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A Differential Evolution Approach to Optimal Generator Maintenance Scheduling of the Nigerian Power System

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***Abstract*--The goal of optimal generator maintenance scheduling is to evolve optimal preventive maintenance schedule of generating units for economical and reliable operation of a power system while satisfying system load demand and crew constraints. In this paper, the differential evolution (DE), an evolutionary computation algorithm that utilizes the differential information to guide its further search, is applied to effectively solve the generator maintenance scheduling (GMS) optimization problem. The proposed method can handle mixed integer discrete continuous optimization problems. Results are presented with the DE algorithm on two different case studies for Nigerian power system.**

***Index Terms*-- Differential evolution, discrete optimization, generator maintenance, Nigerian power system, optimal scheduling.**

I. Introduction

PREVENTIVE maintenance scheduling of generating units is an important task in power system and plays major role in operation and planning of the system. The economic operation of an electric utility system requires the simultaneous solution of all aspects of the operation scheduling problem in the face of system complexity, different time-scales involved, uncertainties of different order, and dimensionality of problems.

All utilities perform maintenance of systems and equipment in order to supply electricity with a high reliability level. The reliability of system operation and production cost in an electric power system is affected by the maintenance outage of generating facilities. Optimized maintenance schedules could safe millions of Dollars and potentially defer some capital expenditure for new plants in times of tightening reserve margins, and allow critical maintenance work to be performed which might not otherwise be done. Therefore, maintenance scheduling for electric utilities system is a significant part of the overall operations scheduling problem.

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Power system components are made to remain in operating conditions by regular preventive maintenance. The task of generator maintenance is often performed manually by human experts who generate the schedule based on their experience and knowledge of the system, and in such cases there is no guarantee that the optimal or near optimal schedule is found. The purpose of maintenance scheduling is to find the sequence of scheduled outages of generating units over a given period of time such that the level of energy reserve is maintained. This type of schedule is important mainly because other planning activities are directly affected by such decisions. In modern power systems, the demand for electricity has greatly increased with related expansions in system size, which has resulted in higher number of generators and lower reserve margins making the generator maintenance scheduling (GMS) problem more complicated. The eventual aim of the GMS is the effective allocation of generating units for maintenance while maintaining high system reliability, reducing production cost, prolonging generator life time subject to some unit and system constraints [1]-[2].

The GMS is a complex multi-objective constrained optimization problem. Various methods exist in literature that addresses optimization problems under different conditions. Different optimization techniques are classified based on the type of the search space and the objective function. The simplest method is linear programming (LP) which concerns the case where the objective function is linear [3]. For a special case, where some or all variables are constrained to take on integer values, the technique is referred to as integer programming [4]. In general, the objective function or the constraints or both may contain nonlinearities, which raise the concept of nonlinear programming (NLP) [5]. This type of optimization technique has been extensively used for solving problems, such as power system voltage security [6], optimal power flow [7], power system operation and planning [8], dynamic security [9], capacitor placement [10] and power quality [11]. Even though deterministic optimization problems are formulated with known parameters, real world problems almost invariably include some unknown parameters. This necessitates the introduction of dynamic programming (DP) [12]. Although the DP technique has been mathematically proven to find an optimal solution, it has its own drawbacks. Solving the dynamic programming algorithm in most of the cases is not feasible and numerical solution requires extensive computational effort, which increases exponentially as the size of the problem increases. The complexity is even further increased when moving from finite horizon to infinite horizon problems, while also considering the stochastic effects, model imperfections and the presence of the external disturbances [12].

Genetic algorithms (GAs) have been compared and confirmed to be superior to other conventional algorithms such as heuristic approaches and branch-and-bound (B&B) in the quality of solutions. GA is shown to be more computationally efficient than the B&B algorithm as the problem's dimension increases [13], [14].

Generally, scheduling of generating units in a raw system may be divided into three stages of long-term, short-term and real-time [1]. The long-term scheduling (LTS) problem tackles fuel allocation and budgeting, emission and production and maintenance costing. The solutions obtained from LTS can then be used as guidelines and bases for addressing unit commitment and optimal power flow problems. The objective of the short-term scheduling (STS) is to minimize the cost of operation over hourly, daily or weekly periods. Because dynamic economic dispatch is fundamental for real time control of power systems, the STS brings up a commitment strategy for real-time economic dispatch for committed units to meet system requirements in an on-line operation. The dynamic economic dispatch is solved for short periods of time in which the system load conditions can be assumed constant.

