

DYNAMIC ECONOMIC DISPATCH WITH WIND ENERGY POWER USING MODIFIED PARTICLE SWARM OPTIMIZATION

N.R.Samal, S. Padhi

Electrical Engg. Dept., Orissa Engg. College, Bhubaneswar, India

Abstract: This article presents the integration to constrained dynamic economic dispatch (DED) with wind energy power (WEP) problems using the modified particle swarm optimization (MPSO) technique. As Wind power Plant increases in power systems, its effects to conventional units should be analyzed. Also the total cost is dependent on wind speed in specific period of time. The proposed methodology easily takes care of different constraints like transmission losses, ramp rate limits and prohibited operating zones and also uses for non-smooth cost functions. To illustrate its efficiency and effectiveness, the developed MPSO approach is tested with different number of generating units and comparisons are performed with other approaches under consideration.

Keyword: Dynamic Economic Dispatch, modified particle Swarm Optimization, Wind Energy Power, Probability Density Function.

1. INTRODUCTION

The dynamic economic dispatch (DED) is an extension of the economic dispatch problem used to determine the schedule of real-time control of power system operation so as to meet the load demand at the minimum operating cost under various operational constraints.

Sustainable energy resources, especially wind power, are currently increasing in power systems. Advantages of this resource can be summarized as follows: i. Reducing dependence on fossil resources. ii. Reducing greenhouse gases emission. iii. Reducing the energy production cost. Therefore, it's important to consider wind power plants in Economic Dispatch (ED) problems. Because of stochastic availability of wind power, the incorporating wind power plant to the ED problems is difficult. This problem can be solved by several investigations have looked at the prediction of wind speed for use in determining the available wind power.

In this paper, the known Weibull Probability Distribution Function (PDF) that its parameters are estimated by the maximum likelihood method is used as the basic numerical solution of the ED model. Because of the uncertainty of the wind energy, factors for overestimation and underestimation of available wind energy must be included in the cost function of wind power plant. Most of the literature addresses DED problem with convex cost function [1-2]. However, in reality, large steam turbines have steam admission valves, which contribute non convexity in the fuel cost function of the generating units [3]. Accurate modeling of the DED problem will be improved when the valve point loadings in the generating units are taken into account. Previous efforts on solving DED problem have employed various mathematical programming methods and optimization techniques. Conventional method like Lagrangian relaxation [1], gradient projection method [2] and dynamic programming etc, when used to solve DED problem suffer from myopia for non-linear, discontinuous search space, leading them to a less desirable performance and these methods often use approximations to limit complexity.

Recently, stochastic optimization techniques such as Genetic algorithm (GA) [4-5], evolutionary programming (EP) [6-7], simulated annealing (SA) [8-9] and particle swarm optimization (PSO) [10-12] have been given much attention by many researches due to their ability to seek for the near global optimal solution.

This paper presents a novel optimization method based on modified particle swarm optimization (MPSO) algorithm applied to dynamic economic dispatch with Wind Energy Power while considering some nonlinear characteristics of a generator such as ramp rate limits, generators constraints, power loss and non-smooth cost function. The proposed methodology emerges as a robust optimization technique for solving the DED with WEP problem for different size power system.

2. Mathematical Model for Integration Of DED With Wind Energy Power:

The objective of the DED is to schedule the outputs economically over a certain period of time under various system and operational constraints. The conventional DED problem minimizes the following incremental cost function associated to dispatchable units.

$$M_{in} F = \sum_{t=1}^T \sum_{i=1}^N F_{it}(P_{it}) \quad \$ \quad (1)$$

Where F is the total operating cost over the whole dispatch period, T is the no. of intervals in the scheduled horizon, N is the no. of generating units and $F_{it}(P_{it})$ is the fuel cost in terms of its real power output P_{it} at time 't'. Taking into valve-point effects, the fuel cost of the i^{th} thermal generating unit is expressed as the sum of a quadratic and a sinusoidal function in the following form is given by

$$F_{it}(P_{it}) = a_i P_{it}^2 + b_i P_{it} + c_i + |e_i \sin(f_i(P_{i,min} - P_{it}))| \quad \$/h \quad (2)$$

Where a_i , b_i , c_i are cost coefficients and e_i , f_i are constants from the valve point effect of the i^{th} generating unit.

