Wind-Thermal Generation Coordination in a Deregulated Electricity Market

OLUROTIMI OLAKUNLE AWODIJI[1], OLUKEMI ROSELINE AWODIJI[2]
[1] *Department of Electrical Engineering University of Jos, Plateau State Nigeria*
[2] *Market Rules and Policy Department Arrowhead Electric Solution, Jos, Plateau State Nigeria*

Abstract- Many counties are advancing down the road of electricity privatization, deregulation and competition as a solution to their electricity demand and challenges. The increase in integration of renewable energy in to the deregulated electricity market by the independent power producers poses a great challenge to the traditional economic load dispatch method used by the system operator. Therefore, development of improved and faster economic dispatch is necessary to determine the optimal dispatch scheme that can integrate wind reliably and efficiently. In this paper, Differential Evolution (DE) is utilized to coordinate the wind – thermal generation dispatch and to minimize the total production cost in the economic dispatch considering wind and thermal generation with transmission losses. Three generating units incorporating one wind power plant is used for numerical simulations. Different simulation scenarios with and without wind power production are simulated and the results shows that DE is capable of solving the coordination scheduling of wind-thermal in a deregulated electricity market.

Indexed Terms- Deregulation, Differential Evolution, Economic Load Dispatch and Quadratic Cost Function.

I. INTRODUCTION

For nearly a century, the electricity in all countries have been thought as a “natural” monopoly industry where efficient generation of electricity required reliance on public monopoly supplier subject to government regulation of prices, entry, investment, service quality and other aspect of firm behavior. But dramatic changes are now taking place in the structure of electric power sector around the world.

The changes are designed to foster competition in the generating segment of the industry and to reform the regulation of the transmission and distribution segment [1].

The trend of large-scale integration and utilization of renewable energy has gained more and more attention in recent years due to dwindling of traditional fossil fuels reserves and environmental concern. [2]

The penetration of renewable generation has changed the existing electricity market structures and policies, unit commitment and economic dispatch methods, bidding strategies and forecasting methodology. But, with the increase penetration of renewable energy into the transmission network comes many challenges to service provider because of the “nature” of the renewable source i.e. its variability and uncertainty [2] There are two types of energy market: day-ahead and real time. The day-ahead market is a forward market whose results are hourly power output schedules of the generators for the operating day whereas the real-time market is based on the real-time load and generation, often evaluated at intervals less than one hour.

In both the day-ahead and real- time markets, the scheduled and dispatch power outputs of generators are determined by a least- cost security constrained economic load dispatch based upon the incremental offers of the generator.

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 [3].

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. 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.

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 [8].

Differential Evolution (DE) is a recently developed heuristic evolutionary method for solving constrained optimization problems. DE is a powerful algorithm that improves the population of individuals over several generations through the operators of mutation, crossover and selection. Differential Evolution offers great convergence characteristics and requires few control parameters which remains fixed throughout the solution process and requires minimal tuning.

II. WIND POWER PLANT MODELLING

The modelling of the wind power plant is based upon a conversion of wind speed to real power. Wind speed variability is modelled statistically by using the Weibull two parameter distribution functions [9]. The wind speed variation is described by its shape and scale parameters.

The Weibull probability density function of a two-parameter continuous distribution is defined as the derivative of the cumulative distribution function (cdf) as expressed by

$$f_w(\mathrm{K, C}) = \frac{K}{C}\left(\frac{K}{C}\right)^{K-1}\exp\left[-\left(\frac{V}{C}\right)^{K}\right] \qquad (1)$$

Where f_w= Weibull density function, K= Shape Parameter
C= Scale Parameter

The Cumulative distribution F (V) defined in equation (2) is the integral of the probability density function, and it is expressed as

$$\mathrm{F\ (V)} = 1- e^{-\left(\frac{v}{c}\right)^{K}} \qquad (2)$$

Wind speed changes with height and most wind speeds are observed at height less than the hub height. It is therefore necessary to re-define the wind speed from the observed height to the hub height using the expression

$$\frac{V}{V_o} = \left(\frac{h}{h_o}\right)^{\alpha} \qquad (3)$$

v= Wind speed at hub height h, v_o= Wind speed at the original h_o, α = surface roughness coefficient

The electrical power of the wind energy conversion system is based on known turbine power curve is estimated as

$$P_e(V) = c_{p*}0.5\eta\, p(h)\, a \int_0^{\infty} v^3 f(v)\, dv \qquad (4)$$

$P_e(V)$ = Electrical output power, c_p= rotor efficiency η =efficiency, v= wind speed. $f(v)$ = Weibull wind distribution, $p(h)$ = time varying air density and a = rotor swept areas.

