Short-Term Economic Load Dispatch of Nigerian Thermal Power Plants Based on Differential Evolution Approach

Awodiji Olurotimi.Olakunle*, Bakare Ganiyu.Ayinde**.' Aliyu Usman .O.***

Abstract--This paper presents the solution of short-term economic load Dispatch problems by means of the Differential Evolution (DE) algorithm. This approach is an evolutionary algorithm useful in solving many real world constrained optimization problems. The developed DE based economic dispatch solution was tested and validated on the Nigerian grid system. The results obtained demonstrate the applicability of the proposed method for solving economic dispatch problems on a short-term basis.

Index terms—Economic Load Dispatch, Differential Evolution, Nigeria, Short-Term, Quadratic Cost Function.

1 INTRODUCTION

The main objective of economic load dispatch of electric power generation is to schedule the committed generating units output so as to meet the load demand at minimum operating cost, while satisfying all the unit and system equality and inequality constraints. Therefore, ELD problem is a large scale constrained non-linear optimization problem.

For the purpose of economic dispatch studies, online generators are represented by functions that relate their production cost to their power output. 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 lamda 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.

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Techniques such as dynamic programming might not be efficient since they require too many computational resources in order to provide accurate result 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.

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 [1].

Other evolutionary algorithm includes Simulated Annealing (SA), Genetic Algorithm (GA), Hybrid Particle Swarm Optimization (PSO) with Sequential Quadratic Programming approach (PSO-SQP), Evolutionary Programming (EP) and Artificial Bee Colony (ABC) [2], [3], [4], [5]. SA is designed to solve the high non-linear ELD problem without restriction on the shape of the fuel cost function. The GA can find a global solution after sufficient iterations, but has high computational burden. 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 [3].

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.

ISSN 2229-5518

The purpose of this paper is to present a solution methodology for the short-term economic load dispatch using the differential evolution method for a period of one week on the Nigerian network using the network data and information from the electric utility company to solve the problem.

The paper is organized as follows, Section II introduces the ELD problem formulation, and Section III describes the Differential Evolution algorithm. Section IV describes the DE based ELD. Then the numerical experiment in Section V. Finally, remarks and conclusion are introduced..

2 PROBLEM FORMULATIONS

Consider an interconnected power system consisting of n thermal power stations as shown in Fig.1, the ELD problem seeks to find the optimal combination of thermal power plants that minimizes the total cost while satisfying the total demand and system constraints.

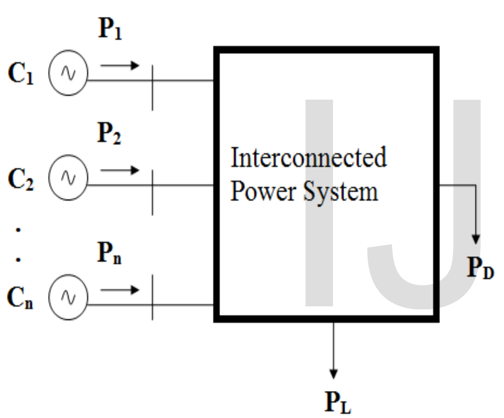

Fig.1. Interconnected power system

The ELD problem is formulated as follows:

$$\text{Min } C_T = \sum_{i=1}^{n} C_i(P_i) \tag{1}$$

Where:

$C_i(P_i)$: Cost function of the i^{th} unit

P_i: The power output of i^{th} unit

The minimization is subject to the following constraints:

2.1 Power Balance

The total power generated must to be equal to the sum of load demand and transmission-line loss:

$$P_D + P_L - \sum_{i=1}^{n} P_i = 0 \tag{2}$$

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:

$$P_L = \sum_{i=1}^{n} \sum_{j=1}^{n} P_i B_{ij} P_j \tag{3}$$

Where B_{ij} is the transmission loss coefficient

2.2 Maximum and Minimum Power Limits

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

$$P_i^{\min} \leq P_i \leq P_i^{\max} \qquad i=1, 2,\ldots\ldots\ldots\ldots, n \tag{4}$$

Where:

$P_i^{\min}$: The minimum power output

$P_i^{\max}$: The maximum power output

The above cast problem is an optimization one. This will be solved using differential evolution approach and demonstrated on Nigerian thermal power plants for a typical weekly load curves, hence short-term economic load dispatch.

