World Journal of Advanced Engineering Technology and Sciences

eISSN: 2582-8266

Cross Ref DOI: 10.30574/wjaets

Journal homepage: https://wjaets.com/

(Review Article)

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Self-adaptive differential evolution approach to solving economic load dispatch problem with renewable energy: Nigerian case study

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World Journal of Advanced Engineering Technology and Sciences, 2025, 14(02), 072-079

Publication history: Received on 28 December 2024, revised on 08 February 2025; accepted on 11 February 2025

Article DOI: https://doi.org/10.30574/wjaets.2025.14.2.0055

Abstract

Renewable energy penetration in power systems comes with many inherent challenges that pose a significant problem with coordination and scheduling with other conventional generation sources. These challenges if not mitigated instantly could affect the reliable operation of power systems and may even lead to a system collapse in severe cases. Therefore, the development of improved and faster economic dispatch is imperative to effectively and reliably integrate renewable energy into the power system. In this paper, four different methods namely: gradient descent, genetic algorithm, differential evolution, and self-adaptive differential evolution were utilized to coordinate the wind–thermal generation dispatch and to minimize the total production cost in the economic dispatch considering the generator ramp rate. The Nigerian grid was modeled consisting of four thermal units' system incorporating wind power plants in each of the five different locations was utilized for the numerical simulations. Different simulation scenarios with and without losses were simulated and the results show that the self-adaptive method gives the least production cost as compared to other methods. Also, considering the case with losses, the self-adaptive differential evolution gives the least transmission losses as compared to others.

Keywords: Differential Evolution; Economic Load Dispatch; Quadratic Cost Function; Nigerian grid

1. Introduction

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 increased penetration of renewable energy into the transmission network comes many challenges to service providers because of the "nature" of the renewable source i.e. its variability and uncertainty [1]

Economic load dispatch (ELD) is important in the operation of the electricity market. ELD aims to allocate power generation to match load demand at the lowest possible cost while satisfying all the power units and system constraints [2].

For 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 generators to simplify the problem's mathematical formulation and 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 is inherently non-linear with valve point loading or ramp rate limits and having multiple local minimum points in the cost function.

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Techniques such as dynamic programming might not be efficient since they require too many computational resources to provide accurate results for large-scale systems. But, with the advent of evolutionary algorithms which are stochastic-based optimization techniques that search for the solution of problems using simplified models 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 algorithms 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 algorithms include 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 contain similar structures [4].

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 [5].

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 remain fixed throughout the solution process and require minimal tuning. The Self-Adaptive Differential Evolution (SADE) is the same as the traditional DE with the exemption of the values of CR and F that are not constant but changing in the simulation.

2. Wind power plant modelling

The modeling of the wind power plant is based upon a conversion of wind speed to real power. Wind speed variability is modeled statistically by using the Weibull two-parameter distribution functions. 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

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

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

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

Wind speed changes with height and most wind speeds are observed at a 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

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

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 the known turbine power curve is estimated as

$$\text{Pe (V)} = c\text{p} * 0.5\eta\, p\,(h)\, a \int_0^{\infty} v^3 f\,(v)\, dv \quad \text{.......(4)}$$

$P_e\,(V)$ = 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_w) of wind generator *can* be obtained from the wind speed by applying equation (4). The total actual wind power generation can be easily calculated using the equation

$$P_{wt} = \sum_{w=1}^{w} P_w \quad \dots \dots . . (5):$$

Where *nw* is the number of connected wind generator

3. Problem formulation

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

3.1.1. The ELD problem is formulated as follows:

$$Minimize\ \ F_T = \sum_{i=1}^{n} C_i\,(\,P_i) \ \dots \dots \ (6)$$

3.1.2. F_T is the total generation cost.

$$C_i\,(P_i) = \alpha_i + \beta_i P + \gamma_i P^2 \quad \dots\dots\dots\dots (7)$$

is a quadratic cost function of the unit i^{th}, α_i, β_i, and γ_i are cost coefficients 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.
- It is assumed that the marginal cost of the wind power plant is zero.
- The minimization is subject to the following constraints

3.1.3. Power balance

$$\sum_{i=1}^{N} P_i + \sum_{w=1}^{W} P_w = P_D \quad \dots \dots \dots \ (8)$$

- Where P_D is the power demand
- The transmission losses is neglected

3.1.4. Maximum and minimum power limits

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

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

Where:

- $P_i^{\ min}$: The minimum power output
- $P_I^{\ max}$: The maximum power output

3.1.5. Ramp–rate constraints

The operating range of all online units is restricted by their corresponding ramp-rate limits. The inequality constraints due to ramp rate can be written as:

$$P_I\,(t) - P_i\,(t-1) \le UR_i \qquad \dots\dots\dots\dots\dots \ (10)$$

$$P_i\,(t-1) - P_i\,(t) \le DR_i \quad \ldots\ldots\ldots \qquad (11)$$

Where P_i (t) is the present output power and P_i (t-1) is the previous power output, UR_i is the up-ramp limit of the i^{th} generator; DR_i is the down–ramp limit of the i^{th} generator.

