Economic Load Dispatch Using Particle Swarm Optimization with Quadratic Cost Function

Sudha Chaudhary
Department of Electrical Engineering,
Gwalior Institute of technology and Science, Gwalior

ABSTRACT

This paper presents the solution of economic load dispatch problem with quadratic cost function by using Particle Swarm Optimization (PSO). PSO technique is useful at solving optimization problems with both single and multiple objective functions with non-convex, discontinuous, noisy and non-differentiable solution.

The method's capability of solving economic dispatch problem in power system is tested and validated on the Nigerian Grid System. The results show that PSO has the ability of minimizing cost of productions in power system operations.

Keywords: *Economic Load Dispatch, Grid System, Particle Swarm Optimization , Quadratic Cost Function.*

1. INTRODUCTION

Economic load dispatch (ELD) is an important task in the electricity market operation, ELD aim to allocate power generation to match load demand at minimal possible cost while satisfying all the power units and system constraints [1].

For the purpose of economic dispatch studies, online generators are represented by functions that relate their production costs to their power outputs. Quadratic cost functions are used to model generator in order to simplify the mathematical formulation of the problem and to allow many of the conventional optimization techniques to be used [2]. The ELD problem is traditionally solved using conventional mathematical techniques such as lambda iteration and gradient schemes. These approaches require that fuel cost curves should increase monotonically to obtain the global optimal solution. The input-output of units are inherently non-linear with valve point loading or ramp rate limits and having multiple local minimum points in the cost function [3].

Techniques such as dynamic programming might not be efficient since they require too many computational resources in order to provide accurate results for large scale systems. But, with the advent of evolutionary algorithm which are stochastic based optimization techniques that searches for the solution of problems using simplified model of the evolutionary process found in nature, this type of constrained optimization problem can easily be solved providing better and faster results. The success of evolutionary algorithm is partly due to their inherent capability of processing a population of potential solutions simultaneously, which allows them to perform an extensive exploration of the search space [3].

Evolutionary algorithm includes Genetic Algorithm (GA), Simulated Annealing (SA), Hybrid Particle Swarm Optimization (PSO) with Sequential Quadratic Programming approach (PSO-SQP), Evolutionary Programming (EP) and Artificial Bee Colony (ABC) [4]-[7], etc. GA methods have been employed successfully to solve complex optimization problems, though recent research has identified deficiencies in its performance which is apparent in applications when optimized parameters are highly correlated thereby, hampering crossover and mutation operations and compromising the improved fitness of offspring because population chromosomes contains similar structures [6].

SA is designed to solve the high non-linear ELD problem without restriction on the shape of the fuel cost function. EP also takes a long computation time to obtain solutions. PSO converges more quickly than EP, but has a slow fine tuning ability of the solution.

2. PROBLEM FORMULATION

The Economic dispatch in a power system incorporating wind power plant involves the allocation of generation among wind and thermal plants so as to minimize the total production cost while satisfying various constraints.

The ELD problem is formulated as follows:

$$= \quad (\ ) \qquad (1)$$

$=1$

where:
F_T is the total generation cost
F_i is the power generation cost of the i^{th} unit

$F_i(P_i)$: + + ^{2} is a quadratic cost function of the unit i^{th}, α, β, and γ arecost coefficient of the i^{th}generator,

which are found from the input-outp

curves of the generators and are dependent on the particular type of fuel used. P_i: The power output of i^{th} unit of thermal plants

The minimization is subject to the following constraints:

Power balance

(2)

where:

P_D is the power demand and P_L is the transmission loss. The transmission loss can be represented by the B-coefficient method as:

(3)

Where B_{ij} is the transmission loss coefficient

Maximum and minimum power limits

The power generated by each generator has some limits and can be expressed as:

where:

: The minimum power output

: The maximum power output

3. PSO CONCEPT

Particle swarm optimization (PSO) is a population based stochastic optimization technique inspired by social behavior of bird flocking or fish schooling.

PSO shares many similarities with evolutionary computation techniques such as Genetic Algorithms (GA). The system is initialized with a population of random solutions and searches for optimal by updating generations. However, unlike GA, PSO has no evolution operators such as crossover and mutation. In PSO, the potential solutions, called particles, fly through the problem space by following the current optimum particles. Each particle keeps track of its coordinates in the problem space which are associated with 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 particles in the neighbors of the particle. This location is called *ibest*. When a particle takes all the population as its topological neighbor, the bestvalue is a global best and is called *gbest*.