This paper presents a differential evolution (DE) optimization algorithm that appears to ally qualities of established computational intelligence techniques with a more striking computational performance, thus suggesting the possibility of having the potential for on line applications in the control centers [15]. It also illustrates the use of DE for solving the GMS problem for the Nigerian power system where load exceeds generation.

II. Problem Formulation

Generally, there are two main categories of objective functions in GMS, namely, based on reliability and economic cost [2]. The reliability criteria of leveling reserve generation for the entire period of study is considered in this paper. The problem studied here is solved by minimizing the sum of squares of the reserve over the entire operational planning period. The problem has a number of unit and system constraints to be satisfied. The constraints include the following:

- Maintenance window and sequence constraints - defines the starting of maintenance at the beginning of an interval and finishes at the end of the same interval. The maintenance cannot be aborted or finished earlier than scheduled.
- Crew and resource constraints - for each period, number of people to perform maintenance schedule cannot exceed the available crew. It defines manpower availability and the limits on the resources needed for maintenance activity at each time period.
- Load and spinning reserve constraints - total capacity of the units running at any interval should be not less than predicted load at that interval.

Suppose $T_i \subset T$ is the set of periods when maintenance of unit i may start, $T_i = \{t \in T : e_i \le t \le l_i - d_i + 1\}$ for each i.

Define

$$X_{it} = \begin{cases} 1 & \text{if unit } i \text{ starts maintenance in period } t \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

to be the maintenance start indicator for unit i in period t. Let S_{it} be the set of start time periods k such that if the maintenance of unit i starts at period k that unit will be in maintenance at period t, $S_{it} = \{k \in T_i : t - d_i + 1 \le k \le t\}$. Let I_t be the set of units which are allowed to be in maintenance in period t, $I_t = \{i : t \in T_i\}$.

The objective function to be minimized is given by (2) subject to the constraints given by (3), (4) and (5).

$$\underset{X_{it}}{Min} \left\{ \sum_t \left(\sum_i P_{it} - \sum_{i \in I_t} \sum_{k \in S_{it}} X_{ik} \cdot P_{ik} - L_t \right)^2 \right\} \tag{2}$$

subject to the maintenance window constraint

$$\sum_{t \in T_i} X_{it} = 1 \quad \forall i, \tag{3}$$

the crew constraint

$$\sum_{i \in T_t} \sum_{k \in S_{it}} X_{ik} \cdot M_{ik} \le AM_t \qquad \forall t, \tag{4}$$

and the load constraint

$$\sum_i P_{it} - \sum_{i \in I_t} \sum_{k \in S_{it}} X_{ik} \cdot P_{ik} \ge L_t \qquad \forall t, \tag{5}$$

i index of generating units
I set of generating unit indices
N total number of generating units
t index of periods
T set of indices of periods in planning horizon
e_i earliest period for maintenance of unit i to begin
l_i latest period for maintenance of unit i to end
d_i duration of maintenance for unit i
P_{it} generating capacity of unit i in period t
L_t anticipated load demand for period t
M_{it} manpower needed by unit i at period t

AM_t available manpower at period t

Penalty cost given by (6) is added to the objective function in (2) if the schedule cannot satisfy the load, crew or resource constraints. The penalty value for each constraint violation is proportional to the amount by which the constraint is violated.

$$\sum_c \omega_c V_c \qquad (6)$$

where ω_c is a weighting coefficient and V_c is the amount of the violation of constraint *c*.

III. DIFFERENTIAL EVOLUTION

Differential evolution is an optimization algorithm that solves real-valued problems based on the principles of natural evolution [16]-[17]. DE uses a population of given size composed of floating point encoded individuals that evolve over generations to reach an optimal solution. It was introduced by Storn and Price in 1995 as heuristic optimization method which can be used to minimize nonlinear and non-differentiable continuous space functions with real-valued parameters. It has been extended to handle mixed integer discrete continuous optimization problem [18]. Design principles in DE are [19]:

- Simple structure, ease of use and robustness.
- Operating on floating point with high precision.
- Effective for integer, discrete and mixed parameter optimization.
- Handling non-differentiable, noisy and/or time dependent objective functions.
- Effective for nonlinear constraint optimization problems with penalty functions, etc.