4. Nigerian Case Study

The Nigerian national grid is a fast-growing power system with different operational challenges at different operating points. The network suffers from reactive power compensation problems leading to widespread voltage fluctuations together with high technical losses and overloading of components during heavy system loading mode [9] The standardized 2010 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 of 330kV [10].

The transmission network will play a major role in the post-deregulation era in Nigeria. Presently, there is technically a limitation on the wheeling power of the transmission network which is about 6000MW, the available transfer capability of the existing transmission network in Nigeria is grossly inadequate to sufficiently transmit the electricity from the generators to the load centers with the addition of the output from the wind generators. However, with the planned expansion of the transmission network infrastructure in the country, it is expected that once completed, it will increase the wheeling capacity of the transmission system to transmit more power from all other forms of energy sources [11][12]. The renewable generation licenses shall be issued to independent power producers for generation and transmission expansion. They shall participate in the day-ahead market electricity trading through competitive offers and bids submitted to the independent system operator. The government plans to encourage renewable generators by providing accessible incentive facilities to ease their operations and also act as guarantor for the investment by minimizing their risk exposure.

Therefore, connecting the wind farms via transmission lines, the independent system operator carries out dispatch with the existing conventional thermal generators for trading activities to begin in the market. Wind energy presently does not contribute any megawatt to the national grid, but it is projected that the contribution will be approximately 50% of all renewable energy integration by the year 2030. The other forms of renewable energy sources will contribute to the other half.

5. Algorithm Formulation of the Different Optimization Methods

5.1. Differential Evolution (DE)

The Salient steps of DE-based ELD realization

- *Step 1:* At the initialization stage, the relevant DE parameters are defined. Also, relevant power system data required for the computational process are actualized from the data files.
- *Step 2:* Run the Newton-Raphson load flow to determine the initial load bus voltage, transmission loss, and active power loss respectively.
- *Step 3:* The objective function for each vector of the population is computed. The vector with the minimum objective function value (the best fit) so far is determined.
- *Step 4:* Update the generation count.
- *Step 5:* Mutation, crossover, selection, and evaluation of the objective function.
- *Step 6:* If the generation count is less than the preset maximum number of generations go to step 4. Otherwise, the parameters of the fittest vector are returned as the desired optimum value. Hence run the final *develd* to obtain the final value of the power loss, total fuel cost, and the appropriate generation schedule.

Table 1 Parameter Settings for DE-based ELD

Control Parameters	Differential Evolution
Maximum number of generation gen^{max}	200
Population size, NP	100
Scaling factor for mutation, F	0.8
Crossover constant, CR	0.5

5.2. Genetic Algorithm (GA)

GA works with a population of strings consisting of a generation. A string is divided into substrings, with each representing a problem variable. In the present ELD problem, the defined problem variables correspond to the power generation of the units. Each string represents a possible solution that is made of substrings, each corresponding to a particular generating unit. The length of each substring is decided based on the maximum/minimum limits on the power generation of the unit it represents and the method of solution accuracy desired. The string length, which depends on the length of each substring, is chosen based on a tradeoff between solution accuracy and solution time. Longer strings may provide better accuracy but result in higher solution time.

5.2.1. The various stages involved in the solution Algorithm for GA are the following

- Choose the Population size, number of generations, substring length, and the number of trials.
- Generate initially randomly coded strings as population members in the first generation.
- Decode the population to get the power generation of the units in the strings.
- Execute load flow considering the unit generations in step (3) except for the slack bus, to evaluate the transmission system losses, slack bus generation, the line flows, and hence any violation for the slack bus generation and violation of the line flow limits.
- Evaluate the fitness of population members.
- Execute selection based on reproduction. Steps (2)-(6) are repeated for all the number of generations and the minimum augmented cost is noted for the first trial. This operation is carried out for the selected number of trials and the overall minimum for the augmented cost is taken as the solution point.

Table 2 Parameter Settings for GA-based ELD

Control Parameters	**Genetic Algorithm**
Maximum number of generation gen^{max}	200
Population size, NP	100
Uniform mutation rate	0.5
Uniform crossover rate	0.9
Selection Method	Elitism

5.3. Self-Adaptive Differential Evolution (SADE)

The formulation of the SADE algorithm for the solution of the economic load is the same as the classical DE with the exemption of the values of *CR* and *F* that are not constant but changing in the simulation.

Table 3 Parameter settings for SADE- based ELD

Control Parameters	**Differential Evolution**
Maximum number of generations gen^{max}	200
Population size, NP	100
Scaling factor for mutation, F	From [0.1-1.0]
Crossover constant, CR	From [0-1]

6. Results and Discussions

The simulation studies are carried out on the Nigerian 31-bus network. This study assumes the installation of wind turbines on the buses that correspond to the six selected wind locations. The Nigerian thermal power plant characteristics are shown in Table 4 with each plant's cost coefficients and their corresponding minimum and maximum power outputs.