The PSO concept consists of, at each time step, changing the velocity (accelerating) each particle toward its *pbest* and *ibest* locations (local version of PSO). Acceleration is weighted by a random term, with separate random numbers being generated for acceleration toward *pbest* and *ibest* locations.

After finding the two best values, the particle updates its velocity and positions with following equation:

In a physical *n*-dimensional search space, the position and velocity of individual *i* are represented as the vectors $X_i = (x_{ii},....,x_{in})$ and $V_i = (v_{ii},......v_i)$ in the PSO algorithm.Let $Pbest = (x_{ii}^{pbest},..., x_{in}^{pbest})$ and $Gbest = (x_{ii}^{Gbest},..., x_{ii}^{Gbest})$ be the best position of individual *i* and its neighbors' best position so far, respectively. Using the information, the updated velocity of individual *i* is modified under the following equations in the PSO algorithm.

$$V_i^{k+I} = \omega V_i^k + c_i rand_i \times (Pbest_i^k - X_i^k) + c_2 rand_2 \times (Gbest_i^k - X_i^k) \qquad (4)$$

where,

V_i^k is the velocity of individual *i* at iteration *k*,

ω is the weight parameter,

c_1, c_2 the weight factors,

$rand_1$, $rand_2$ random numbers between 0 and 1,

X_i^k position of individual *i* at iteration *k*,

$Pbest_i^k$ best position of individual *i* until iteration *k*

$Gbest_i^k$ best position of the group until iteration *k*.

In this velocity updating process, the values of parameters such as ω, c_1, c_2 should be determined in advance. In general, the weight ω is set according to the following eqn.(11)

$$\omega = \quad - \_\_\_\_\_ . \_\_\_\_\_ \times iter \qquad (5)$$

where,

ω_{max} ,ω_{min} initial, final weights

$Iter_{max}$ maximum iteration number

$Iter$ current iteration number

Each individual moves from the current position to the next one by the modified velocity in eqn. (10) using the following equation

$$X_i^{k+1} = X_i^k + V_i^{k+I} \qquad (6)$$

A simple block diagram showing the basics of particle swarm optimization works is shown in Fig.1.

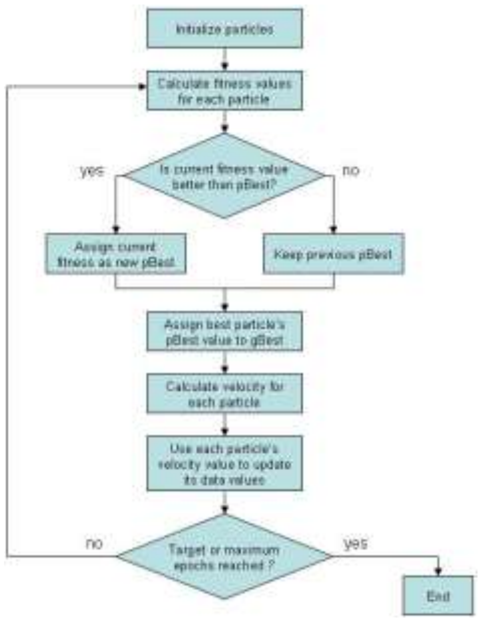

Fig.1. Simple block diagram of particle swarm optimization.

Pseudo Code

For each particle

Initialize particle

Do until maximum iterations or minimum error criteria

For each particle

Calculate Data fitness value
If the fitness value is better than pbest

Set pbest = current fitness
value If pbest is better than gbest

Set gbest = pbest

4. SIMULATION, RESULTS AND DISCUSSION

To examine the effectiveness of the proposed method, two sample networks: IEEE 3-generating units, 6-bus test system and the Nigerian network were considered in order to verify the performance of the approach in practical applications.