Like the other evolutionary (EA) family, DE also relies on initial random population generation, which is then improved using selection, mutation, and crossover repeated through generations until the convergence criterion is met.

Although the canonical form of differential evolution solves optimization problems over continuous spaces, minor adjustments to the code allow DE to solve mixed integer optimization problems [18]. This is achieved with the use of operator that rounds the variable to the nearest integer value, when the value lies between two integers.

An initial population composed of vectors $P^o{}_{i}$, $i = 1,2,\ldots np$, is randomly generated within the parameter space. The adaptive scheme used by the DE ensures that the mutation increments are automatically scaled to the correct magnitude. For reproduction, DE uses a tournament selection where the offspring vectors compete against one of their parents. The parallel version of DE maintains two arrays, each of which holds a population of *np*, D - dimensional, real value vectors. The primary array holds the current population vector, while the secondary array accumulates vectors that are selected for the next generation. In each generation, *np* competitions are held to determine the composition of the next generation. Every pair of randomly chosen vectors P_1 and P_2 defines a vector differential: (P_1 - P_2). Their weighted differential is used to perturb another randomly chosen vector P_3 according to (7) given by:

$$P_3' = P_3 + F * (P_1 - P_2) \qquad (7)$$

Where F is the scaling factor for mutation and its value is typically ($0 \le F \le 1.2$). F of 0.7 is taken in this study. It controls the speed and robustness of the search; a lower value increases the rate of convergence but also the risk of being stuck at the local optimum. The crossover is a complimentary process for DE. It aims at reinforcing the prior successes by generating the offspring vectors. In every generation, each primary array vector P_i, is targeted for crossover with a vector like P_3' to produce a trial vector P_t according to (8).

$$P_t = \begin{cases} P_3' & if\ rand < C_R \\ P_i & otherwise \end{cases} \qquad (8)$$

Where C_R ($0 \le C_R \le 1.0$) is a crossover constant. C_R of 0.9 is taken in this study. The newly created vector will be evaluated by the objective function and the corresponding value is compared with the target vector. The best fit vector is kept for the next generation as given by (9). The best parameter vector is evaluated for every generation in order to track the progress made throughout the minimization process; thus making the DE elitist method.

$$P_i(t+1) = \begin{cases} P_i(t) & if\ \ fit(P_i(t)) \le fit(offspring\ (t)) \\ offspring & otherwise \end{cases} \qquad (9)$$

IV. CASE STUDIES AND RESULTS

A. Nigerian Power System

The Nigerian power system consists of a total of 49 units positioned in 7 generating plants located in distinct areas (AFAM, DELTA, EGBIN, SAPELE, JEBBA, KAINJI and SHIRORO plants) as shown in Fig. 1 and Table I. AFAM, DELTA and 8 units of EGBIN thermal plants are gas fired, while SAPELE and 6 units of EGBIN thermal plants are steam driven. JEBBA, KAINJI and SHIRORO hydro plants are water driven. Table II shows the units' base case ratings.

B. Kainji Lake

The Kainji lake that services the three Nigerian hydro plants, namely Jebba, Kainji and Shiroro hydro plants is located between 9^0 51`N to $10^0$ 57`N and $4^0$20`E to $4^0$ 50`E in Northwestern Nigeria with water-level variation and rainfall distribution shown in Fig. 2 [20]. The variation in the lake water-level is controlled mainly by the inflow into the lake, rainfall at the lake, outflow through turbines and irrigation water supply.