3 DIFFERENTIAL EVOLUTION CONCEPTS

Differential Evolution (DE) is a relatively new evolutionary algorithm proposed by Storn and Price (1995) which is simple, yet powerful, for solving complex optimization problems. Practical optimization problems are often characterized by several non-linearities and competing objectives. The presence of multiple objectives in a problem, in principle, gives rise to a set of optimal solutions known as Pareto-optimal solutions, instead of a single optimal solution (Coello, 1999). In the absence of any further information, it is not possible to decide which of these Pareto-optimal solutions is better than the other. Hence, the operator has to find as many Pareto-optimal solutions as possible from which the most suitable solution is chosen to meet a particular dominant requirement.

In a DE algorithm, candidate solutions are randomly generated and evolved to individual solution by simple technique combining simple arithmetic operators with the classical events 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 eqn. (4):

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

Where $X_{i,k}$ is given by eqn. (5)

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

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

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

ISSN 2229-5518

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 in eqn. (7).

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

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 the following eqn. (8):

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

Where, CR is the cross over 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. (9):

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

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

Step 5: Verification of the stopping criterion

Loop to step 3 until stopping criterion is satisfied, usually a maximum number of iterations, G_{max}. .

4 DEVELOPMENT OF DE BASED STELD

The generalized steps of the DE algorithm as presented in detail in section III are pertinent in its application to the economic load dispatch problem under consideration. As a first step in DE based STELD, we randomly generate an initial population comprising feasible power generated at all the on-line thermal units within the multi-dimensional search space. We define the initial power generated population matrix $[P^O]$ dimensioned $\mathcal{R}^{\mathcal{M}X\mathbb{N}_P}$ thus:

$$[P^O] = \begin{bmatrix} P_{11}^0 & \cdots & P_{1\mathbb{N}_P}^0 \\ \vdots & P_{ij}^0 & \vdots \\ P_{\mathcal{M}1}^0 & \cdots & P_{\mathcal{M}\mathbb{N}_P}^0 \end{bmatrix}$$

$$P_{ij}^0 = P_i^{min} + rand * (P_i^{max} - P_i^{min})$$
$$i = 1,2,3 \ldots.\mathcal{M};\ j = 1,2,3 \ldots..N_p \quad \ldots (10)$$

Where, P_{ij}^0 : is the initialized i^{th} candidate power generated of j^{th} column of population matrix;

$'rand'$: is function that generates random values uniformly in the interval [0, 1];

N_p : is the population size;

$\mathcal{M}$: is the number of online generating units;

P_i^{min} and P_i^{max} : are the lower and upper bound on the i^{th} generating unit, respectively.

In each generation, N_p competitions are held to determine the composition of the next generation via mutation, crossover and selection processes which are basically similar to those of genetic algorithm (GA).

Mutation operations are applied in DE during offspring generation and of necessity play pivotal role in the reproduction cycle. The mutation operation creates mutant population vector $\bar{P}_i^{\prime(k)}$ by perturbing a randomly selected vector or best current population vector (based on minimum objective function value returned) $\bar{P}_{l_1}^{(k)}$ with the difference of two other randomly selected vectors $\bar{P}_{l_2}^{(k)}$ and $\bar{P}_{l_3}^{(k)}$ at k^{th} iteration according to eqn. (11).

$$\bar{P}_i^{\prime(k)} = \bar{P}_{l_1}^{(k)} + F * (\bar{P}_{l_2}^{(k)} - \bar{P}_{l_3}^{(k)}) \qquad i = 1,2,3 \ldots N_p \quad (11)$$

Where,

$\bar{P}_i^{\prime(k)}$: is generated i^{th} column population vector after performing mutation operation at k^{th} iteration;

$\bar{P}_{l_1}^{(k)}, \bar{P}_{l_2}^{(k)}$ and $\bar{P}_{l_3}^{(k)}$: are randomly chosen vectors at k^{th} iteration;

l_1, l_2 & $l_3 \in \{1, N_p\}$: are randomly chosen integers, mutually different and also chosen to be different from the running index i (i.e. $l_1 \neq l_2 \neq l_3 \neq i$).