2.1. ED Problem Incorporating Wind Farm Power Plant:

Due to lack of using fuel to generate energy, the cost function of the wind power plant must be described in another model. Also, because of the uncertain nature of wind and output of the wind power plant, the factors must be considered for underestimation and overestimation of the available wind energy in this model. Thereby, the cost function of wind power plant can be calculated as:

$$C = \sum_{i=1}^N C_{wi}(W_i) + \sum_{i=1}^N C_{pi}(W_{i,ac} - W_i) + \sum_{i=1}^N C_{ri}(W_i - W_{i,ac}) \quad (3)$$

C_{wi} : operating cost of i^{th} wind power

C_{pi} : Imbalance cost of i^{th} wind power due to over generation

$W_{i,ac}$: Actual wind power from i^{th} wind farm

W_{ri} : rated output of i^{th} wind power

W_i : Scheduled output of i^{th} wind power

The three cost term can be represented as:

$$C_{wi} = d_i W_i$$

$$C_{pi} = K_{pi}(W_{i,ac} - W_i)$$

$$= K_{pi} \int_{wi}^{w_{ri}} (W - W_i) f_w(W) dW$$

$$C_{ri} = K_{ri}(W_i - W_{i,ac})$$

$$= K_{ri} \int_0^{w_{ri}} (W_i - W) f_w(W) dW$$

d_i : cost coefficient of i^{th} wind farm

K_{pi} : Penalty cost coefficient for over generation of i^{th} wind farm

$f_w(W)$: Probability Density Function (PDF) of wind power output

The PDF of wind energy power output is represented as:

$$f_w(W) = \frac{klv_i}{c} \left(\frac{(1+\rho l)v_i}{c} \right)^{k-1} \exp \left(- \left(\frac{(1+\rho l)v_i}{c} \right)^k \right) \quad \text{for } 0 \leq W \leq W_r \quad (4)$$

$$f_w(0) = 1 - \exp\left(-\left(\frac{v_i}{c}\right)^k\right) + \exp\left(-\left(\frac{v_0}{c}\right)^k\right) \quad (5)$$

$$\text{Where } \rho = \frac{w}{w_r} \text{ and } l = \frac{v_r - v_i}{w_0}$$

k and c are weibull PDF parameters; ρ and l are intermediate variable; v_r, v_i, v_0 are rated value, cut in and cut out wind speed.

The overall cost operation for thermal energy and wind energy of power system is calculated as:

$$\text{Min}, C(p, w, e) = a_i P_{it}^2 + b_i P_{it} + C_i + |e_i \sin(f_i(P_{i,\min} - P_{it}))| + \sum_{i=1}^N C_{w,i}(W_i) + \sum_{i=1}^N C_{pi}(W_{i,ac} - W_i) + \sum_{i=1}^N C_{ri}(W_i - W_{i,ac}) \quad (6)$$

Subject to the following equality and inequality constraints of thermal power plant

a. Real power balance

$$\sum_{i=1}^N P_{it} - P_{Dt} - P_{Lt} = 0 \quad (7)$$

Where $t = 1, 2 \dots T$, is the total power demand at time t and P_{Lt} is the transmission power loss at i^{th} interval in MW.

b. Real power operating limits

$$P_{t\min} \leq P_{it} \leq P_{t\max} \quad (8)$$

Where $P_{t\min}$ and $P_{t\max}$ are respectively the minimum and maximum real power output of i^{th} generator in MW.