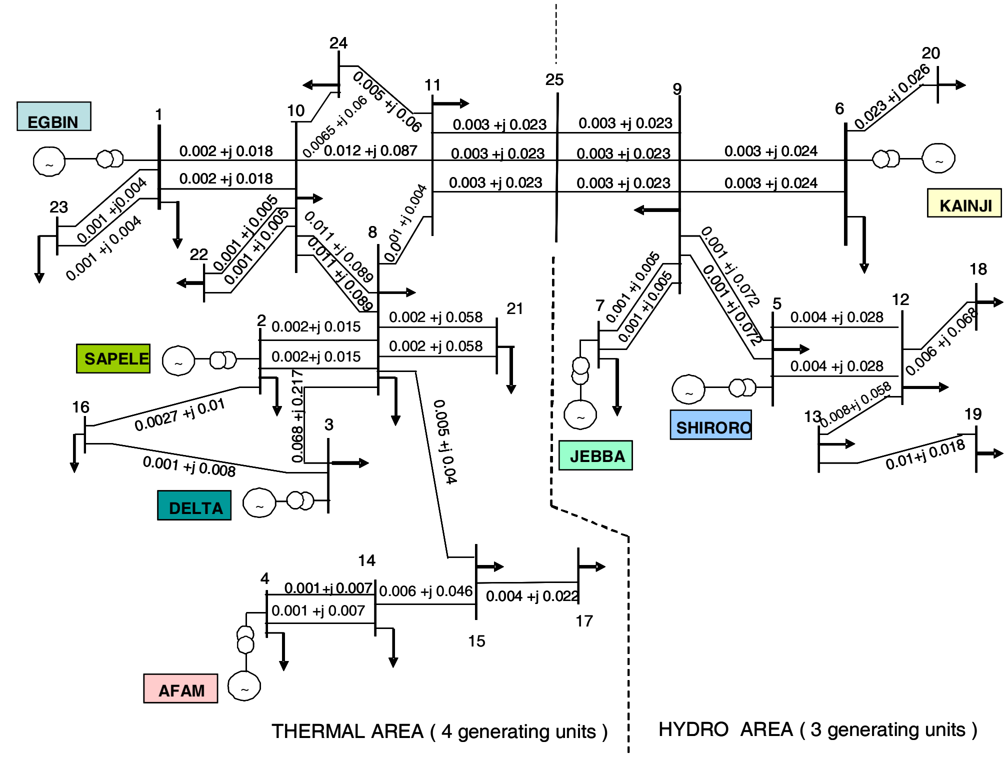

Fig. 1. The Nigerian 330KV, 25 bus grid power system

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This water-level variation has significant impact on the generated output of the hydro plants, and also influences the allowed periods for the maintenance of the three hydro plants

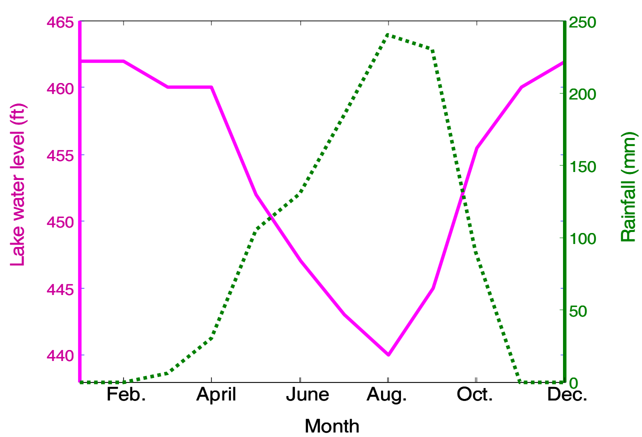

Fig. 2. Lake-water level variation and rainfall distribution.

At high water-level, the three plants operate at their best generating maximum power possible, and none of these plants is allowed to be shut down for maintenance. But when the water level is low, they operate at their worst condition and could be scheduled for maintenance.

These scenarios have been taken into consideration in solving this GMS problem using the DE-a and DE-b case studies described below. DE-a and DE-b represent two case studies having different schedules for maintenance. A detailed description of these case studies is presented below.

C. *Case I: DE-a*

Table I present the data for the Nigerian power system used to investigate the performance of the proposed DE algorithm. The Nigerian data comprises 49 units to be scheduled for maintenance over a planning period of 52 weeks. The table shows the allowed periods for which planned preventive maintenance of generating units could be possible. Thermal and steam turbines could be shut down for maintenance only when the hydro plants are operating at their maximum generation as dictated by the lake water level variation in Fig. 1. This corresponds to the months of January to April and November to December each year. The hydro plants can be scheduled for maintenance during low water level corresponding to the months of May to October. Within these months no thermal plant should be shut down for maintenance. The maintenance duration of each unit and crew required weekly for each unit are shown in Table II. 5% increased load variation is considered during the hot season of March to July every year.