Table 4 Nigerian Thermal Power Plant Characteristics

Units	a_i (\$/MWh^2)	b_i (\$/MWh)	c_i (\$/h)	e_i (\$/h)	f_i (\$/h)	P_{Gi}^{min} (MW)	P_{Gi}^{max} (MW)
Sapele	6929	7.84	0.13	600	0.052	137.5	550
Delta	525.74	6.13	1.2	260	0.028	75	300
Afam	1998	56	0.092	450	0.048	135	540
Egbin	1278	13.1	0.031	850	0.094	275	1100

$= US dollar

The experiment aimed at optimizing the fuel cost and for simplicity purposes, the fixed wind speed turbine is selected. In the problem formulation for the economic load dispatch with wind integration, two different cases with and without transmission losses were considered. The solution of the problem was solved using four different methods: DE, GA, SADE, and conventional gradient descent for comparison. In this work, the ELD is applied to the four thermal plants of Egbin, Sapele, Delta, and Afam and the six wind farms located in Jos, Kaduna, Kano, Katsina, Bauchi, and Maiduguri. The simulations were run on a Dell Laptop with Intel ® Core ™ i5 -5200U CPU @ 2.20GHZ with a RAM size of 8GB. The convergence rate for each of the algorithms varies, thereby adding different computational burdens to the system. The SADE has the fastest convergence rate of about 55 minutes amongst the different algorithms, followed by the DE (about 1 hour) and the GA (above 1 hour) respectively. The gradient descent method is slow to converge with the simulation running for about an hour before it finally converges. The results of the ELD with and without transmission losses considered are shown in Table 5 and Table 6 respectively. Table 7 shows the cost of generation obtained with and without losses for the different optimization techniques

Table 5 Results of Economic Load Dispatch without Losses

Power Stations	**Gradient Descent (MW)**	**DE (MW)**	**GA (MW)**	**SADE (MW)**
Egbin	968.58	1020.85	1060.52	1045.23
Sapele	486.68	471.69	476.58	466.58
Delta	286.42	260.62	240.3	250.47
Afam	520.33	510.24	480.36	495.36
Jos	24.41	25.32	28.25	26.62
Katsina	21.57	21.78	22.14	20.84
Kano	15.62	14.87	13.56	14.48
Kaduna	19.63	18.43	20.58	21.69
Bauchi	12.24	11.96	12.43	13.26
Maiduguri	12.52	12.24	12.65	13.47
Total generation	2368	2368	2368	2368
Demand	2368	2368	2368	2368

Table 6 Results of Economic Load Dispatch with Losses

Power stations	Gradient Descent (MW)	DE (MW)	GA (MW)	SADE (MW)
Egbin	1015.48	1026.49	1043.52	1068.51
Sapele	471.32	476.34	481.62	446.58
Delta	278.54	263.54	256.21	265.28
Afam	533.14	529.79	512.14	513.52
Jos	25.41	26.4	27.62	26.15
Katsina	22.47	22.56	22.56	21.45
Kano	15.85	15.52	16.23	16.54
Kaduna	20.35	19.22	20.52	21.14
Bauchi	11.53	13.56	12.62	13.14
Maiduguri	12.65	12.79	12.86	13.24
Total generation	2406.74	2406.21	2405.9	2403.55
Demand	2368	2368	2368	2368
Losses	38.74	38.21	37.9	37.55

Table 7 Cost of Production for the Different Methods

	DE($/hr)	GA($/hr)	SADE($/hr)	Conventional($/hr)
Without losses	7360.34	7498.27	7150.15	8634.41
With losses	7542.57	7621.36	7325.4	8715.55

The generators' schedule reflects the best possible contributions of all the individual generators based on the demand for that hour. Table 7 shows the cost of production obtained from the simulation results of the four different methods. The SADE gives the least production cost as compared to other methods. Also, considering the case with losses, the SADE gives the least transmission losses as compared to others. This task of economic dispatch is carried out by the system operator to first ascertain if the transmission network can accommodate the volume of trading activities for that day. Once the ISO guarantees the reliability of the transmission network, then trading activities can commence and the marginal cost price for that hour can be achieved by several bids and offers received. The present transmission wheeling capacity of the Nigerian network is less than 6000MW, it is expected that the transmission network can sustain the number of trade activities in the interim pending the completion of the various ongoing renewable projects across the country. However, as the penetration of renewable energy into the grid increases the volume of trading activities, there will be a need for transmission expansion to increase the available transfer capability (ATC) and to maintain the reliability of the transmission system during operation.

The most important step in any wind farm project is a good wind feasibility study which shows a detailed analysis of all the necessary parameters, identifies any likely risk, and further recommends the best way to proceed with the project.

7. Conclusion

The economic load dispatch problem was formulated using the quadratic cost function model incorporating wind energy and considering the valve point effect. The solutions were found with and without transmission losses considered subject to many constraints. The constrained optimization problem was formulated for scheduling the online generators and was solved using three different evolutionary algorithms and gradient descent methods for results comparison purposes.

Also, the self-adaptive differential (SADE) evolution techniques give the least cost generator result, amongst all the optimization methods used in solving the formulated economic load dispatch problem with wind energy of the Nigerian power system. The power sector reform in Nigeria is an ongoing process and the integration of renewable energy is among the several aspects of the reform stages. It is expected that the next stages will strengthen the development of the electricity supply industry and the electricity market respectively.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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