F : is scaling factor for mutation and its value is typically (0 ≤ F ≤ 1.2) to control amplification of the differential perturbation in the mutation process so as to secure good convergence characteristics.

The next task after mutation operation is crossover process so introduced to diversify the perturbed population matrix for the online thermal units. Fundamentally, crossover operation represents a typical case of 'genes' exchange. Here, the j^{th} column target power output vector $\bar{P}_j^{(k)} = [P_{1j}^{(k)}, P_{2j}^{(k)} \ldots P_{ij}^{(k)} \ldots P_{\mathcal{M}j}^{(k)}]^T$ is mixed with the j^{th} column mutated power output vector $\bar{P}_j^{\prime(k)} = [P_{1j}^{\prime(k)}, P_{2j}^{\prime(k)} \ldots P_{ij}^{\prime(k)} \ldots P_{\mathcal{M}j}^{\prime(k)}]^T$ to create a j^{th} column trial power output vector $\bar{P}_j^{\prime\prime(k)} = [P_{1j}^{\prime\prime(k)}, P_{2j}^{\prime\prime(k)} \ldots P_{ij}^{\prime\prime(k)} \ldots P_{\mathcal{M}j}^{\prime\prime(k)}]^T$. Thus, the procedure to building trial power output vector is anchored on eqn. (12):

$$P_{ij}^{\prime\prime(k)} = \begin{cases} P_{ij}^{\prime(k)} \ if\ (randb(i) \le CR\ or\ i = rnbr(j) \\ P_{ij}^{(k)} \ if\ (randb(i) > CR\ or\ i \ne rnbr(j) \end{cases} \quad (12)$$

Where: $j = 1,2,3 \ldots N_p; i = 1,2,3 \ldots . \mathcal{M}$.

$P_{ij}^{(k)}$, $P_{ij}^{\prime(k)}$ and $P_{ij}^{\prime\prime(k)}$: are i^{th} individual of the j^{th} target power output vector, mutant power output vector and trial power output vector at k^{th} iteration, respectively; $randb(i)$: is i^{th} randomly generated value in the interval [0, 1];

CR : is crossover constant $\epsilon\,[0,1]$ that regulates the diversity of the population and aids the algorithm escape from local optima;

$rnbr(j)$:is randomly chosen index $\in (i = 1,2,3 \ldots, \mathcal{M})$ to insure that the trial vector, $\bar{P}_j^{\prime\prime(k)}$ gets at least one value from the mutated vector, $\bar{P}_j^{\prime(k)}$.

The selection procedure is the final step of any classical DE algorithm. More specifically, selection procedure is used among the set of trial vector and the target vector to choose the better vector. Each solution in the population has equal chance of being selected as parents. Selection process is realized by comparing the objective function values of target vector and trial vector. For a minimization problem for example, if the trial vector has lower value of the objective function, then it replaces the target vector in the next generation otherwise the current target vector is retained. This is cast mathematically, using objective function evaluation criterion $F(.)$, as follows:

$$\bar{P}_j^{(k+1)} = \begin{cases} \bar{P}_j^{\prime\prime(k)} \ if\ F(\bar{P}_j^{\prime\prime(k)}) \le F(\bar{P}_j^{(k)}) \\ \bar{P}_j^{(k)} \ if\ F(\bar{P}_j^{\prime\prime(k)}) > F(\bar{P}_j^{(k)}) \end{cases} \quad (13)$$

We have also incorporated the application of elitist strategy of GA to keep track of the fittest vector and the specification of algorithmic convergence criterion. If the convergence criterion is met, the power output values contained in the fittest vector are returned as the desired optimal values. With the desired optimal values of power output specified at the respective thermal generating units, the final power flow is carried out again to determine the active power losses, fuel cost and generating units loading profile.