TABLE I
OUTAGE AND MANPOWER DATA FOR THE 49 UNITS IN THE NIGERIAN POWER SYSTEM

S/N	Plant number	Name of turbine	Type of turbine	Base case rating (MW)	Allowed period	Maintenance duration (Weeks)	Manpower required for each week
1	1	AFAMGT19	GT	138	November - December (44 - 52 weeks)	5	5+5+4+3+3
2	1	AFAMGT20	GT	138		5	5+5+4+3+3
3	2	DELTAG03	GT	19.6		2	4+3
4	2	DELTAG04	GT	19.6		2	4+3
5	2	DELTAG06	GT	19.6		2	4+3
6	2	DELTAG07	GT	19.6		2	4+3
7	2	DELTAG08	GT	0		4	4+4+3+3
8	2	DELTAG15	GT	85		4	4+4+3+3
9	2	DELTAG16	GT	85		4	4+4+3+3
10	2	DELTAG17	GT	85		4	4+4+3+3
11	2	DELTAG18	GT	85		4	4+4+3+3
12	3	EGBINST1	ST	190	January - April (1 - 17 weeks)	5	6+5+5+4+2
13	3	EGBINST2	ST	190		5	6+5+5+4+2
14	3	EGBINST3	ST	190		5	6+5+5+4+2
15	3	EGBINST4	ST	190		5	6+5+5+4+2
16	3	EGBINST5	ST	190		5	6+5+5+4+2
17	3	EGBINST6	ST	190		5	6+5+5+4+2
18	4	EGBINGT1	GT	30		2	4+3
19	4	EGBINGT2	GT	30		2	4+3
20	4	EGBINGT3	GT	30		2	4+3
21	4	EGBINGT4	GT	30		2	4+3
22	4	EGBINGT5	GT	30		2	4+3
23	4	EGBINGT6	GT	30		2	4+3
24	4	EGBINGT7	GT	30		2	4+3
25	4	EGBINGT8	GT	30		2	4+3
26	5	SAPELST1	ST	0		4	4+3+3+2
27	5	SAPELST2	ST	0		4	4+3+3+2
28	5	SAPELST3	ST	0		4	4+3+3+2
29	5	SAPELST4	ST	0		4	4+3+3+2
30	5	SAPELST5	ST	0		4	4+3+3+2
31	5	SAPELST6	ST	85.3		4	4+3+3+2
32	6	JEBBGH1	H	88.3	May - October (18 - 43 weeks)	4	5+4+3+3+2
33	6	JEBBGH2	H	88.3		4	5+4+3+3+2
34	6	JEBBGH3	H	88.3		4	5+4+3+3+2
35	6	JEBBGH4	H	88.3		4	5+4+3+3+2
36	6	JEBBGH5	H	88.3		4	5+4+3+3+2
37	6	JEBBGH6	H	88.3		4	5+4+3+3+2
38	7	KAING05	H	112.5		4	5+5+4+3
39	7	KAING06	H	0		4	5+5+4+3
40	7	KAING07	H	0		3	4+3+2
41	7	KAING08	H	0		3	4+3+2
42	7	KAING09	H	0		3	4+3+2
43	7	KAING10	H	76.5		3	4+3+2
44	7	KAING11	H	90		4	5+4+3+3
45	7	KAING12	H	0		4	5+4+3+3
46	8	SHIRGH1	H	140		2	4+3
47	8	SHIRGH2	H	140		2	4+3
48	8	SHIRGH3	H	140		2	4+3
49	8	SHIRGH4	H	0		2	4+3

GT- Gas turbine, ST- Steam turbine, H- Hydro.

D. Case II: DE-b

In this case study, the advantage and cost benefits of appropriate combination of thermal and hydro plants for maintenance within the period of low water level from May to October is investigated. Five thermal plants, namely AFAMG 19, AFAMG 20, EGBINST 1, EGBINST 2 and SAPELEST 6 are scheduled for maintenance along with the hydro plants within the period of low water level. The remaining thermal plants are maintained in the months of January to April and November to December each year. There is 5% load variation between the months of March and July. Though the practice in DE-b may not be acceptable to the Nigerian power utility, since the thermal plants are expected to give their best generation when hydro plants are experiencing low water level, the results of this comparison are worth noting for good energy management and planning.

