Economic Power Dispatch using Particle Swarm Optimization

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Abstract: ***The optimal power flow (OPF) is being used to find the optimal setting to operate the system. When operating cost is minimized, the generator schedule is calculated by OPF. Traditionally, the cost function of each generator is represented by a simple quadratic function. However thermal units are sometimes made to run on multiple fuels like coal, natural gas and oil. The work reported in this paper is carried out with the objective to make use of particle swarm optimization (pso) method for solving the optimal power flow (OPF) problem for units. The objective function in the OPF problem has been decided as minimization of total cost of real power generation. The performance of the proposed method has been demonstrated under simulated conditions on 5-Bus system with 3-Generation units. The problem has been formulated as a single optimization problem to obtain the solution for optimal power flow problem with combined fuel cost and environment impact as objectives compared favorably with results of other methods.***

Keywords: optimal power flow (OPF), Particle swarm optimization (PSO).

1. Introduction

Optimal power flow (OPF) has been widely used in power system operation and planning. In deregulated environment of power sector, it is of increasing importance, for determination of electricity prices and also for congestion management.OPF is a computationally intensive tool when analyzing many generation plants, transmission lines and demands. Finally the engineering constraints and economic objectives for system operations are combined by formulating and solving the optimal power flow problem. OPF is used in economic analysis of the power system as well.

Optimal Power Flow (OPF) is a method to find steady state operation point which minimizes generation cost, loss etc. or maximizes social welfare, loadability etc while maintaining an acceptable system performance in terms of limits on generator's real and reactive powers, line flow limits, output of various compensating devices etc.

The OPF problem may also have the formulation of active power generation dispatch (Economic Dispatch Problem, EDP) and reactive power generation dispatch .The main purpose of the EDP is to determine the generation schedule of the electrical energy system that minimizes the total generation and operation cost and does not violate any of the system operating constraints such as line overloading, bus voltage profiles and deviations.

On the other hand, the objective of reactive power dispatch is to minimize the active power transmission losses in an electrical system while satisfying all the system operating constraints .The objective function of the OPF can take different forms other than minimizing the generation cost and the losses in the transmission system. The OPF can be used to obtain the settings of the control variables under the steady-state functions of the power system. These control variables may include generator control and transmission system control variables. For generators, the control variable can be generator MW output. For the transmission system, the control variable can be bus voltages of the generator buses, the tap ratio or phase shift angle for transformers, settings of switched shunt or flexible ac transmission system (FACTS) devices.

2. Optimal Power Flow Solution Methods

A. **Classical Methods [2]:**
1. Linear Programming (LP) Method
2. Newton-Raphson (NR) Method
3. Quadratic Programming (QP) Method
4. Nonlinear Programming (NLP) Method
5. Interior Point (IP) Method

Artificial Intelligence (AI) Methods
1. Artificial Neural Network (ANN)
2. Fuzzy Logic Method (FL)
3. Genetic Algorithm (GA) Method
4. Evolutionary Programming (EP)
5. Ant Colony Optimization (ACO)
6. Particle Swarm Optimization (PSO)

2.1 Comparison of above Method

The classical methods are suffered with the following disadvantages

(1) Mathematical formulations have to be simplified to get the solutions because of the extremely limited capability to solve real-world large scale power system problems.
(2) They are weak in handling qualitative constraints. They have poor convergence, may get stuck at local optimum, they can find only a single optimized solution in a single simulation run, they become too slow if the number of variables are large and they are computationally expensive for the solution of a large system.

