Particle Swarm Optimization based Optimal Power Flow for Units with Non-Smooth Fuel Cost Functions

Djillani BEN ATTOUS [1], Yacine LABBI [2]

Department of Electrotechnics, Faculty of Electrical Engineering
El-Oued University Center, Algeria.
[1]dbenattous@yahoo.com
[2]yacinelabbi@gmail.com

Abstract

This paper presents a Particle Swarm Optimization (PSO) based algorithm for optimal flow with generating units having non-smooth fuel costs curves while statisfying the constraints such as generator capacity limits, power balance, line flow limits, bus voltages and transformer tap setting, The conventional loed flow and incorporation of the proposed method using PSO has been examined and tested for standard IEEE 30 bus system. The PSO method is demonstrated and compared with conventional OPF method and the intelligence heuristic algorithm such as genetic algorithm, evolutionary programming. The superiority of th method over other methods has been demonstrated on two test cases.
From simulation results, it has been found that PSO method is highly competitve for its better general convergence performance.

Keywords: load flow, optimal power flow, particle swarm optimization, non-smooth fuel cost functions, valve point effects.

1. Introduction

In power system operation, the economic dispatch (ED) problem is an important optimization problem. Moreover, it has complex and nonlinear characteristics with heavy equality and inequality constraints. Generally, there are two types of ED problem, i.e. static and dynamic. Solving the static ED problem is subject to the power balance constraints and generator operating limits. For the dynamic ED, it is an extension of the static ED problem. The dynamic ED takes the ramp rate limits and prohibited operating zone of the generating units into consideration. [1]

The methods for solving this kind of problem include traditional operational research algorithms (such as linear programming, quadratic programming, dynamic programming, gradient methods and Lagrange relaxation approaches) and modern methods (such as simulated annealing and evolutionary algorithms). Some of these methods are successful in locating the optimal solution, but they are usually slow in convergence and require heavy computational cost. Some other methods may risk being trapped to a local optimum, which is the problem of premature convergence. [2]

Recently, intelligence heuristic algorithms, such as genetic algorithm, evolutionary programming, and meta-heuristic algorithms have been proposed for solving the OPF problem. Like other meta-heuristic algorithms, particle swarm optimization (PSO) algorithm was developed through simulation of a simplified social system such as bird flocking and fishing school. PSO is an optimization method based on population [3], and it can be used to solve many complex optimization problems, which are nonlinear, non-differentiable and multi-modal. The most prominent merit of PSO is its fast convergence speed. In addition, PSO algorithm can be realized simply for less parameters need adjusting. PSO has been applied to various power system optimization problems with impressive success. The results for a 30-bus system shows that PSO is an effective method to solve OPF problem [4].

The main objective of this study is to introduce the use of Particle Swarm Optimization (PSO) technique to the subject of power system economic load dispatch. In this paper, the PSO method has been employed to solve economic dispatch problem with a valve point effects. A valve point effects is the rippling effects added to the generating unit curve when each steam admission valve in a turbine starts to open. More-over, to assure accurate results for this model, an additional term representing the valve point effects should be added to the cost function. The addition of the valve point effects poses a more challenging task to the proposed method since it increases the non-linearity of the search space as well as the number of local minima. (See Fig. 1).

2. Problem Formulation

2.1. The OPF with quadratic fuel cost functions

The optimal power flow problem is concerned with optimization of steady state power system performance with respect an objective F while subject to numerous constraints. For optimal active power dispatch, the objective function F is total generation cost as expressed follows:

$$F = \sum_{i=1}^{N} C_i(P_{Gi}) = \sum_{i=1}^{N} a_i + b_i P_{Gi} + c_i P_{Gi}^2 \qquad (1)$$