E. Results

Table II shows yearly summary of the load availability (with and without maintenance), load demand and the cost in Nigerian Naira to purchase energy from outside, possibly the West African Power Pool (WAPP), Independent Power Producers (IPP), or other sources to supply loads that would have been suppressed as a result of maintenance activities. As seen from the Table II, the annual base case generation for Nigeria cannot meet the yearly load demand due to inadequate generation from some generating units. Some of these units' contributions to the national grid are marginally low and are represented with a zero generation. What this means is that there will be persistent load shedding to be carried out by the utility through out the year.

TABLE II
ANNUAL LOAD AVAILABILITY, DEMAND AND COST OF PURCHASING ENERGY

	Annual generation - without maintenance (MW)	Annual generation - with maintenance (MW)	Annual load demand (MW)	Annual suppressed load - without maintenance (MW)	Annual suppressed load - with maintenance (MW)	Increase in suppressed load due to maintenance
ED-a						
	1,233,414.00	1,139,530.00	1,332,954.00	-99,540.00	-193,424.00	94.30%
Cost of purchasing energy (Naira/year)	-	-	-	14,333,760.00	27,853,056.00	13,519,296.00
ED-b						
	1,233,414.00	1,139,586.00	1,332,954.00	-99,540.00	-193,368.00	94.26%
Cost of purchasing energy (Naira/year)	-	-	-	14,333,760.00	27,844,992.00	13,511,232.00

Cost of energy in Nigeria: 6 Naira/kWh

The effect of scheduling thermal units for maintenance along with the hydro units within the months of May to October is seen in Table II. The DE-b produced good result that shows not only an even annual generation as seen in Fig. 2, but also an improved energy management as there is 0.04% decline in suppressed load during maintenance due to 0.04% increase in annual generation, and an equivalent reduction in the cost of energy to be purchased when compared to the results obtained by DE-a. Though this percentage is small, it shows that better energy management is achievable with proper scheduling of the generating units.

Table III shows the cost of improving system reliability for DE-a and DE-b with and without maintenance. Without maintenance for the two cases, there is 14,333,760.00 Naira to be expended on purchase of energy if 100% system reliability is required. For zero cost there is better system reliability for DE-b than for DE-a with maintenance. The costs for 89% and 100% system reliabilities with maintenance is seen to be higher for DE-a than for DE-b.

TABLE III
COST OF IMPROVING RELIABILITY

	Without maintenance		With maintenance		
	DE-a				
Reliability index	0.89	1	0.68	0.89	1
Cost (Naira)	0	14,333,760.00	0	13,519,296.00	27,853,056.00
	DE-b				
Reliability index	0.89	1	0.72	0.89	1
Cost (Naira)	0	14,333,760.00	0	13,511,232.00	27,844,992.00

Table A of the Appendix presents the generator schedules obtained by DE-a and DE-b, while Fig. 3 shows the available generation for DE-a and DE-b during maintenance, the maximum generation and a 5% varying load within the hot season of March to July each year. For DE-a, between the months of May and October when the hydro plants are undergoing maintenance, the bulk of the generation comes in from the thermal plants as non of them is scheduled for maintenance within this period. It leads to an uneven generation over the entire maintenance period, resulting to an unpredictable energy profile, sharp and large variations in load shedding. DE-b however, produced better and more even generation throughout the year under maintenance, with an average generation and standard deviation of 3130.5200±226.68MW, while DE-a produces average generation and standard deviation of 3130.5000±232.40MW.

Fig. 4 shows the corresponding crew availability for DE-a and DE-b during maintenance. DE-b scheduling produced better crew distribution over the maintenance period than DE-a. Both cases are seen to have satisfied the crew constraint. DE-a generates average crew requirement and standard deviation of 12±9.89, while DE-b produces 12±8.77.