4.1 Evaluation of Fitness

Each individual in the population is evaluated using the fitness function of the problem to minimize the fuel cost function. The power balance constraint is augmented with the objective function to form a generalized fitness function f_k as given by

$$f_k = \sum_{i=1}^{n} C_i + \mu \left[\sum_{i=1}^{n} P_i - P_D - p_L \right] \quad (14)$$

Where μ is the penalty parameter, the penalty term reflects the violation of the equality constraint and assigns a high cost of penalty function to candidate point far from feasible region. The upper and lower generation limit of generating unit is violated then it can be fixed in the bound range by forcing it to lower/upper limit.

4.2 Handling of Constraints

The reproduction operation of DE can extend the search outside the range of the parameters. A simple strategy is adopted in this study to ensure that the parameter values lies within the allowable range after reproduction. Any parameter that violates the limits is replaced with random values.

4.3 Stopping Criterion

The above iterative process of mutation, crossover and selection on the population will continue until there is no appreciable improvement in the minimum fitness values or predefined maximum number of iteration is reached.

4.4 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 using eqn. (13). The vector with the minimum objective function value (the best fit) so far is determined.

Step 4: Update of 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 numbers of generations go to step 4. Otherwise the parameters of the fittest vector are returned as the desired optimum value. Hence run the final *load flow* to obtain the final value for the power loss, total fuel cost and the appropriate generation schedule.

5 NIGERIAN GRID SYSTEMS

The Nigerian national grid belongs to rapidly growing power systems faced with complex operational challenges at different operating regimes. Indeed, it suffers from inadequate reactive power compensation leading to wide spread voltage fluctuations couple with high technical losses and component overloads during heavy system loading mode. 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 2,830.1MW and bears technical power network loss of 39.85MW. The single line diagram of the 330kV Nigerian grid system is set forth in Fig. 2.

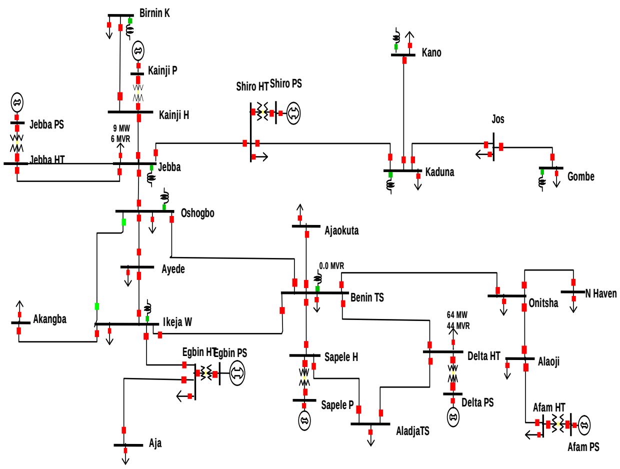

Fig.2. Single line diagram of Nigerian 330kV 31-bus grid systems

5.1Short-Term ELD for Nigerian Thermal Power Plant

The short term ELD was carried out for a typical load demand profile shown in Fig.3. The 8-hourly duration peak demand for a period of one week was obtained from the daily operational reports of the transmission company of Nigeria.

