{ij}\cos\theta_{ij} - B_{ij}\cos\theta_{ij})$$
$$i = 1,2,\ldots,N_{PQ} \quad (6)$$

Voltage constraints:

$$V_i^{\min} \leq V_i \leq V_i^{\max} \qquad i \in N_b \quad (7)$$

Unit constraints

$$P_{gi}^{\min} \leq P_{gi} \leq P_{gi}^{\max} \qquad i \in N_g \quad (8)$$
$$Q_{gi}^{\min} \leq Q_{gi} \leq Q_{gi}^{\max} \qquad i \in N_g \quad (9)$$

V Results and discussions

This section presents the details of the study carried out on IEEE-30 bus and IEEE-14 bus test systems fortesting the OPF methodology. The proposed algorithm was implemented in MATLAB computing environment with Pentium-IV, 2.66 GHz computer with 512 MB RAM. the proposed PSO based algorithm was applied to obtain the optimal-control variables in the IEEE 30 & 14 bus systems under base load conditions.

The upper and lower voltage limits at all the bus bars except slack were taken as 1.1 and 0.95 respectively. The slack bus bar voltage was fixed to a value 1.07p.u. Here the contingencies are not considered and the proposed PSO based algorithm was applied to find the optimal scheduling of the power system for the base case loading condition. The objective function in this case is minimization of total fuel cost. Generator active-power outputs, generator busbar terminal voltages, transformer tap settings and shunt reactive power compensating elements were taken as optimization variables. The optimization variables are represented as floating point numbers in the population. The optimal values of control variables along with the real power generation of the slack busbar generator are given in Table 1 & 2 for IEEE-30 & 14 bus systems respectively. The minimum cost obtained with the proposed PSO algorithm for IEEE-30 bus system is $800.966/h, which is less than the minimum generation cost of $803.1916/h obtained with interior point method. Also, it was found that all the state variables satisfy the lower and upper limits.

For comparison, the OPF problem was solved using an evolutionary programming method with the population size of 20 and 250 generations. All the solutions satisfy the constraints on reactive power generation limits and line flow limits. The convergence of generation cost is shown in Fig.2 & 3 for IEEE 30 & 14 bus systems respectively.. From Fig. 2 & 3, it can be observed that the PSO took approximately 60 generations to reach the same production cost reached by EP. This shows that the proposed PSO algorithm occupies less computer space and takes less time to reach the optimal solution.

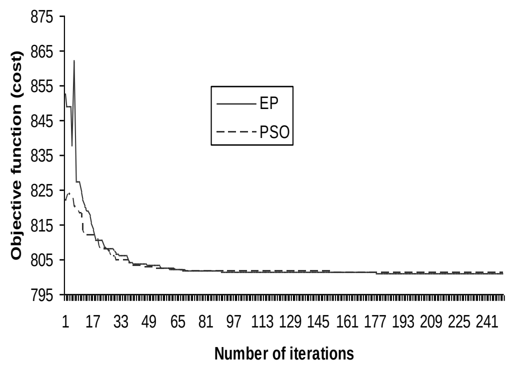

Fig.2 Convergence of generation cost for 30-bus system

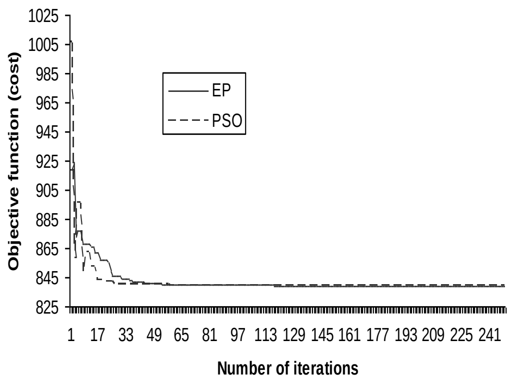

Fig.3 Convergence of generation cost for 14-bus system

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Table 1 Solution for IEEE 30-bus system

Control Variables		IPM	EP	PSO
Real power generation (p.u)	P_{G1}	1.7735	1.7642	1.7808
	P_{G2}	0.4877	0.4880	0.4823
	P_{G3}	0.2150	0.2257	0.2051
	P_{G4}	0.1209	0.1103	0.1236
	P_{G5}	0.2148	0.2130	0.2142
	P_{G6}	0.1200	0.1239	0.1200
Generator voltages (p.u)	V_{G1}	1.0700	1.0700	1.0700
	V_{G2}	1.0450	1.0567	1.0538
	V_{G3}	1.0100	1.0335	1.0355
	V_{G4}	1.0500	1.0849	1.1000
	V_{G5}	1.0100	1.0322	1.0299
	V_{G6}	1.0500	1.0496	1.0595
Transformer tap	Tap-1	0.9780	1.0077	1.0650
	Tap-2	0.9690	1.0401	0.9566
	Tap-3	0.9320	1.0023	1.0182
	Tap-4	0.9680	0.9791	0.9942
Shunt compensation	Q_{SVC1}	0	0.0738	0.0567
	Q_{SVC2}	0	0.0807	0.1000
	Q_{SVC3}	0	0.0873	0.0671
	Q_{SVC4}	0	0.0629	0.0214
	Q_{SVC5}	0	0.0609	0.0501
	Q_{SVC6}	0	0.0402	0.0720
	Q_{SVC7}	0	0.0222	0.0748
	Q_{SVC8}	0	0.0348	0.0541
	Q_{SVC9}	0	0.0434	0.0010
Cost ($/hr)		803.1916	801.0204	800.966

Table 2 Solution for IEEE 14-bus system

Control Variables	EP	PSO
P_{G1}	1.1394	1.1219
P_{G2}	0.6979	0.7000
P_{G3}	0.2727	0.2809
P_{G4}	0.2562	0.2632
P_{G5}	0.2735	0.2726
V_{G1}	1.0700	1.0700
V_{G2}	1.0576	1.0589
V_{G3}	1.0364	1.0309
V_{G4}	1.0376	1.0492
V_{G5}	1.0379	1.0241
Tap-1	0.9956	1.0182
Tap-2	0.9718	0.9174
Tap-3	0.9885	1.0187
Q_{SVC1}	0.0985	0.0789
Q_{SVC2}	0.0837	0.0163
Q_{SVC3}	0.0890	0.0459
Q_{SVC4}	0.1000	0.0956
Q_{SVC5}	0.0689	0.0671
Cost ($/hr)	839.2810	839.2236

VI Conclusion

In this chapter PSO based OPF algorithm has been validated with EP-OPF method using MATLAB software. It has been observed that optimal solution obtained by PSO-OPF is very close to that obtained by classical methods and it is clear that it is better than EP-OPF. So the proposed OPF methods are most suitable and valid for incorporating new objective functions and constraints. The algorithm is capable of determining the global optimum solution to the OPF problem in the presence of multiple local optima. This provides the opportunity to better model power system operations and therefore determine a more accurate operating state.

The performance of the developed OPF algorithms has been demonstrated by its application to the modified IEEE 30-bus and 14-bus test systems. The algorithms were accurately and reliably converged to the global optimum solution in each case. The PSO-algorithm is also capable of producing more favorable voltage profile while still maintaining a competitive cost.

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