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Research Paper

A NOVEL APPROACH TO SOLVING THE OPTIMAL POWER FLOW PROBLEM BASED ON PARTICLE SWARM OPTIMIZATION

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This paper presents an efficient and reliable evolutionary-based algorithm to solve the Optimal Power Flow (OPF) problem of electric power systems. The proposed algorithm employs the concept of swarm behavior in finding the optimum (e.g., food source) in nature, called Particle Optimal Swarm (PSO). The problem is to determine the set-point of the power system, including the power output of generators, the voltage of PV bus, etc., to supply the demand at least cost, at the same time subject to the equality and inequality constraints of the system. The algorithm was successfully tested in a 5-bus system and the simulation result showed its robustness and effectiveness compared to the conventional method in literature.

Keywords: Optimal power flow, Particle swarm optimization, Evolutionary computation, Newton-raphson method

INTRODUCTION

Optimal Power Flow (OPF) is a well-known numerical analysis of interconnected power systems to optimize the system operation while subject to constraints (Branke, 2002). Dependent on circumstance, the objective function of OPF can be minimizing fuel cost, minimizing environment impact, maximizing profit, or combination of those. The constraint normally concerns with power flow equations (equality constraints) or the physical limits of generating units, transmission lines, etc. (inequality constraints). The problem control variables include the generator real power and voltage, the transformer, the switches VAR sources, while the problem dependent variables include the load voltage, the generator reactive power and the power flow in transmission lines (Goldberg, 1989).

To solve OPF problems, a variety of optimization techniques have been studied those can be classified into two approaches. The first approach employs the basic theory of analytics and optimization to search for the

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extremum point in the feasible region based on the initial assumption of solution, e.g., Gradient-based, Linear Programming, Non-linear Programming, Lagrangian methods, etc. These methods take advantages of less computation and fast convergence. However, the main drawback is that these methods can find only one solution at one simution time and can get stuck at local optimum. In addition, the computation load increases exponentially as the number of variable increases, making them slow when solving for a large system (Van Veldhuizen and Lamont, 1998).

To overcome the above limitation, a new approach to optimization problem has been developed, called Evolutionary Computing Techniques. This approach is based on Darwinian principles of evolutions, employs advanced computation to search for global optimum with heuristic or stochastic optimization characters. Evolutionary techniques involve evolutionary algorithms such as Genetic Algorithm (GA), Genetic Programming (GP), Evolutionary Programming (EP), etc., and swarm algorithms such as Ant Colony Optimization (ACO), Artificial Bee Colony Optimization (ABCO), Particle Swarm Optimization (PSO), etc. (Poli *et al.*, 2007).

In this paper, we will apply the new evolutionary computing technique, particularly PSO method, to solve OPF problems. The PSO algorithm is developed to determine the optimal operation of thermal generating units, supplying the system at least fuel cost while considering the limits of generating units and power losses. The algorithm is then applied to solve the OPF problem of a 5-bus power system. The result of simulation showed its accuracy and effectiveness.

OPTIMAL POWER FLOW

General Problem Formulation

Optimal Power Flow (OPF) is an intelligent load flow module that employs techniques to automatically adjust the settings of power systems while solving the load flow and optimizing the operating conditions within specific constraints, simultaneously. OPF employs the state-of-the-art techniques with barrier functions and infeasibility handling to achieve the high-level of accuracy and flexibility. Like other optimization problem, optimal power flow problem can be formulated mathematically, as follows:

$$\min_{u} F(x,u) \quad ...(1)$$

$$g_e(x,u) = 0 \quad ...(2)$$

$$g_o(x,u) \le 0 \quad ...(3)$$

$$g_c(x,u) \le 0 \quad ...(4)$$

where, Equation (1) represents the objective function F(x, u) with the vector of variables is partitioned into the controllable quantities (control variables) u and the dependent (state) variables; Equation (2) represents the equality constraints, e.g., power flow equations, load demand, etc., Equation (3) are the operating constraints, in OPF problem, that can be the limitations of voltage at load buses, reactive power of generators; transmission capacity, etc.; and finally, Equation (4) are the control variable constraints which, normally, are real power of generators, transformer tap-changer, switched capacitors, etc.