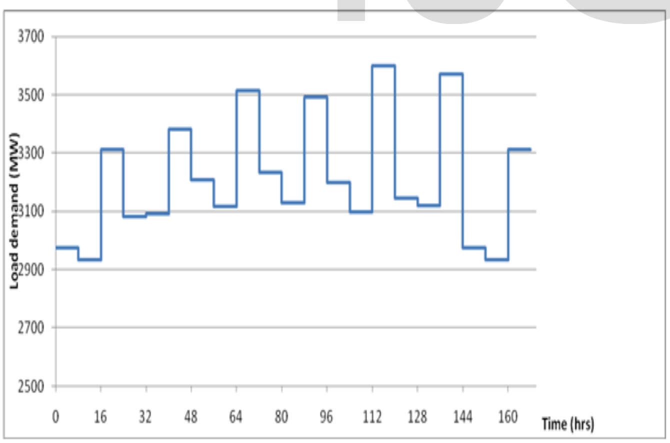

Fig.3. Load demand profile for a week

Table 1
Nigerian Thermal power Plants Characteristics

Unit	α	β	γ	P_G^{min} (MW)	P_G^{max} (MW)
Sapele	6929.0	7.84	0.13	137.5	550.0
Delta	525.74	-6.13	1.20	75 .0	300.0
Afam	1998.0	56.0	0.092	135.0	540.0
Egbin	12787.0	13.1	0.031	275.0	1100.0

Table 2
Optimum Parameter Settings for DE Based Tools

Control Parameter	Differential Evolution
Maximum number of generation, gen^{max}	200
Population size, NP	30
Scaling factor for mutation, F	0.8
Crossover constant, CR	0.5

6 SIMUATION RESULTS

The results obtain for the one week are presented on daily basis.

Table 3
Economic Load Dispatch for Day 1

PARAMETERS	0-8 HRS	9-16 HRS	17-24HRS
Egbin P_{G1} (MW)	800.4	780.5	1074.7
Sapele P_{G2} (MW)	317.2	393.8	407.9
Delta P_{G3} (MW)	106.4	75.8	85.5
Afam P_{G4} (MW)	394,5	327.3	390.8
Shiroro P_{G5} (MW)	561	561	561
Kainji P_{G6} (MW)	416	416	416
Jebba P_{G7} (MW)	419	419	419
$\sum P_G$ (MW)	3014.476	2973.345	3,355
P_D (MW)	2975.203	2933.502	3311.81
P_L (MW)	39.2732	39.8433	43.0378
Total Cost (₦/hr)	117,510.00	109,130.00	141,140.00

Table 4

Economic Load Dispatch for Day 2

PARAMETERS	0-8 HRS	9-16 HRS	17-24HRS
Egbin P_{G1} (MW)	1018.6	1032.7	1077.3
Sapele P_{G2} (MW)	422.7	417.8	459.9
Delta P_{G3} (MW)	106.2	86.3	105
Afam P_{G4} (MW)	322.6	340.9	531.5
Shiroro P_{G5} (MW)	403	403	403
Kainji P_{G6} (MW)	430	430	430
Jebba P_{G7} (MW)	420	420	420
$\sum P_G$ (MW)	3123.086	3130.619	3426.741
P_D (MW)	3083.105	3090.605	3382.211
P_L (MW)	39.9809	40.0135	44.5298
Total Cost (₦/hr)	134,850.00	132,940.00	171,560.00

Table 5
Economic Load Dispatch for Day 3

PARAMETERS	0-8 HRS	9-16 HRS	17-24HRS
Egbin P_{G1} (MW)	1063	888.6	1053.6
Sapele P_{G2} (MW)	400.8	482.2	444.1
Delta P_{G3} (MW)	107	114	142.8
Afam P_{G4} (MW)	300.7	291.3	536
Shiroro P_{G5} (MW)	547	547	547
Kainji P_{G6} (MW)	415	415	415
Jebba P_{G7} (MW)	420	420	420
$\sum P_G$ (MW)	3253.488	3158.131	3558.576
P_D (MW)	3209.608	3116.906	3514.214
P_L (MW)	43.8807	41.2248	44..3627
Total Cost (₦/hr)	133,430,00	131,370.00	179,640.00