The actual output (P_{wj}) of wind generator j can be obtained from the wind speed by applying equation (4). The total actual wind power generation can be easily calculated using the equation:

$$P_{wt} = \sum_{J=1}^{nw} P_{wj} \qquad (5)$$

Where nw is the number of connected wind generator

III. 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:

$$Minimize\ \ F_T = \sum_{i=1}^{n} F_i(P_i) \qquad (6)$$

where:
F_T is the total generation cost
F_i is the power generation cost of the ith unit
$F_i(P_i) : \alpha_i + \beta_i P + \gamma_i P^2$ is a quadratic cost function of the unit i^{th}, α, β, and γ are cost coefficient of the i^{th} generator, which are found from the input-output 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

$$\sum_{i=1}^{N} P_i + \sum_{j=1}^{NW} P_{wj} = P_D + P_L \qquad (7)$$

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:

$$P_L = \sum_{i=1}^{N}\sum_{j=1}^{N} P_i B_{ij} P_j \qquad (8)$$

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:

$$P_i^{min} \le P_I \le P_I^{max} \qquad (9)$$

Where:
P_i^{min}: The minimum power output
P_I^{max}: The maximum power output

In this study, the ramp-rate limits and valve-point effect are not considered for simplicity.

IV. DIFFERENTIAL EVOLUTION CONCEPT

Differential Evolution (DE) is an evolutionary algorithm proposed by Storn and Price (1995) [11]. The algorithm is simple, yet powerful, for solving complex optimization problems. Practical optimization problems are often characterized by several non-linearities and competing objectives.

In a DE algorithm, candidate solutions are randomly generated and evolved to individual solution by a simple technique combining simple arithmetic operators with the classical operators of mutation, crossover and selection. The basic evolutionary search mechanisms for DE are summarized in the following salient steps:

Step 1: *Initialization operation*
In DE, a solution or individual i, in generation G is a multi-dimensional vector given by:

$$X_i^G = \left(X_{i,1}, \ldots X_{i,D}\right) \qquad (5)$$

Where $X_{i,k}$ is given by:

$$X_{i,k} = X_{k\min} + rand[0,1] * (X_{k\max} - X_{k\min}) \qquad (6)$$

$$i \in (1, N_P) \text{ and } k \in (1, D)$$

Where, N_P is the population size, D is the solution's dimension i.e. number of control variables and *rand*[0,1] is a random number uniformly distributed between 0 and 1. Each variable k in a solution vector i in the generation G is initialized within its boundaries $X_{k\min}$ and $X_{k\max}$.

Step 2: Mutation operation

DE does not use a predefined probability density function to generate perturbing fluctuations. It relies upon the population itself to perturb the vector parameter. Several population members are involved in creating a member of the subsequent population. For every $i \in [1,N_P]$ the weighted difference of two randomly chosen population vectors, X_{r2} and X_{r3}, is added to another randomly selected population member, X_{r1}, to build a mutated vector V_i given as :

$$V_i = X_{r1} + F * (X_{r2} - X_{r3}) \tag{7}$$

With r_1, r_2, $r_3 \in [1, N_P]$ are integers and mutually different, and $F > 0$, is a real constant mutation rate to control the different variation $d_i = X_{r2} - X_{r3}$.

Step 3: Crossover operation

The crossover function is very important in any evolutionary algorithm. In DE, three parents are selected for crossover and the child is a perturbation of one of them whereas in GA, two parents are selected for crossover and the child is a recombination of the parents. The crossover operation in DE can be represented by:

$$U_i(j) = \begin{cases} V_i(j), if\ U_i(0,1) < CR \\ X_i(j), \quad otherwise \end{cases} \tag{8}$$

Where, CR is the crossover rate of DE.