The major advantage of the AI methods as under:

(1) They are relatively versatile for handling various qualitative constraints. AI methods can find multiple optimal solutions in a single simulation run. So they are quite suitable in solving multi-objective optimization problems. They can find the global optimum solution.
(2) The ANN are Possesses learning ability, fast, appropriate for non linear modeling, etc.
(3)The Fuzzy method are accurately represents the operational constraints and fuzzified constraints are softer than traditional constraints.
(4)The advantages of GA methods are: It only uses the values of the objective function and less likely to get trapped in a local optimum. (5)The EP are adaptable to change, ability to generate good enough solutions and rapid convergence.
(6) The ACO are positive feedback for recovery of good solutions, distributed computation, which avoids premature convergence. It has been mainly used in finding the shortest route in the transmission network, short-term generation scheduling and optimal unit commitment.
(7) The PSO can be used to solve complex optimization problems, which are non-linear, non-differentiable and multi-model and its fast convergence speed and it can be realized simply for less parameters need adjusting. PSO has been mainly used to solve Bi-objective generation scheduling, optimal reactive power dispatch and to minimize total cost of power generation.

Some disadvantages are

(1) ANN has large dimensionality and the choice of training methodology.
(2) GA methods have higher computational time.

3. Particle Swarm Optimization

In many engineering disciplines a large spectrum of optimization problems has grown in size and complexity. In some instances, the solution to complex multidimensional problems by means of classical optimization techniques is extremely difficult and/or computational expensive. This realization has led to an increased interest in a special class of searching algorithms, namely, heuristic algorithms. In general, they are referred to as “stochastic” optimization techniques and their foundations lie in the evolutionary patterns and behaviors observed in living organisms. Particle Swarm Optimization (PSO) is a relatively new evolutionary algorithm that may be used to find optimal (or near optimal) solutions to numerical and qualitative problems. Particle Swarm Optimization was originally developed by James Kennedy and Russell Eberhart in 1995, and emerged from earlier experiments with algorithms that modeled the flocking behavior seen in many species of birds. Although there were a number of such algorithms getting quite a bit of attention at the time, Kennedy and Eberhart became particularly interested in the models developed by biologist Frank Heppner .Heppner studied birds in flocking behaviors mainly attracted to a roosting area.

In simulations, birds would begin by flying around with no particular destination and spontaneously formed flocks until one of the birds flew over the roosting area. Due to the simple rules the birds used to set their directions and velocities, a bird pulling away from the flock in order to land at the roost would result in nearby birds moving towards the roost. Once these birds discovered the roost, they would land there, pulling more birds towards it, and so on until the entire flock had landed.

Finding a roost is analogous to finding a solution in a field of possible solutions in a solution space. The manner in which a bird who has found the roost, leads its neighbors to move towards it, increases the chances that they will also find it. This is known as the “socio-cognitive view of mind”. The “socio-cognitive view of mind” means that a particle learns primarily from the success of its neighbors.

Eberhart and Kennedy revised Heppner's methodology so that particles could fly over a solution space and land on the best solution simulating the birds’ behavior. Each particle should compare themselves to others and imitate the behavior of others who have achieved a particular objective successfully. Eberhart and Kennedy developed a model that balances the cooperation between particles in the swarm. An appropriate balance between exploration (individuals looking around for a good solution) and exploitation (individuals taking advantage of someone else's success), is a main concern in the Eberhart and Kennedy model.

Too little exploration and the particles will all converge to the first good solution found (typically a local solution). Too little exploitation and the particle will take longer to converge (or may not converge at all). In summary, the Eberhart and Kennedy model attempts to find the best compromise between its two main components, individuality and sociality.
Particle swarm optimization (PSO) which is a population based stochastic optimization technique shares many similarities with evolutionary computation techniques such as Genetic Algorithms (GA). The system is initialized with a population of random feasible solutions and searches for optima by updating generations.

However, unlike GA, PSO has no evolution operators such as crossover and mutation. PSO algorithm has also been demonstrated to perform well on genetic algorithm test function. In PSO, the potential solutions, called particles, fly through the problem space by following the current optimum particles.

In a PSO algorithm, particles change their positions by flying around in 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 fine tune 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.

Each particle keeps track of its coordinates in the problem space, which are associated with 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 neighbors of the particle. This location is called lbest. When a particle takes all the population as its topological neighbors, the best value is a global best and is called gbest.