c. Generating unit ramp rate limits

$$P_{it} - P_i(t-1) \leq UR_i, \quad i = 1, 2, 3, \dots, N \quad (9)$$

$$P_i(t-1) - P_{it} \leq DR_i, \quad i = 1, 2, 3, \dots, N \quad (10)$$

Where UR_i and DR_i are the ramp-up and ramp-down limits of i^{th} unit in MW. So the constraint given by Eq. (5) is modified as follows:

$$\max(P_{i\min}, P_{i(t-1)} - DR_i) \leq \min(P_{i\max}, P_{i(t-1)} + UR_i) \quad (11)$$

3. Overview Particle Swarm Optimization (PSO):

The idea of Particle Swarm Optimization (PSO) was adopted by Kennedy et al. in 1995 as an optimization technique being inspired by swarm intelligence bird flocking, fish schooling and human social behavior. Soon PSO became a novel optimization tool having a population based search procedure in which individuals (called particles) fly in an m -dimensional search space in which each dimension corresponds to a parameter of the function being optimized. These particles change their positions with time in the search space and each represents a candidate solution to the optimization problem.

During flight, each particle adjusts its position according to its own experience and the experience of neighboring particles through constructive cooperation. The position mechanism of the particle in the search space is updated by adding the velocity to its position. The basic principle of PSO is that it initializes a population of particles with the randomness of both positions and velocities. There are three main components that affect the changing of velocity. They are inertia, cognitive and social components. The inertia component represents the particle's behavior for moving in the previous direction while the cognitive component represents the memory of the particle for attracting to its previous best position (pbest). The social component represents the memory of the particle for attracting its previous best position among the group (gbest). Correspondingly, each particle can be adjusted or updated to its new position according to its modified velocity. The updated velocity and position of each particle is expressed as [8]:

$$v_{id}^{t+1} = k \times [\omega \cdot v_{id}^t + c_1 \times rand_1 \times (pbest_{id} - x_{id}^t) + c_2 \times rand_2 \times (gbest_d - x_{id}^t)] \quad (12)$$

$$x_{id}^{t+1} = x_{id}^t + v_{id}^{t+1} \quad (13)$$

The constriction factor (k) is expressed as follows:

$$k = \frac{2}{2 - \phi - \sqrt{\phi^2 - 4\phi}}, \quad \text{where } \phi = c_1 + c_2 \text{ and } \phi > 4 \quad (14)$$

The inertia weight factor (ω) is given by the following expression:

$$\omega = \omega_{max} - \frac{\omega_{max} - \omega_{min}}{iter_{max}} \times iter \quad (15)$$

ω_{min} : minimum inertia weight factor

ω_{max} : maximum inertia weight factor

$iter$: current number of iterations

$iter_{max}$: maximum number of iterations (generations)

v_{id}^t : Velocity of i^{th} particle at iteration t in d -dimensional space

x_{id}^t : Current position of i^{th} particle at iteration t in d -dimensional space

t : No. of iterations

c_1, c_2 : Acceleration constants

2.1. Modified PSO algorithm for proposed approach:

1. Initialize the system data and parameters of the MPSO algorithm e.g. Population size (pop), initial/final inertia weight ($\omega_{max}, \omega_{min}$), constriction constant (k), acceleration constants (c_1 and c_2), initialize positions (x_{ij}) and velocities (v_{ij}) of each particle.
2. Update the velocity and the position for each particle using Eq. (12) and (13).
3. Mutating some selected particle using Gaussian mutation operator
4. Modify the particle using constriction factor operator.
5. Update pbest and gbest by calculating and comparing the fitness value with previous values.
6. If the termination criteria are satisfied, then stop. Otherwise go to Step 2.