In OPF problems, there are many control variables to be adjusted, while Economic Dispatch (ED) problem or reactive power generation dispatch has much less. The control variable, u is the control variable of OPF problems which can be expressed as follows.

$$u = [Q_C^T \ TC^T \ V_G^T \ P_G^T] \qquad ...(5)$$

While its state variables x are stated as:

$$x = [V_L^T \ {-}^T \ P_{SG} \ Q_G^T] \qquad ...(6)$$

where, Q_c is the reactive power supplied by all shunt capacitors; TC is the transformer load tap changer; V_G is the voltage magnitude at PV-buses; P_G is the active power generated at PV-buses; V_L is the voltage magnitude of PQ-buses (except the slack bus); θ is the voltage angle of all buses; P_{SG} is the active power of all buses; Q_G is the reactive power supplied by all generating units.

The Proposed OPF Objective Function

As aforementioned, the objective function of OPF can be mimimizing cost, maximizing profit, minimizing envirmental impact or the combination of those. In this paper, we consider the most prevalent OPF objective: Minimizing the fuel cost of thermal generating units that are modeled as a quadratic function.

$$\min_{P_G, V_G} \sum_{i=1}^{N_G} C_i\left(P_{Gi}\right) \qquad ...(7)$$

$$C_i(P_{Gi}) = a_i + b_i P_{Gi} + c_i P_{Gi}^2 \qquad ...(8)$$

where, N_G is the number of generating units including the slack generator in all buses; $C_i(P_i)$ is the fuel cost of unit G_i; a_i, b_i, c_i are the coefficients of the fuel cost models; P_{Gi} is the real power output. P_G, V_G are the vector of real power outputs and voltage magnitudes of all generating units and PV-buses, defined as

$$P_G = [P_{G1}, P_{G2} \cdots P_{Gn}]^T \qquad ...(9)$$

$$V_G = [V_{G1}, V_{G2} \cdots V_{Gn}]^T \qquad ...(10)$$

The Problem Constraints

The OPF constraints include equality and inequality constraints. The equality constraints are power/reactive power equalities, while the inequality constraints include bus voltage constraints, generators' real and reactive power limits, reactive power source capacity and the transformer tap position limits, etc. They can be expressed mathematically as follows.

$$\sum_{i=1}^{N_G} P_{Gi} = P_D + P_{loss} \qquad ...(11)$$

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max}, \quad i = 1, 2 \cdots N_G \qquad ...(12)$$

$$Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max}, \quad i = 1, 2 \cdots N_G \qquad ...(13)$$

$$V_i^{\min} \le V_i \le V_i^{\max}, \quad i = 1, 2 \cdots N_G \qquad ...(14)$$

$$¤_i^{\min} \le ¤_i \le ¤_i^{\max}, \quad i = 1, 2 \cdots N_G \qquad ...(15)$$

$$MVA_{ij} \le MVA_{ij}^{\max} \qquad ...(16)$$

where, P_D is the system demand of real power; P_{loss} is the total power losses in the transmission lines; $P_{Gi}^{\min}$ and $P_{Gi}^{\max}$ are the real power limits of i-th generation, respectively; and are the voltage limits at i-th bus bus; $¤_i^{\min}$ and $¤_i^{\max}$ are the phase angle limits at i-th bus; and $MVA_{ij}^{\max}$ is the capacity of the transmission line between i-th and j-th buses.

PARTICLE SWARM OPTIMIZATION

Particle Swarm Optimization (PSO) is a population-based stochastic optimization technique developed by Dr. Kennedy and Dr.

Eberhart in 1995. This is inspired by the social behavior of bird flocking or fish schooling (van den Bergh, 2002; and Poli *et al.*, 2007). In PSO, the potential solutions, called particles, fly through the problem space by following the current optimality of the population. Particles change their position by flying around in a multidimensional search space until a relatively unchanged position has been encountered, or until computational limitations are exceeded. This movement is determined according to not onlyits own experience, called individual best, but also thethe whole population, called global best. This method has many advantages over others techniques and has been successfully applied to various problems in electric power systems.

PSO Algorithm

Initially, PSO algorithm chooses candidate solutions, particles, randomly within the search space and determines their fitness. Each particle memorizes the best fitness value it has achieved thus far, referred to as the individual best fitness, and the candidate solution that achieved this fitness referred to as the individual best position or individual best candidate solution. Additionally, PSO algorithm determines the best fitness value achieved among all particles in the swarm, called the global best fitness, and the candidate solution that achieved this fitness, called the global best position or global best candidate solution. Therefore, PSO algorithm consists three main steps, which are repeated until some stopping condition is met:

1. Evaluate the fitness of each particle.
2. Update the individual and global best fitness and positions.
3. Update the velocity and position of each particle.