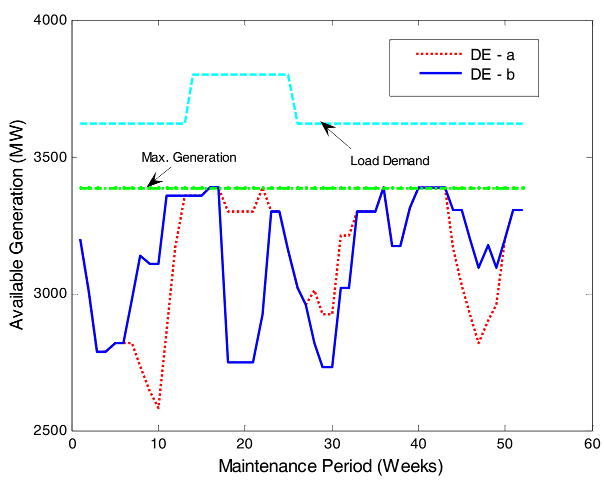

Fig. 3. Generation plots during maintenance period.

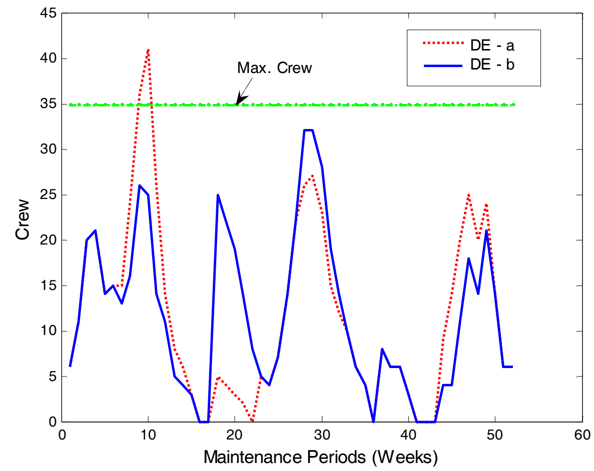

Fig. 4. Crew plots during maintenance.

Fig. 5 presents the reliability indices for DE-a and DE-b during maintenance period, compared against the system reliability index without maintenance. DE-b produces better system reliability than DE-a after 100 iterations of 5000 trials. The reliability index describe the degree of performance of the algorithms that results in optimal maintenance schedules. The functional aspect of the reliability indices is that they show the generation adequacy and the ability of the system to supply the aggregate electrical energy and meet demand requirements of the customers at all times during maintenance period.

The reliability index (RI) is computed by taking the minimum of the ratio of available generation to load demand over 5000 trials and the entire operational period as given by (10).

$$RI = \underset{\substack{(over\ 5000\\ trials)}}{Min} \left(\underset{\substack{(over\ 52\\ weeks)}}{Min} \begin{pmatrix} \dfrac{Avail.Gen.}{Load} & if\ Avail.Gen. \leq Load \\ 1 & otherwise \end{pmatrix} \right) \quad (10)$$

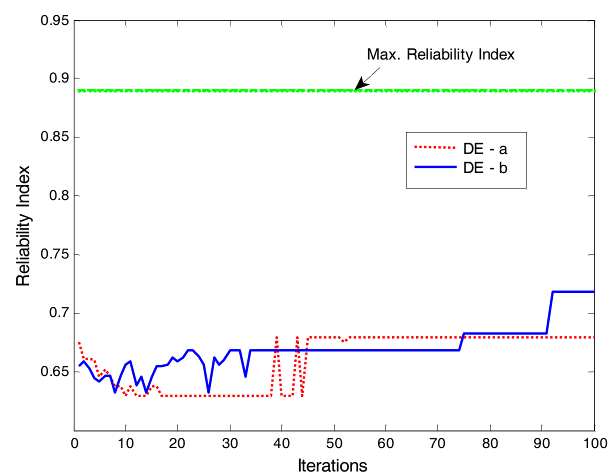

Fig. 5. Reliability index plots for DE-a and DE-b.

Fig. 6 shows the plots of costs of purchasing energy versus the reliability indices with the solutions obtained for DE-a and DE-b. It can be seen from the figure that at any system reliability index, the corresponding energy cost for DE-a solution is higher than that for DE-b solution. Similarly, at any energy cost, DE-b gives better reliability than DE-a. Without maintenance, the system has much higher reliability index than the two cases considered with maintenance, and there is no need to purchase energy as a result of maintenance activities.