3. Simulation and Result: In order to demonstrate the performance of the proposed MPSO algorithm, a five-unit test system with nonsmooth fuel cost function for both thermal and wind energy is used. The demand of the system has been divided into 24 intervals. Unit data has been adopted from [7]. Simulations have been carried out on a P-IV, 80 GB, 3.0 GHz personal computers and coding is written using MATLAB. The result obtained in proposed algorithm is shown in Table 1. For PSO the control parameters are Population size (N_p) = 50, $c_1 = c_2 = 2$, $\omega_{max} = 0.9$, $\omega_{min} = 0.7$ and No. of iteration (N_{max}) = 400. To validate the proposed MPSO based approach, the same five-unit test system is solved by the author using EP. In case of EP, the control parameters are scaling factor (β) = 0.04, $N_p = 50$, $N_{max} = 400$. The result obtained from EP is shown in Table 2 and Table 3 shows the comparison between other methods.

Table 1: Optimal Generation Dispatch of Five Units Test System Using MPSO

No. of hours	P_{G1} (MW)	P_{G2} (MW)	P_{G3} (MW)	P_{G4} (MW)	P_{G5} (MW)
1	11.367	101.473	103.930	31.401	135.391
2	40.470	94.973	106.638	43.102	125.677
3	70.057	93.629	120.275	43.981	125.772
4	42.023	95.962	111.764	72.022	165.830
5	14.743	103.258	106.794	84.906	145.750
6	41.947	103.349	106.669	92.896	202.132
7	10.946	87.434	106.764	134.815	203.961
8	22.674	83.344	111.974	201.011	215.950
9	43.435	95.098	111.764	202.051	225.519
10	64.110	94.538	111.674	203.185	218.538
11	41.011	101.542	123.633	217.169	215.159
12	34.759	95.359	145.979	203.581	212.321
13	42.675	93.538	144.959	205.985	221.359
14	43.603	93.738	110.704	205.994	224.661
15	14.603	93.377	110.765	217.644	134.923
16	13.170	82.405	110.854	202.224	192.550
17	12.180	95.669	92.432	203.576	123.485
18	21.558	93.539	110.684	205.815	112.137
19	21.043	100.519	111.675	2.198	134.157
20	45.449	103.341	112.428	214.631	145.134
21	32.415	103.678	113.061	214.896	206.961
22	11.720	94.540	101.599	191.705	208.035
23	13.003	60.143	98.009	143.903	212.276
24	12.020	32.694	81.006	142.971	221.629

Table 2: Optimal Generation Dispatch of Five Unit Test System Using EP

No. of hours	P_{G1} (MW)	P_{G2} (MW)	P_{G3} (MW)	P_{G4} (MW)	P_{G5} (MW)
1	12.367	104.473	108.930	38.401	140.391
2	42.470	95.973	113.638	40.102	138.677
3	72.057	96.629	121.275	43.981	139.772
4	45.023	97.962	116.764	75.022	179.830
5	19.743	105.258	115.794	89.906	197.750
6	41.947	103.349	116.669	96.896	215.132
7	11.946	89.434	116.764	171.815	221.961
8	23.674	85.344	117.974	210.011	228.950
9	47.435	98.098	117.764	208.051	231.519
10	64.110	99.538	116.674	209.185	229.538
11	43.011	101.542	142.633	210.169	230.159
12	39.759	97.359	164.979	207.581	229.321
13	42.675	96.538	143.959	208.985	228.359
14	48.603	96.738	118.704	208.994	220.661
15	19.603	95.377	110.765	200.644	201.923
16	11.170	87.405	112.854	206.224	191.550
17	11.180	97.669	97.432	207.576	178.485
18	23.558	99.539	113.684	209.815	156.137
19	21.043	100.519	114.675	211.198	188.157
20	49.449	105.341	114.428	210.631	196.134
21	34.415	103.678	116.061	210.896	213.961
22	11.720	90.540	108.599	198.705	215.035
23	10.003	62.143	92.009	160.903	223.276
24	10.020	39.694	83.006	135.971	225.629