Where:
N: total number of generation units
ai, bi, ci: cost coefficients of generating unit.
Pgi: real power generation of ith unit. i= 1, 2 … to N.
Subject to:
Equality constraints as:

$$F = \sum_{i=1}^{N} \mathrm{P}_{gi} = \mathrm{P}_D + \mathrm{P}_L \qquad (2)$$

Inequality constraints as:
Branch flow limits:

$$|Si| \leq S_i^{\max} \qquad i = 1,\dots nl \qquad (3)$$

Where: nl: number of lines.
Voltage at load buses

$$|S_D|^{\min} \leq |Si| \leq |S_D|^{\max} \qquad i = 1,\dots nd \qquad (4)$$

Where: nd: number of load buses.
Generator MVAR

$$Q_{Gi}^{\min} \leq Q_{Gi} \leq Q_{Gi}^{\max} \qquad i = 1,\dots N \qquad (5)$$

Slack bus MW

$$P_G^{\min} \leq P_G \leq P_G^{\max} \qquad (6)$$

2.2. valve-point effects

The generating units with multi-valve steam, turbines exhibit a greater variation in the fuel cost functions. Since the valve point results in the ripples as show in fig.1, a cost function contains higher order nonlinearity. Therefore, the equation (1) should be replaced as the equation (7) to consider the valve point effects. Here, the sinusoidal functions are thus added to the quadratic cost function as follows.

The incremental fuel cost function of the generation units with valve-point loading is represented as follows.

$$Fi(P_{gi}) = a_i + b_i P_{Gi} + c_i P_{Gi}^2 + \left|e_i \times \sin(f_i \times (P_{Gi\min} - P_{Gi}))\right| \quad (7)$$

Where e_i and f_i are the coefficients of generator i reflecting valve point effects.

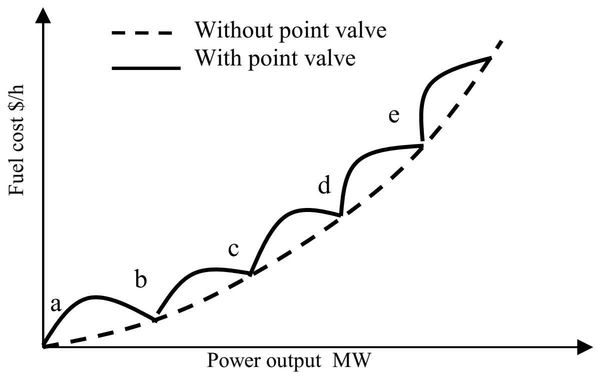

Fig. 1. Fuel cost versus power output for 6 valve steam turbine unit.

3. Particle Swarm Optimization

Particle swarm optimization (PSO) is a population-based optimization method first proposed by Kennedy and Eberhart in 1995, inspired by social behavior of bird flocking or fish schooling. The PSO as an optimization tool provides a population-based search procedure in which individuals called particles change their position (state) with time. In a PSO system ,particles fly around in a multidimensional search space . During flight, each particle adjusts its position according to its own experience (This value is called pbest), and according to the experience of a neighboring particle
(This value is called gbest), made use of the best position encountered by itself and its neighbor (Fig. 2).

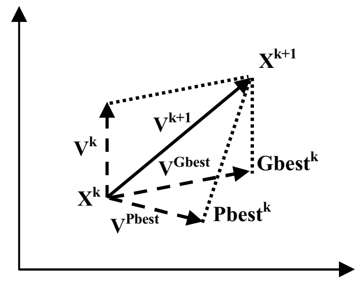

Fig. 2. Concept of a searching point by PSO

This modification can be represented by the concept of velocity. Velocity of each agent can be modified by the following equation:

$$v_{k+1} = w.v_k + c_1 rand^* (pbest - x^k) + c_2 rand^* (gbest - x^k) \quad (8)$$

Using the above equation, a certain velocity, which gradually gets close to pbest and gbest can be calculated .
The current position (searching point in the solution space) can be modified by the following equation:

$$x^{k+1} = x^k + v_{k+1} \;, k = 1,2,\dots, \; n \qquad (9)$$

Where
x^k is current searching point , x^{k+1} is modified searching point , v_k is current velocity , v_{k+1} is modified velocity of agent Vpbest is velocity based on pbest ,Vgbest is velocity based on gbest, n is number of particles in a group, m is number of members in a particle, $pbest_i$ is pbest of agent k, $gbest_i$ is gbest of the group, w is weight function for velocity of agent k , c_i is weight coefficients for each term .