The concept of the PSO consists of, at each time step, changing the velocity of (accelerating) each particle toward its pbest and lbest locations (local version of PSO). Acceleration is weighted by a random term, with separate random numbers being generated for acceleration toward pbest and lbest locations. In past several years, PSO has been successfully applied in many research and application areas. It is demonstrated that PSO gets better results in a faster, cheaper way compared with other methods. Another reason that PSO is attractive is that there are few parameters to adjust. One version, with slight variations, works well in a wide variety of applications. Particle swarm optimization has been used for approaches that can be used across a wide range of applications, as well as for specific applications focused on a specific requirement.

Advantages of PSO

a. PSO is a population-based search algorithm. This property ensures PSO to be less susceptible in being trapped on local minima.
b. PSO makes use of the 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 robust than conventional methods.
c. PSO can easily deal with non-differentiable objective functions because PSO uses payoff (performance index or objective function) information to guide the search in the problem space. Additionally, this property relieves PSO of assumptions and approximations, which are often required by traditional optimization models.
d. The solution quality of the proposed approach does not depend on the initial population. Starting anywhere in the search space, the algorithm ensures the convergence to the optimal solution. Therefore, this method is different from traditional techniques.
e. 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 which makes it different from Genetic Algorithm (GA) and other heuristic algorithms.

3.1 PSO Algorithm

A general engineering optimization problem can be defined as follows:

Minimize

$$f(X),\ X=\{x_1, x2\ldots\ldots\ldots X_n\} \in R$$

subject to $f_0(X) \le 0$

$f_E(X)=0$

Where

$X_i^L \le X i \le X_i^U \quad i=1,2,\ldots.\ n$

Where (L) and (U) represents lower and upper limits of the i^{th} decision variable

Also,

f (X) represents the objective function.

$f_0(X) \le 0$ represents inequality constraint.

$f_E(X)=0$ represents the equality constraint.

Basic Terms Used in PSO

The basic terms used in PSO technique are stated and defined as follows:

1) **Particle X (i):** It is a candidate solution represented by a k-dimensional real-valued vector, where k is the number of optimized parameters. At iteration i, the jth particle X (i,j) can be described as:

$$X_i(i)=[X\ j1(i); X\ j2(i); \ldots\ldots. X\ jk(i); \ldots.. X\ jd(i)]$$

Where:

x's are the optimized parameters

d represents number of control variables

2) **Population:** It is basically a set of n particles at iteration i.

$$Pop(i)=[X_1(i),\ X_2(i), \ldots\ldots X_n(i)]^T$$

Where:

n represents the number of candidate solutions.

3) Swarm: Swarm may be defined as 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 (i): Particle velocity is the velocity of the moving particles represented by a d-dimensional real-valued vector. At iteration i, the jth particle Vj (i) can be described as:

Where:

$$V_i(i)=[V\ j1(i); V\ j2(i); \ldots\ldots. V\ jk(i); \ldots.. V\ jd(i);]$$

is the velocity component of the jth particle with respect to the kth dimension.

5). Individual best X* (i): When particles are moving through the search space , it compares its fitness value at the current position to the best fitness value it has ever reached at any iteration up to the current iteration. The best position that is associated with the best fitness encountered so far is called the individual best X* (i).For each particle in the swarm, X*(i)can be determined and updated during the search For the jth particle, individual best can be expressed as:

$$X_i(i)=[X\ j1(i)^*\ X\ j2(i)^* \ldots\ldots. X\ jk(i); \ldots.. X\ jd^*(i)]^T$$

In a minimization problem with only one objective function f, the individual best of the jth particle Xj*(i) is updated whenever f (Xj*(i)) < f (Xj*(i-1)). Otherwise, the individual best solution of the jth particle will be kept as in the previous iteration.

6) Global best X (t):** Global best is the best position among all of the individual best positions achieved so far.

7) Stopping criteria: Termination of search process will take place whenever one of the 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.

The particle velocity in the kth dimension is limited by some maximum value, This limit enhances the local exploration of the problem space and it realistically simulates the incremental changes of human learning.