The velocity of each particle in the swarm is updated as the following rules:

$$v_i(k+1) = \underbrace{wv_i(k)}_{\text{Inertia}} + \underbrace{c_1 r_1 [P_{best} - x_j(k)]}_{\text{Cognitive}} + \underbrace{c_2 r_2 [G_{best} - x_i(k)]}_{\text{Social}} \quad ...(17)$$

where, w, c_1 and c_2 are user-supplied coefficients; r_1 and r_2 are uniformed random variables generated for each velocity update; P_{best} is the personal best or individual best candidate solution for i-th particle and G_{best} is the swarm's global best candidate solution.

The first term, $wv_1(k)$ is the inertia or damping component, responsible for keeping the particle moving in the same direction it was originally heading. The value of the inertial coefficient w is typically between 0.8 to 1.2, which can either dampen the particle's intertia or accelerate the particle in its original direction (Andries Engelbrecht, 2002; and Ray and Liew, 2002).

The second term, $c_1r_1[P_{best} – x_j(k)]$, called the cognitive component, acts as the particle's memory, making it to return to the region of the search space in which it has experienced with high individual fitness. The cognitive coefficient c_1 is usally close to 2, and affects the size of the step the particle takes towards its individual best candidate solution.

The third term, $c_2r_2[G_{best} – x_i(k)]$, called the social component, causes the particle to move to the best region the swarm has found so far. The social coefficent c_2 is typically close to 2, and represents the size of step the particle takes toward the global best candidate solution Gbest the swarm has found up.

In order to keep the particles from moving too far beyond the search space, we use a technique called velocity clamping to limit the maximum velocity of each particle. For a search space bounded by the range [$-x_{max}$, x_{max}], velocity clamping limits the velocity to the range [$-v_{max}$, v_{max}], where $v_{max} = k.x_{max}$. The value k represents a user-supplied velocity clamping factor ($0.1 \leq k \leq 1.0$). In many optimization tasks, the search space is not centered around 0 and thus the range [$-x_{max}$, x_{max}], is not an adequate definition of the search space. In such a case where the search space is bounded by [x_{min}, x_{max}], we define $v_{max} = k.(x_{max} - x_{min})/2$ (Fieldsend and Singh, 2002).

Once the velocity for each particle is calculated, the position is updated as follows.

$$x_i(k+1) = x_i(k) + v_i(k+1) \quad \text{...(18)}$$

This process is repeated until some stopping condition is met, for example:

- The positions of the particles are relatively unchanged between iterations.
- The number of iterations since the last update of the best solution is greater than a predefined number.

ILLUSTRATIVE EXAMPLES

In this example, we consider a 5-bus electric power system with three generators connected to Bus 1, 2 and 3, supplies load at Bus 4 and 5. In addition, there are capacitors at Bus 4 and 5 to compensate for the reactive power required by the load. It is assumed that the impedance in all lines are $z_L = r_L + jx_L = 0.0099 + j0.099$. Bus 1 is slack ($V\delta$) bus; Bus 2 and 3 are generator (PV) buses; and Bus 4 and 5 are load (PQ) buses. The OPF in this case is to determine the value of P_2, P_3, V_2 and V_3,

Figure 1: Bus Electric Power System

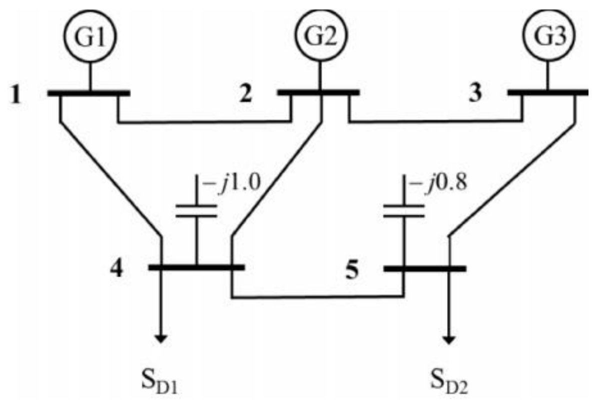
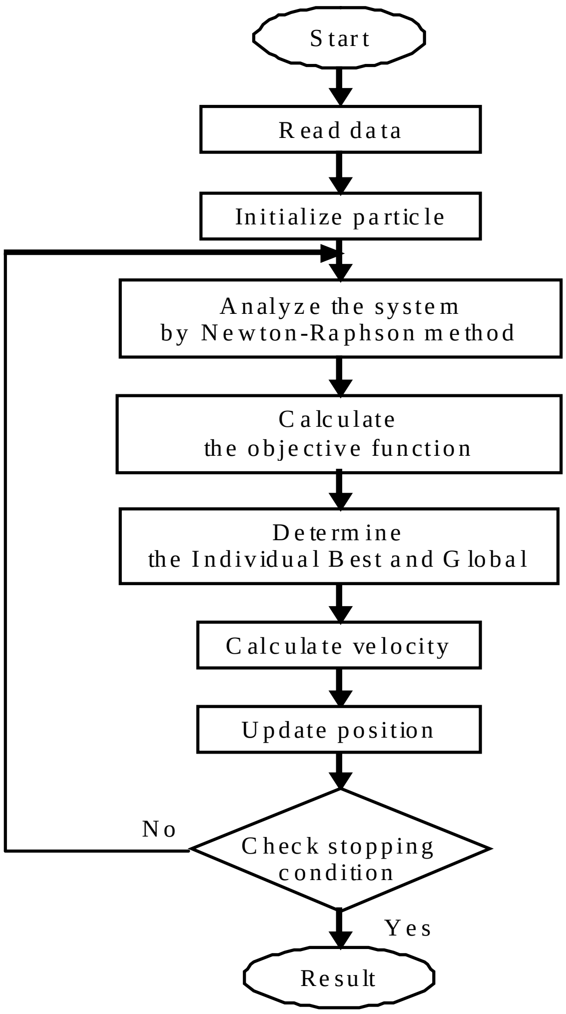