Step 4: Selection operation

In DE algorithm, the target vector $X_{i,G}$ is compared with the trial vector $V_{i,G+1}$ and the one with the better fitness value is admitted to the next generation. The selection operation in DE can be represented by eqn. (8):

$$X_{i,G} = \begin{cases} U_{i,G+1}\ if\ (U_{i,G+1}) < f(X_{i,G}) \\ X_{i,G}, \quad otherwise \end{cases} \tag{9}$$

Where, $i \in [1, N_P]$.

V. SIMULATION RESULTS

To examine the effectiveness of the proposed method, a three-thermal unit and one wind generator test system is considered. The system unit data is given in Table 1, the load demand of the system is divided into 8hourly for the 24hours in a whole day as shown in Figure1.

For the simulation, the total contribution of the wind power plant is assumed to be 10% of the total 8hourly demand.

Three different load demands (385MW, 935MW and 1100MW) were used to study the effect of wind integration (with or without) on the total generating cost.

The power loss equation is given as:

$$P_L = 0.00003 P_{G1}^2 + 0.00009 P_{G2}^2 + 0.00012 P_{G3}^2$$
(10)

Table 1. Data for the three-unit system

	Unit 1	Unit 2	Unit 3
P_{max} (MW)	600	400	200
P_{min} (MW)	150	100	50
α($/MWh)	561	310	78
β($/MWh)	7.92	7.85	7.97
γ ($/MWh)	0.001562	0.00194	0,00482

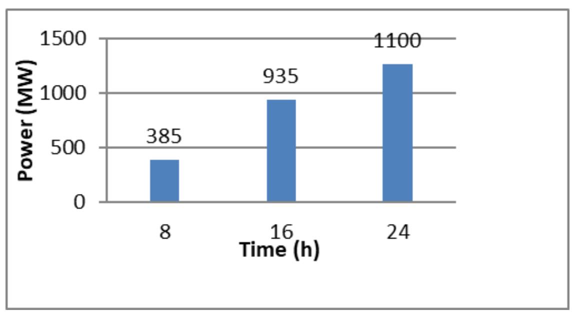

Figure1. 8 hourly Load demand

Table. 2 Parameter setting for DE

Control Parameters	DE Setting
Maximum Generation, gen^{max}	200
Population size, NP	30
Scaling factor for Mutation, F	0.8
Crossover constant, CR	0.5

Table. 3 Simulation results for different load demand with and without wind generation using DE

	Study 1 (385MW)		Study 2 (935MW)		Study 3 (1100MW)	
	With Wind	Without Wind	With Wind	Without Wind	With Wind	Without Wind
P_1 (MW)	178.8507	179.4784	436.0029	522.5107	512.2529	582.5272
P_2 (MW)	116.2029	146.3693	295.002	302.8534	352.0467	374.3647
P_3 (MW)	57.5183	62.5161	134.7123	127.9687	157.7114	169.3429
P_W (MW)	35	0	85	0	100	0
P_L (MW)	2.5719	3.6436	15.7130	18.4130	22.0112	26.2348
Total cost ($/h)	3826.87	4127.08	8336.81	9157.21	9785.75	10776.95

CONCLUSION

This paper shows a new approach for the independent system operator to solving the economic load dispatch optimization problem, of a power system, incorporating thermal power plant and wind generation using differential evolution approach in a deregulated electricity market. The comparative simulations with and without wind generator illustrate that the wind power contribution affects the total generation cost in all the cases study examined. The results shows that total production cost and consumption of fossil fuel can be minimized notably by utilizing wind power generation.

REFERENCES

[1] Ameobi, M.C. 2007. *Deregulating the electricity industry in Nigeria: Lesson from the British reform.* http://www.dindee.ac.uk.

[2] Zheng., Y., Zhu. S., Chudhury A.A. and Zheng, P. 2010. *An integrated transmission planning framework for including renewable energy technologies in a deregulated power system.* IEEE Transaction Power and Energy.

[3] Fang. Y., Key M., Zhao X., Zhao Y.D., Herbert L Jun H.Z., Kit P.W. 2011. *Differential evolution algorithm for multi-objective economic load dispatch considering minimum emission costs.* IEEE Power and Energy Society. http://ieeexplore.ieee.org.

[4] Perez-Guerrero, P.E. and Cedeno-Maldonado. C.R. 2005. *Economic power dispatch with non-smooth cost function using differential evolution,* IEEE Power symposium proceeding. http://ieeexplore.ieee.org.