The maximum velocity in the kth dimension is characterized by the range of the kth optimized parameter and given by:

$$V_k^{max} = (X_k^{max} - X_k^{min}) / N$$

Where:
N is a chosen number of intervals in the K^{th} dimension.
The basic principle of PSO is shown in figure 1.1

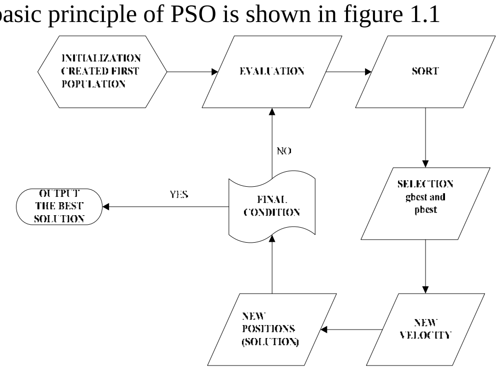


Figure 1. The principle of PSO

The Algorithm

The general Particle Swarm Optimization algorithm may be applied to any optimization problem. 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 steps taken to build up PSO basic algorithm are:

Step 1: Random Initialization: Firstly we set i=0 and randomly generate n particles, {Xj(0), j =1,2,....n}. Each particle is considered to be a solution for the problem and it can be described
As

$$X_j(0) = [X_{i,1}(0) ; X_{i,2}(0) ;…..; X_{i,k}(0)]$$

Every control variable has a range [X_{min} , X_{max}]. Random initialization of each particle and velocity is done using the objective function .If the candidate solution is a feasible solution, i.e. all the problem constraints have been met, then we go to step-2 else we repeat this step.

Step 2: Counter is Updated: The next step we do is Updating the counter i= i +1.

Step 3: Calculation of the objective function: Then the objective function is calculated.

Step 4: Velocity is updated: By using the global best and individual best, the jth particle velocity in the kth dimension is updated according to the following equation:

$$V(k, j, i+1) = V(k, ,j, i) + C_1 \times rand \times (p_{best}\, x(j, k) - x(k, j, i)) + C_2 \times rand \times (g_{best}(x(k) - x(k, j, i))$$

Where,
i is the iteration number.
j is the particle number.
k is the kth control variable.
c1, c2 are acceleration constant.
rand () is a uniform random value in the range of [0,1] .
V(k,j,i) is the velocity of particle j at iteration i.
x(k,j,i) is the current position of particle j at iteration j.
Then, the velocity limits are checked. If the velocity violates its limit, it is set 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 their own thinking and memory. The third term of the above equation represents the social part of PSO where the particle changes its velocity based on the social-psychological adaptation of knowledge.

Step 5: Position is updated: On the basis of the updated velocity, each particle changes its position.

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

Step 6: Individual best updating: Evaluation of each particle is done and particle is updated according to the update position.
Step 7: Search Minimum value: The minimum value in the individual best is searched and its solution, if it has ever been reached in any iteration and considered the minimum.
Step 8: Stopping criteria: If one of the stopping criteria is satisfied, then the whole process is stopped otherwise go to step-2.
The flow chart for the above algorithm is shown in Fig. 1.2

4. Result and Discussion

To verify the feasibility of the PSO method, three as well as six unit thermal plants of a power system are tested. A reasonable Bmn loss coefficients matrix of power system network is employed. The program is developed in MATLAB and executed and compared with GA.

Table 1. Comparison of results of Optimal Scheduling of Generators between GENETIC ALGORITHEM and PSO Method of a Three- unit system

Method	*P1 (MW)*	*P2 (MW)*	*P3 (MW)*
GA	124.589330	147.153552	36.283370
PSO	202.4664	80.7365	27.39193