A. Case study 1: IEEE 3- Generating Units, 6-Bus Test system

This example is a 6-bus test system fed by three thermal generating units [ ]. The system unit data is given in Table 1. Two load demand scenarios of 340MW and 850MW respectively were considered in the simulation using PSO algorithm. The schedules for the three generators were obtained with the corresponding transmission losses. The Power loss equation is given as:

$$P_L = 0.00003P_{G1}{}^2 + 0.00009P_{G2}{}^2 + 0.00012P_{G3}{}^2 \quad (7)$$

Table 1. Data for the three unit system

	Unit 1	Unit 2	Unit 3
P_{max} (MW)	650	450	250
P_{min} (MW)	150	100	50
α($/MWh)	561	310	78
β($/MWh)	7.92	7.85	7.97
γ ($/MWh)	0.00156	0.0019	0.0048

B. Case Study 2: Nigerian Power System Grid

The standardized 1999 model of the Nigerian network comprises 7 generators, out of which 3 are hydro whilst the remaining generators are thermal, 28 bulk load buses and 33 extra high voltage (EHV) lines. The typical power demand is 2930.1 MW and bears technical power network loss of 39.85MW. The single line diagram of the 330kV Nigerian grid system is shown in Fig.2.

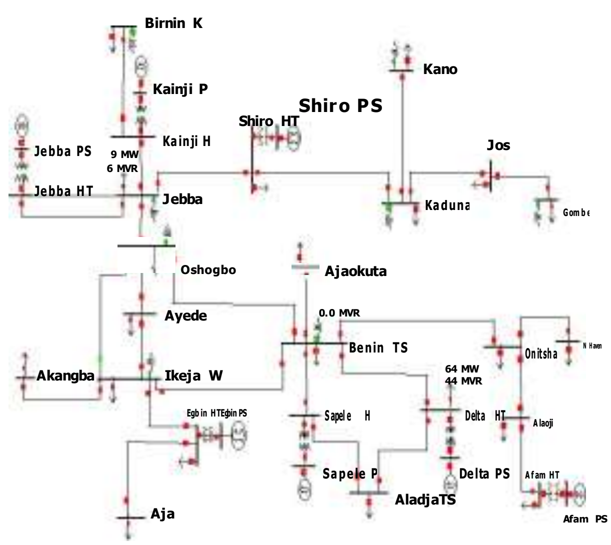

Fig.1. Single line diagram of Nigeria 330kV 31-bus grid systems

Table 2:Nigerian thermal power plants characteristics

Units	α	β	γ	P_{imin}	P_{imax}
A	6929	7.84	0.13	137.5	550
B	525.74	-6.13	1.2	75	300
C	1998	56	0.092	135	540
D	12787	13.1	0.031	275	1100

Table 3: Parameters setting for PSO

Control parameters	
Number Particle	100
Maximum Iteration number	500
Weight Factors c_1, c_2	2, 1
Weight Parameter ω_{max}, ω_{min}	0.9, 0.1

The results obtained for Case Study 1 using PSO is shown in Table 3 with the different generators scheduling and the corresponding production cost for each of the two load demand.

Table 4: PSO Computational Result for Case Study 1

Parameters	360 MW	950MW
P_{G1}	170.64	425.2
P_{G2}	120.42	302.65
P_{G3}	51.38	148.35
P_T	340	850
P_L	2.44	16.2
$P_D + P_L$	342.44	876.2
Total Cost ($/hr)	3742.1	8346.43

The total cost of production for the demand P_D = 340MW and 850MW is 3742.1$/hr and 8346.43$/hr respectively. The transmission losses is 2.44MW for P_D= 360MW and 16.2 MW for P_D=950MW

Table 5: Result for Case Study 2

	PSO
Egbin	873.20
Sapele	193.45
Delta	109.37
Afam	381.32
Shiroro	490
Kainji	350
Jebba	450
P_G	2852.34
P_D	2823.1
P_L	37.27
Cost $/hr	107430

Table 4 shows the results of the economic load dispatch of the Nigerian Grid system. The hydro units' power allocations are fixed in conformity with the utility's operating practices. Subsequently, PSO is applied to schedule the thermal units with the transmission losses considered. The total production cost is given as 108430$/hr while the losses is 27.27MW.

5. CONCLUSION

In this paper PSO based economic load dispatch was investigated on two sample networks (a 6-bus IEEE test system and 31-bus Nigerian grid system).The results shows that PSO can minimize total production cost and also compute transmission losses. The penetration of renewable will pose a major challenge to power utility's planning and operations as a result of their intermittence and uncertainty nature. Therefore, further ELD research should emphasize on larger networks with renewable penetration in power systems.

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