Table 6
Economic Load Dispatch for Day 4

PARAMETERS	0-8 HRS	9-16 HRS	17-24HRS
Egbin P_{G1} (MW)	1027.8	1001.8	1092.8
Sapele P_{G2} (MW)	323.7	275.1	482.1
Delta P_{G3} (MW)	81.2	132	155.6
Afam P_{G4} (MW)	482	401.1	444.2
Shiroro P_{G5} (MW)	525	525	525
Kainji P_{G6} (MW)	411	411	411
Jebba P_{G7} (MW)	424	424	424
$\sum P_G$ (MW)	3274.629	3169.949	3534.617
P_D (MW)	3233.308	3129.806	3490.713
P_L (MW)	41.3206	40.1433	43.9038
Total Cost (₦/hr)	140,400.00	135,830.00	178,670.00

Table 7
Economic Load Dispatch for Day 5

PARAMETERS	0-8 HRS	9-16 HRS	17-24HRS
Egbin P_{G1} (MW)	966.7	899.4	1082
Sapele P_{G2} (MW)	326.3	326.2	506.9
Delta P_{G3} (MW)	108.4	106.6	88
Afam P_{G4} (MW)	402.6	369.4	531.8
Shiroro P_{G5} (MW)	539	539	539
Kainji P_{G6} (MW)	401	401	401
Jebba P_{G7} (MW)	498	498	498
$\sum P_G$ (MW)	3241.927	3139.628	3646.711
P_D (MW)	3199.407	3097.705	3599.615
P_L (MW)	42.52	41.9224	47.0958
Total Cost (₦/hr)	131,260.00	121,740.00	174,620.00

Table 8
Economic Load Dispatch for Day 6

PARAMETERS	0-8 HRS	9-16 HRS	17-24HRS
Egbin P_{G1} (MW)	892.3	894.7	1099.4
Sapele P_{G2} (MW)	419.3	286.6	483.3
Delta P_{G3} (MW)	104.5	93.2	120.9
Afam P_{G4} (MW)	361.6	479.2	505
Shiroro P_{G5} (MW)	516	516	516
Kainji P_{G6} (MW)	408	408	408
Jebba P_{G7} (MW)	484	484	484
$\sum P_G$ (MW)	3185.717	3161.767	3616.606
P_D (MW)	3144.606	3120.406	3570.215
P_L (MW)	41.111	41.3614	46.3913
Total Cost (₦/hr)	129,430.00	129,480.00	176,820.00

Table 9
Economic Load Dispatch for Day 7

PARAMETERS	0-8 HRS	9-16 HRS	17-24HRS
Egbin P_{G1} (MW)	968.4	872.9	1090.4
Sapele P_{G2} (MW)	470	414	548.8
Delta P_{G3} (MW)	79.7	84.1	131.4
Afam P_{G4} (MW)	336.1	409.9	529.9
Shiroro P_{G5} (MW)	450	450	450
Kainji P_{G6} (MW)	392	392	392
Jebba P_{G7} (MW)	496	496	496
$\sum P_G$ (MW)	3192.199	3119.02	3638.467
P_D (MW)	3151.206	3080.105	3590.915
P_L (MW)	40.9926	38.9148	47.5521
Total Cost (₦/hr)	132,890.00	129,200.00	192,580.00

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6 DISCUSSIONS

The ELD was implemented on Mat Lab platform. The contributions of the hydro power plants to the load demand were fixed for each day, while ELD was carried out in other to determine the contribution of the thermal power plants for each day. The result shows the contribution of each of the thermal generators for the 8-hourly period in a day. The corresponding power loss and the total cost of production for each period are also calculated. The schedule reflects the best possible contribution of the individual generators based on the demand for the given period in a day.

ISSN 2229-5518

7 CONCLUSIONS

In this paper, differential evolution method has been applied to schedule generators on a short term basis for the Nigerian thermal power plants. The result shows that this method is capable of being applied successfully to the economic dispatch problem of larger thermal power plants and can also be extended for longer duration say a month. The result shows that the generating companies can plan ahead of time in meeting the energy demand of their customers. Both customers and generating companies enjoys the benefit of the solution presented in this paper which has a positive effect on the electricity market of the country. The future work entails the use of load forecasting by means of artificial neural network to determine the load demand for a given period to be used for the economic load dispatch problem.

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