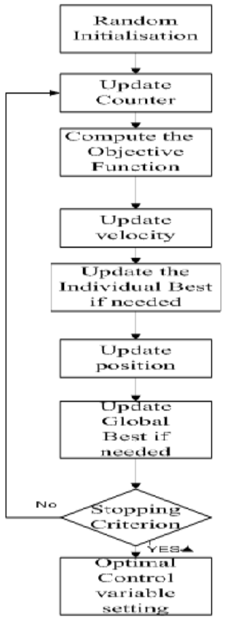
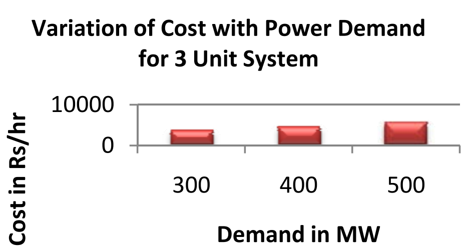


Figure 2. Flow chart of PSO based OPF

Table 2: Comparison of results of fuel cost of Generators between Classical Method and PSO method of a Three- unit system

Method	*FUEL COST (RS/h)*
GA	3656.225311
PSO	3615.487612



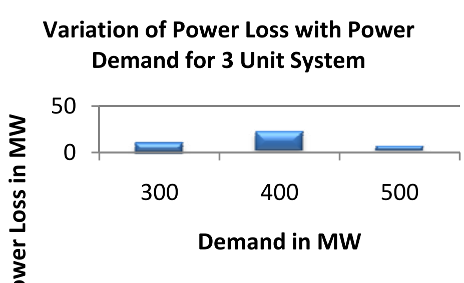
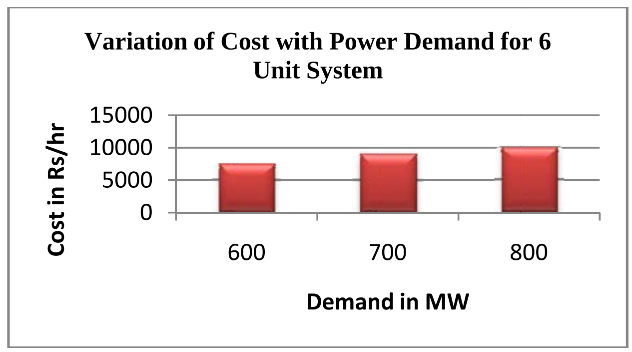


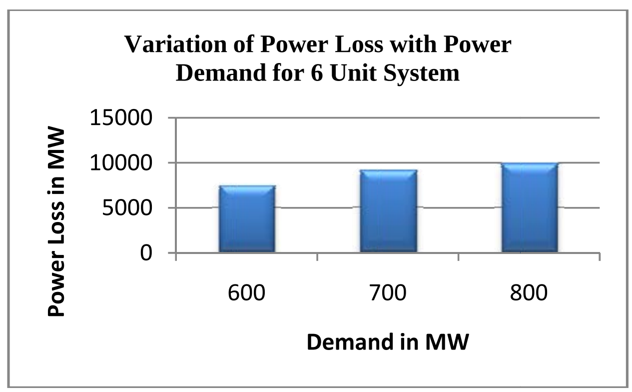
Table 3: Comparison of results of Optimal Scheduling of Generators between GENETIC ALGORITHEM and PSO Method of a six- unit system

Method	*P1 (MW)*	*P2 (MW)*	*P3 (MW)*	*P4 (MW)*	*P5 (MW)*	*P6 (MW)*
GA	104.468749	169.107930	127.494196	142.369386	78.612308	96.999953
PSO	323.66266	76.731699	158.21045	50.0000	52.13006	50.000000

Table 4: Comparison of results of fuel cost of Generators between Classical Method and PSO method of a six- unit system

Method	*FUEL COST (RS/h)*
GA	9162.814991
PSO	8352.611628





5. Conclusion

In this paper the difficult optimization problem is solved by using PSO algorithm. In order to prove the effectiveness of algorithm it is applied to TWO different cases with THREE AND SIX generating units. The multi-objective problem is converted in to single objective form by means of price penalty factor with the consideration of problem constraints. After comparing the results with other algorithm it is observed that PSO is well suited for obtaining the best solution, so that fuel cost is reduced for different load demands.

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