- c1 and c2 are two positive constants.
- r1 and r2 are two randomly generated numbers with a range of [0,1].
- w is the inertia weight and it is defined as a function of iteration index k as follows:

$$w(k) = w_{\max} - \left(\frac{w_{\max} - w_{\min}}{Max.Iter.}\right) * k. \qquad (10)$$

Where $Max.Iter$, k is maximum number of iterations and the current number of iterations, respectively.
To insure uniform velocity through all dimensions, the maximum velocity is as.

$$v^{\max} = (x^{\max} - x^{\min}) / N. \qquad (11)$$

Where N is a chosen number of iterations.

4. Applied to Optimal Power Flow

To minimize F is equivalent to getting a minimum fitness value in the searching process.

The particle that has lower cost function should be assigned a larger fitness value.

The objective of OPF has to be changed to the maximization of fitness to be used as follows:

$$fitness = \begin{cases} F / f_{\max}\,; & if \quad f_{\max} > F \\ 0\ ; & otherwise \end{cases} \qquad (12)$$

The PSO-based approach for solving the OPF problem to minimize the cost takes the following steps:

Step 1: randomly generated initial population.
Step 2: For each particle, the construction operators are applied.
Step 3: the Newton Raphson routine is applied to each particle.
Step 4: fitness function evaluation.
Step 5: compare particles fitness function and determine pbest and gbest.
Step 6: change of particles velocity and position according to (11) and (12) respectively.
Step 7: If the iteration number reaches the maximum limit, go to Step 8. Otherwise, set iteration index k = k + 1, and go back to Step 2.
Step 8: Print out the optimal solution to the target problem.

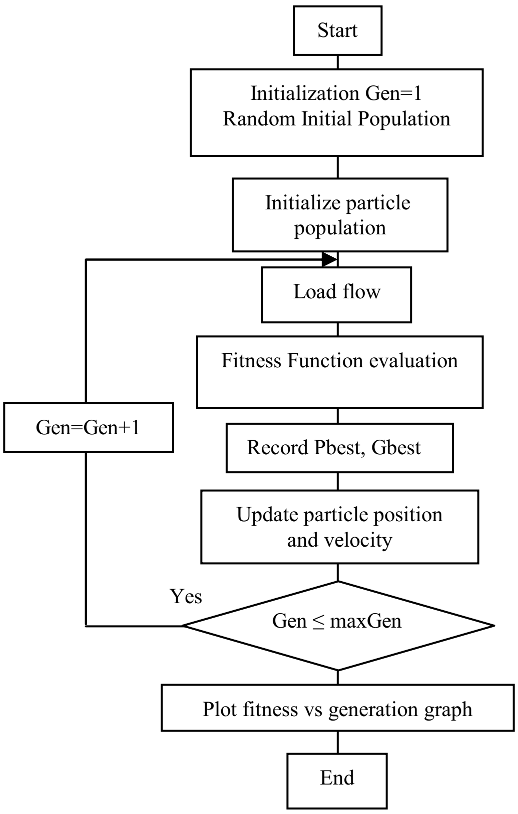

Fig. 3. PSO-OPF computational procedure.

5. Load Flow Calculation

Once the reconstruction operators have been applied and the control variables values are determined for each particle a load flow run is performed. Such flows run allows evaluating the branches active power flow, the total losses and voltage magnitude this will provide updated voltages angles and total transmission losses. All these require a fast and robust load flow program with best convergence properties; the developed load flow process is upon the full Newton Raphson algorithm.

6. Simulation Results and Discussion

The proposed PSO algorithm is tested on standard IEEE 30 bus system. The test system consists of 6 thermal units (Table1), 24 load buses and 41 transmission lines.

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The total system demand is 283.4 MW.

The program was written and executed on Pentium 4 having 2.4 GHZ 1GB DDR RAM.

The optimal setting of the PSO control parameters are:

c1=0.5, c2=0.5, numbers of particles is 50 and number of generations is 30.

The Inertia weight was kept between 0.4 and 0.9.

6.1. Case 1: The OPF with quadratic fuel cost functions

In this case the units cost curves are represented by quadratic function. The generator cost coefficients are given in Table A.1. The proposed PSO-OPF is applied to standard IEEE 30 bus system.