Figure 2: PSO Algorithms for OPF Problems



which minimizes the total cost of the system, while satisfies the equality and inequality constraints.

The problem is coded in Matlab software. The parameters of the network, PSO algorithm are provided in Appendixe. With the number of particles is arbitrarily chosen to be 100, the PSO converges pretty well with the number of iteration is about 28. The convergence of the particles in (V_2, V_3) and (P_2, P_3) planes are displayed in Figures 3 and 4.

Figure 3: The Convergence of the Particles in (V_2, V_3) Plane

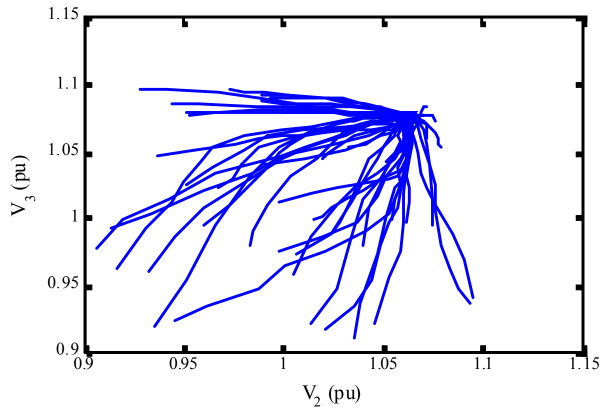
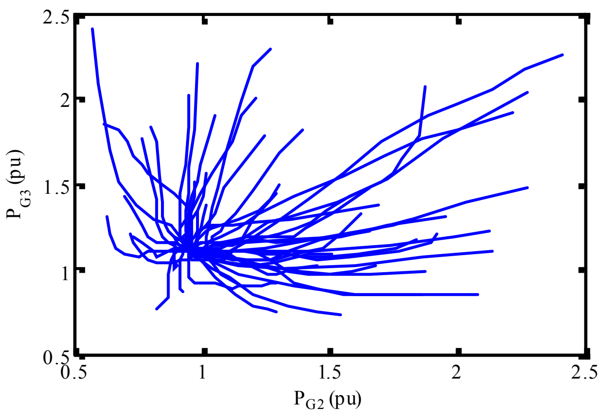


Figure 4: The Convergence of the Particles in (P_2, P_3) Plane



In Figures 3 and 4, it can be seen that the starting points of the particles are arbitrarily selected in the searching space. By communicating with others and memorizing the best position being taken, the particles tend to move and converge at the optimum point. The process stops when the particles' position is relatively unchanged ($\varepsilon = 10^{-3}$).

With $S_{D1} = 1.7 + j1.35$ and $S_{D2} = 1.7 + j1.42$; the convergence of 1-th particle is displayed in Figure 5.

Figure 5: The Convergence of 1st Particle in PSO Algorithm (V_2 = 1.06 pu; V_3 = 1.08; P_{G2} = 0.95 pu; and P_{G3} = 1.11 pu)