[5] Thitithamrunehai., C. Eua-Arpon, B. 2006. *Economic load dispatch for piecewise quadratic cost function using hybrid self- adaptive differential evolution with augmented lagrange multiplier method.* IEEE Power conference. http://ieeexplore.ieee.org.

[6] Chang, C.L. 2007. Genetic based algorithm for power economic dispatch. IET Generation-Transmission Distribution. Doi: 10.1049/et-gtd:20080273

[7] Singh, S.N., Ostergaard, J. and Yadagiri, J. *Application of Advanced Particle Swarm Optimization Techniques to Wind-Thermal Coordination.* 2009. IEEE Power conference. http://ieeexplore.ieee.org.

[8] Chia-Liang. L., Chun-Lung, C., Daw-Shang, H. and Yuang-Tung, C. 2008. *Effects of wind energy supplied by independent power producers on the generation dispatch of electric power utilities.* http://doi.:10.1016/j.ijepes.

[9] Temitope, R.A., Adisa, A.J., Josiah, L.M and John, T.A. 2012. *Statistical analysis of wind speed and wind power potential of Port Elizabeth using Weibull parameters.* Journal of Energy in Sothern Africa

[10] Liu. Y and Shang T. 2007. *Economic Dispatch of Power Incorporating Wind Power Plant.* http://ieeexplore.ieee.org.

[11] Bakare, G.A., Krost, G., Venayagamoorthy, G.K., Aliyu,U.O. 2007. *Differential Evolution Approach for Reactive Power Optimization of Nigerian Grid System. IEEE Power Engineering Society Meeting.*

[12] Price, K. and Storn, R. 1997. Differential Evolution – A simple evolution strategy for fast optimization. *Dr. Dobb's journal*.

[13] Saadat, H. 2004. Power System Analysis. International Edition, McGraw Hill.

[14] Wood, A.J. and Woolenberg, B.F, 1996. Power Generation Operation and Control**.** John Wiley and Sons, New York.

[15] John H., David, C.Y and Kalu, B. 2008. *An Economic Dispatch Model Incorporating Wind Power. IEEE Transaction on Energy Conversion*. http://ieeexplore.ieee.org. doi: 10.1109/TEC.2007.9141.

[16] Mishra, S., Mishra and. Y., Vignesh. 2008. *Security Constrained Economic Dispatch Considering Wind Energy Conversion Systems*. IEEE on Energy Conversion. DOI 97814577100211 http://ieeexplore.ieee.org.

[17] Y. Fang, M.Key, X. Zhao, Y.D, Zhao, H.Z. Jun, and P.W. Kit, "Differential evolution algorithm for multi-objective economic load dispatch considering minimum emission costs," *IEEE Power and Energy Society*, pp. 1-5,2011.

[18] R.E. Perez-Guerrero and J.R. Cede no-Maldonado,"Economic power dispatch with non-smooth cost function using differential evolution," *IEEE Power symposium proceeding*, pp.183-190,2005

[19] C.L. Chang, " Genetic based algorithm for power economic dispatch," *IET Generation-Transmission Distribution*, pp. 261-269,2007.

[20] G.D. Mehdi, A. Javad, and K. Mohsen., "Economic dispatch of wind power plant using particle swarm optimization," *IEEE Conference on Renewable Energy and Distributed Generation*, pp.1-6, 2012.

[21] J.S., Dhillion, J.S. Dhillion, and D.P. Kothari "Generation pattern search for different kinds of load dispatch," *IEEE large Engineering system conference*, pp.250-255, 2007.

[22] Y. Liu. and T. Shang, "Economic Dispatch of Power System incorporating Wind Power plant". *IEEE power Engineering Conference.*pp. 1-5, 2007.

[23] H. John, C.Y. David, and B. Kalu, " An Economic Dispatch Model Incorporating Wind Power," *IEEE Transaction on Energy Conversion*, vol. 23. no:2, pp.1-6,2006.

[24] G..A. Bakare, G. Krost, G.K. Venayagamoorthy, U.O. Aliyu, "Differential Evolution Approach for Reactive Power Optimization of Nigerian Grid System," IEEE *Power Engineering Society Meeting*, pp 1-6, 2007.