Table 3: Comparison results of fuel cost for five-unit systems

Different Methods	Minimum Value	Mean Value	Maximum Value	Computational Time
SA [7]	47356.0000	-	-	5 min 51.98 sec
EP [13]	44385.4300	44758.8363	45553.7707	4 min
Proposed MPSO	43360.0000	44637.5683	44723.2430	3 min 42 sec

4. Conclusion: This paper has presented a novel approach based on MPSO for solving the overall cost of thermal as well as wind energy power dispatch, while satisfying some operational constraints. The paper also advocates the application of MPSO algorithm to five unit test system DED for Thermal - Wind Energy problem considering effect of wind power. The efficiency of the proposed algorithm is confirmed by comparing the results with the most recently reported literatures. The method is easy to apply and the convergence rate is relatively fast. Also the computational complexities are very less as number of tuning parameters is very less compared to other methods. From the simulation results it can be concluded that proposed method is a competitive tool to solve the non-smooth nature of generation scheduling problem in power system with nonlinear wind speed model.

References:

1. Victoire T. A. A. and Jeyakumar A. E. "Reserve Constrained Dynamic Dispatch of Units with Valve-Point Effects". *IEEE Trans. Power Systems* 2005; 20:1273-1282
2. Li F. and Aggarwal R. K. "Fast and Accurate Power Dispatch Using a Relaxed Genetic Algorithm and a Local Gradient Technique". *Expert Syst. Application* 2000; 19: 159-165
3. Attaviriyanupap D., Kita H., Tanaka E. and Hasegawa J. "A Hybrid EP and SQP for Dynamic Economic Dispatch with Non-smooth Incremental Fuel Cost Function". *IEEE Trans. Power Syst.* 2002; 17: 411-416
4. Victoire T. A. A. and Ebenezer J. A. "A Modified Hybrid EP-SQP Approach for Dynamic Dispatch with Valve-Point Effect". *International Journal of Electrical Power & Energy Systems* 2005; 27: 594-601

5. Jayabarathi T., Jayaprakash K., Jeyakumar D. N., and Raghunathan T. "Evolutionary Programming Techniques for Different Kinds of Economic Dispatch Problems". *Electric Power Systems Research* 2005; 73: 169-176
6. Victoire T. A. A. and Ebenezer J. A. "Deterministically Guided PSO for Dynamic Dispatch Considering Valve-Point Effect". *Electric Power Systems Research* 2005; 73: 313-322
7. Panigrahi C. K., Chatopadhyay P. K., Chakrabarti R. N. and Basu M. "Simulated Annealing Technique for Dynamic Economic Dispatch". *Elect. Power Comp. Syst.* 2006; 34: 577-586
8. Gaing Z. L. "Constrained Dynamic Economic Dispatch Solution using Particle Swarm Optimization". In *IEEE Power Engineering Society General Meeting* 2004; 1: 153-158
9. Chakrabarti R., Chattopadhyay P. K., Basu M., and Panigrahi C. K. "Particle Swarm Optimization Technique for Dynamic Economic Dispatch". *Institute of Engineers (India)* 2005; 48-54
10. Basu M. "Hybridization of Artificial Immune Systems and Sequential Quadratic Programming for Dynamic Economic Dispatch", *Electric Power Components and Systems* 2009; 37: 1036-1045.
11. H.T. Jadhav, Ranjit Roy, "Gbest guided artificial bee colony algorithm for economic environmental considering wind power" *Expert Systems with Applications* 2013; 40; 6385-6399.
12. Julia Tholath Jose, "Comparison Of Economic Load Dispatch Of Wind Hydrothermal Systems", *International Journal of Engineering Research & Technology* , 2013; 2; 4; 2315-2319
13. N. Sinha, R. Chakrabarti and P. K. Chattopadhyay, "Evolutionary Programming Techniques for Economic Load Dispatch", *IEEE Trans. Evol. Comput.*, Vol. 7, pp. 83-94, February 2003.