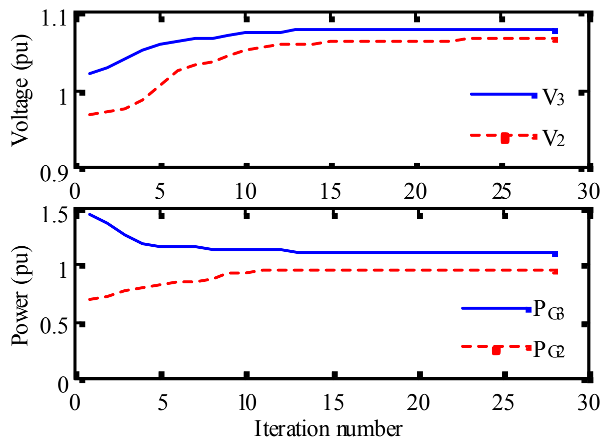
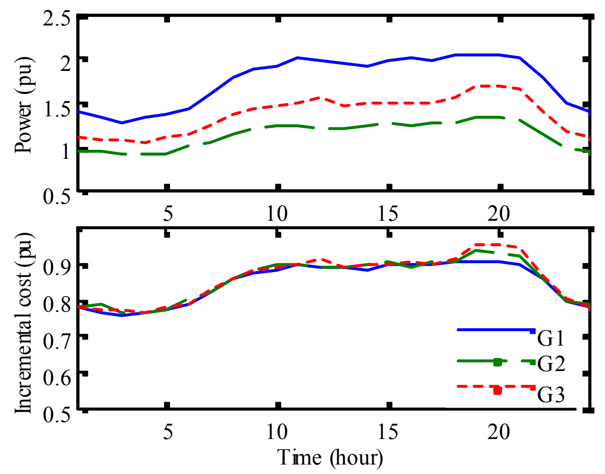


Figure 6: Optimal Generation and the Incremental Costs of Three Generators



In this case, the P_{G1} = 1.41 pu; the voltage in all buses, the current in all lines are kept within the limits. In addition, the validity of PSO algorithm is checked since the incremental cost at all generators are relative the same (IC = 0.78).

When the system load changes during the day (24 hours), the optimal generation of three generators is obtained in Figure 6. The incremental costs of different generators are slightly different due to penalty factor caused by power losses.

CONCLUSION

In this paper, we have proposed a novel PSO-based algorithm to solve the OPF problem. The proposed algorithm utilizes the global and personal exploration capabilities of PSO's particles to search for the optimal settings of the control variables, i.e., power output, voltage of generators. The proposed algorithm has been tested in a 5-bus electric power system tominimize the fuel cost of generators. The result of simulation showed that the algorithm has been successful in maintaining the increamental cost of all generators relatively the same with small difference caused by the penalty factor of power losses. In addition, the system constraints are satisfied such as voltage in all buses, line current, etc., and are kept within the limits. The simulation also showed that the algorithm converges pretty well with the number of iteration is as small as 28; and the simulation time for the whole 24-hour load level is less than 1 minute. More simulation results are shown in Appendix.

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APPENDIX

Appendix A: The System Parameters in the Illustrative Example

Table 1: The Coeffients of the Fuel Cost Model

Coeffients	G1	G2	G3
a(pu)	0.10	0.20	0.15
b(pu)	0.50	0.40	0.45
c(pu)	1.50	2.50	2.0
P_{max}(pu)	2.5	2.0	2.0
P_{min}(pu)	1.0	0.8	0.8
Q_{max}(pu)	2.0	2.0	2.0
Q_{min}(pu)	0.5	0.5	0.5

Table 2: Voltage Limits in All Buses

Voltage Limits	Value
V_{max}	1.1
V_{min}	0.9

Table 3: The Parameters of PSO Algorithms

Parameters	Notation	Value
Number of particles	N_p	100
Inertia coeffient	ω	0.5
Cognitive coeffient	c_1	0.2
Social coeffient	c_2	0.2
Accuracy to stop	ε	0.001

Appendix B: Simulative Results

Figure 1: The Voltage at Bus 2, 3, 4, and 5 Changes According to the Variation of Loads in the Day

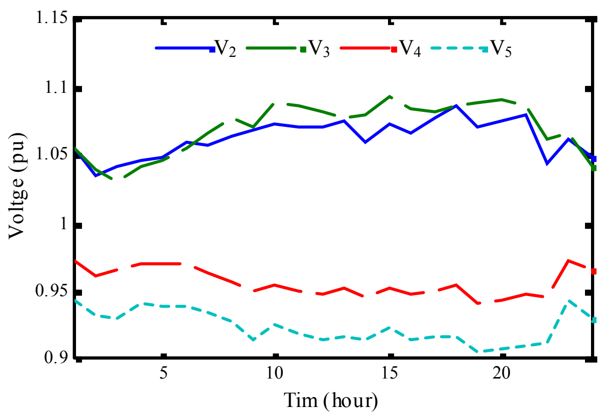

Figure 2: The Fuel Cost, Real and Reactive Power Losses According to the Variation of Loads in the Day