The obtained results using PSO-OPF are given in Tables 1- 2.

Fig.4. shows the cost convergence of PSO based OPF algorithm for various numbers of generations. It was clearly shown that there is no rapid change in the fuel cost function value after 30 generations. Hence it is clears from the Fig. That the solution is converged to a high quality solution at the early iterations (13 iterations).

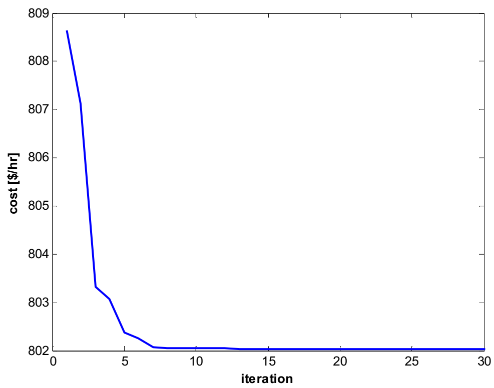

Fig. 4. Convergence characteristic of the IEEE 30 bus system.

The minimize cost and power loss obtained by the proposed algorithm is less than value reported in [7, 8, 9] using the evolutionary copulation techniques, genetic algorithm, Ant colony optimization for the some test systems. The results gotten including cost and power losses are compare with those acquired by others methods and present on tables 1 and 2.

Table 1. Results PSO-OPF compared with N.R and QN-OPF Methods for the IEEE 30-BUS Electrical Network

	N-R	QN-OPF	PSO-OPF
Pg_1 [MW]	99.211	170.237	175.6915
Pg_2 [MW]	80.00	44.947	48.6390
Pg_5 [MW]	50.00	28.903	21.4494
Pg_8 [MW]	20.00	17.474	22.7200
Pg_{11} [MW]	20.00	12.174	12.2302
Pg_{13} [MW]	20.00	18.468	12.0000
Power Loss [MW]	**5.812**	**8.805**	**9.3301**
Generation cost [\$/hr]	**901.918**	**807.782**	**802.0136**

The results show that PSO algorithm gives much better results than the classical method.
The difference in generation cost between these methods and in Real power loss clearly shows the advantage of this method. In addition, it is important to point out that this simple PSO algorithm OPF converge in an acceptable time. For this system was converged to highly optimal solutions set after 13 generations.

Table 2. Comparison of the PSO-OPF with different evolutionary methods of optimization viewpoint cost, losses and times of convergence

	IEP [7]	SADE_ALM [9]	PSO-OPF
Pg_1 [MW]	176.2358	176.1522	175.6915
Pg_2 [MW]	49.0093	48.8391	48.6390
Pg_5 [MW]	21.5023	21.5144	21.4494
Pg_8 [MW]	21.8115	22.1299	22.7200
Pg_{11} [MW]	12.3387	12.2435	12.2302
Pg_{13} [MW]	12.0129	12.0000	12.0000
Power Loss [MW]	**9.5105**	**9.4791**	**9.3301**
Generation cost [\$/hr]	**802.465**	**802.404**	**802.0136**
Time	**99.013 (minutes)**	**15.934 (minutes)**	**77.672 (Sec)**

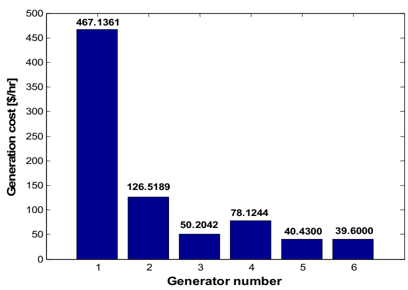

Fig. 6. Generating operating states.

Fig.6 shows operating states of generating obtained by PSO based OPF algorithm for the minimum solution of the PSO algorithm.

The security constraints are also checked for voltage magnitudes and angles. Simulation results give the voltage magnitudes are from the minimum of 1.0040 p.u to maximum of 1.06 p.u (Fig.5).