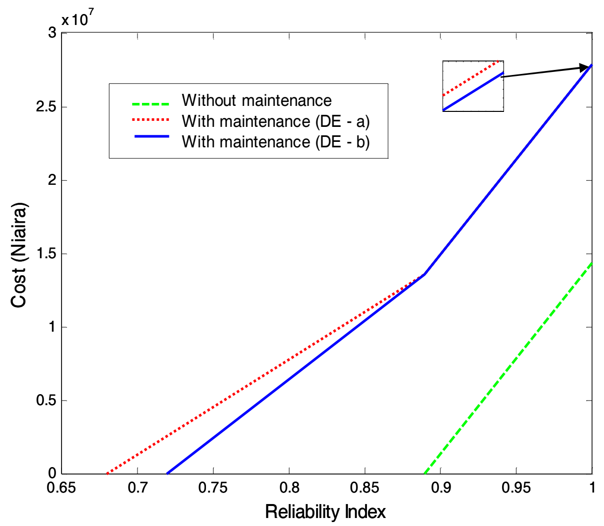

Fig. 6. Cost versus reliability index plots for DE-a and DE-b.

V. Conclusion

This paper has shown the application of differential evolution technique for solving the GMS problem, featuring the advantages of established computational intelligence techniques. The problem of generating optimal preventive maintenance schedule of generating units for economical and reliable operation of a power system while satisfying system load demand and crew constraints over one year period, has been presented in the Nigerian power system comprising 49-units.

The results reflect a feasible and practical optimal solution that can be implemented in real time. Two cases of the Nigerian power system to investigate the importance and appropriate placement of some thermal plants for maintenance along with the hydro plants during low water level have been studied using the DE. The result shows the way forward for the Nigerian power utility in terms of better energy management, improving system reliability and energy cost curtailment through appropriate maintenance scheduling. This provides planning platforms for implementing other short-term scheduling such as solving the unit commitment, load flow and optimal power flow problems. Future work is to examine and study the stability issues of the Nigerian network as a result of GMS.

VI. Appendix

TABLE A
TYPICAL GENERATOR MAINTENANCE SCHEDULES OBTAINED BY DE-A AND DE-B AFTER 5000 TRIALS

Week no.	Generating units scheduled for maintenance		Week no.	Generating units scheduled for maintenance	
	ED-a	ED-b		ED-a	ED-b
1	11	10	27	33,38,44,45,48	28,33,39,40,43
2	11,12	10,11	28	33,37,38,39,44,45	28,33,34,39,40,49
3	11,12,13,18	10,11,12,17	29	33,36,37,38,39,44,45	28,31,32,33,34,39,40,49
4	11,12,13,18,25	10,11,12,24	30	33,36,37,38,39,42,44	28,31,32,33,34,37,39,49
5	11,12,13,25	10,11,12,24	31	36,37,39,40,42	31,32,34,35,37,49
6	12,13,14,25	11,12,13,24	32	34,36,40,42	29,31,35,37,49
7	13,14,15,25	12,13,14,24	33	34,40,41	29,36
8	14,15,16,26	13,14,15,25	34	34,41	29,36
9	14,15,16,21,22,24,26,27,30	13,15,20,21,23,25,26	35	41	29,36
10	14,15,16,17,21,22,23,24,26,27,28,30	13,16,20,21,22,23,25,26	36	-	-
11	15,16,17,23,26,27,28,29,30	16,22,23,25,26	37	43,46	38,41
12	16,20,27,28,29	19,22,23,26	38	43,46	38,41
13	20,29	19,22,23	39	43,49	38,44
14	19,29	18	40	49	44
15	19	18	41	-	-
16	-	-	42	-	-
17	-	-	43	-	-
18	31	27,45,46,47,48	44	1,11	9
19	31	27,45,46,47,48	45	1,2,11	9
20	31	27,45,46,47,48	46	1,2,3,8,11	1,6,9
21	31	27,45,46,47,48	47	1,2,3,4,8,10,11	1,2,6,8,9
22	-	45,46,47	48	1,2,4,5,8,10	2,3,6,8
23	35	30	49	2,5,6,8,9,10	3,4,5,6,7,8
24	35,47	30	50	6,7,9,10	4,5,7,8
25	35,47	30,42	51	7,9	5,7
26	35,45,48	30,40,42,43	52	7,9	5,7

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