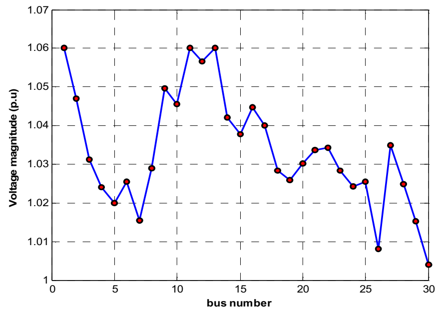

Fig. 5. The Voltages after optimization for the IEEE 30 bus system.

6.1. Case 2: The OPF for units with valve-point effects

In this case, the generator fuel cost curves of generator at bus 1 and 2 are represented by quadratic functions with rectified sine components using (10). Bus 1 is selected as the slack bus of the system to allow more accurate control over units with discontinuities in cost curves.

The generator cost coefficients of those two generators are given in Table A.2. The simulation results are shown in Table 3 .

	IEP [7]	SADE_ALM [9]	PSO-OPF
Pg_1 [MW]	149.7331	193.2903	199.6336
Pg_2 [MW]	52.0571	52.5735	20.0000
Pg_5 [MW]	23.2008	17.5458	22.2786
Pg_8 [MW]	33.4150	10.0000	29.5909
Pg_{11} [MW]	16.5523	10.0000	10.0000
Pg_{13} [MW]	16.0875	12.0000	12.0000
Power Loss [MW]	**7.6458**	**12.0096**	**10.1031**
Generation cost [\$/hr]	**953.573**	**944.031**	**920.9775**
Time	**93.583 (minutes)**	**16.160 (minutes)**	**85.163 (sec)**

Fig.4. shows the outer loop convergence characteristic of PSO-OPF with valve effect point. It was clearly shown that there is no rapid change in the non-smooth fuel cost functions value after 50 generations. Hence it is clears from the Fig. That the solution is converged to a high quality solution at the early iterations (20 iterations).

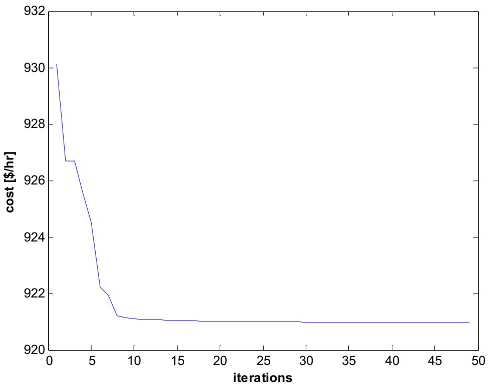

Fig. 7. Convergence plot with valve point Effect.

7. Conclusion

Particle Swarm Optimization based Optimal Power Flow (PSO-OPF) was applied to solve the OPF problems for generators with non-smooth fuel cost functions. The effectiveness of the proposed algorithm has been tested on the IEEE 30-bus system with different fuel cost characteristics. The PSO-OPF is successfully and effectively implemented to find the global or quasi-global optimum of the OPF problems.

The results show that the optimal dispatch solutions determined by PSO lead to lower active power loss then that found by other methods, which confirms that the PSO is well capable of determining the global or near global optimum dispatch solution [10].

Major drawback of PSO, like in other heuristic optimization techniques, is that it lacks somewhat a solid mathematical foundation for analysis to be overcome in the future, development of relevant theories. Also, it can have some limitations for real-time ED applications considering network constraints since the PSO is also a variant of stochastic optimization techniques requiring relatively a longer computation time than mathematical approaches [10].

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Table A.1. Generator cost coefficients in case 1

Bus No.	Real power output limit (MW)		Cost Coefficients		
	Min	Max	a	b	c
1	50	200	0.00375	2.00	0
2	20	80	0.01750	1.75	0
5	15	50	0.06250	1.00	0
8	10	35	0.00834	3.25	0
11	10	30	0.02500	3.00	0
13	12	40	0.02500	3.00	0

Table A.2. Generator cost coefficients in case 2

Bus No.	Real power output limit (MW)		Cost Coefficients				
	Min	Max	a	b	c	e	f
1	50	200	0.00160	2.00	150	50	0.063
2	20	80	0.01000	2.50	25	40	0.098