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Yusuf Yare

Ganesh K. Venayagamoorthy
Missouri University of Science and Technology

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Comparison of DE and PSO for Generator Maintenance Scheduling

Y. Yare, *Student Member, IEEE*, and G. K. Venayagamoorthy, *Senior Member, IEEE*

***Abstract*— This paper presents a comparison of a differential evolution (DE) algorithm and a modified discrete particle swarm optimization (MDPSO) algorithm for generating optimal preventive maintenance schedules for economical and reliable operation of a power system, while satisfying system load demand and crew constraints. The DE, an evolutionary technique and an optimization algorithm utilizes the differential information to guide its further search, and can handle mixed integer discrete continuous optimization problems. Discrete particle swarm optimization (DPSO) is known to effectively solve large scale multi-objective optimization problems and has been widely applied in power systems. Both the DE and MDPSO are applied to solve a multi-objective generator maintenance scheduling (GMS) optimization problem. The two algorithms generate feasible and optimal solutions and overcome the limitations of the conventional methods including extensive computational effort, which increases exponentially as the size of the problem increases. The proposed methods are tested, validated and compared on the Nigerian power system.**

I. Nomenclature

AM_t	Available manpower at period t
c_1 & c_2	Cognitive and social acceleration constants respectively
d	Particle's dimension
d_i	Duration of maintenance for unit i
DPSO	Discrete particle swarm optimization
e_i	Earliest period for maintenance of unit i to begin
ES	Evolutionary strategy
F	Scaling factor for mutation
GA	Genetic algorithm
GMS	Generator maintenance scheduling
i	Index of generating units
k	Discrete time step
I	Set of generating unit indices
l_i	Latest period for maintenance of unit i to end
L_t	Anticipated load demand for period t
MDPSO	Modified discrete particle swarm optimization
M_{it}	Manpower needed by unit i at period t
N	Total number of generating units
P_{ibd}	*i-th* Particle best position for dimension d
P_{gd}	Swarm's best position for dimension d
P_{gn}	*n-th* dimension coordinate of the global best position (P_g)
P_{it}	Generating capacity of unit i in period t
PSO	Particle swarm optimization
$rand_1$ & $rand_2$	Random numbers with uniform distribution in the range of [0, 1]
$randn()$	Gaussian distributed random number with a zero mean and a variance of 1
t	Index of period
T	Set of indices of periods in planning horizon
$\|V_1\|$, $\|V_2\|$ & $\|V_3\|$	Amount of violations of maintenance window, crew and load constraints
V_{id}	*i-th* Particle velocity in dimension d
w	Inertia weight constant
ω_1, ω_2 & ω_3	Weighting coefficients of maintenance window, crew and load constraints respectively

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Y. Yare and G. K. Venayagamoorthy are with the Real-Time and Intelligent Systems Laboratory, Department of Electrical and Computer Engineering, Missouri University of Science and Technology, Rolla, MO 65409-0249 USA (e-mail: yyqh3@mst.edu & gkumar@ieee.org). Y. Yare is also with the National Electric Power Authority (now PHCN), Nigeria.

II. Introduction

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.

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 primary goal 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].

Basically, different optimization techniques applied so far to solving GMS can be classified according to the type of the search space and/or the objective function [1]-[12]. Thus, much earlier work relied on methods such as branch and bound technique [3], dynamic programming [4] and integer programming [5] with their performances demonstrated with respect to simple case studies. Depending on the problem formulation, the objective function could be minimization of the unit maintenance costs or some predefined reliability risks subject to some constraints resulting in nonlinear optimization as proposed in [7]-[10]. Solving such nonlinear optimization problems for most cases may not be feasible because their numerical solutions require extensive computational efforts, which increase exponentially with the problem complexities. Even though deterministic optimization problems are formulated with known parameters, real world problems almost invariably include some unknown parameters.

In order to obtain approximate solution of a complex GMS, new concepts have emerged in recent years [10]-[13]. They include applications of probabilistic approach [10], simulated annealing [11], decomposition technique [12] and genetic algorithm (GA) [13]. A flexible GMS that considered uncertainties is proposed with a fuzzy 0-1 integer programming technique adopted and applied to Taiwan power system [13]. The application of GA to GMS presented in [13] have been compared with, and confirmed to be superior to other conventional algorithms such as heuristic approaches and branch-and-bound (B&B) in the quality of solutions.

Statistical evaluations and comparison between discrete particle swarm optimization (DPSO) algorithm and the improved modified discrete particle swarm optimization (MDPSO) algorithm using wide range of PSO parameters are presented in [14]-[15].

This paper presents a comparison of differential evolution (DE) optimization algorithm and modified discrete particle swarm optimization (MDPSO) algorithm. The two algorithms appear 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 practical electric power industry. It also illustrates the use of DE and MDPSO algorithms for solving the GMS problem for the Nigerian power system which operates the traditional utility market, and where load frequently exceeds generation.

III. PROBLEM FORMULATION

Basically, 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 [16]-[17]. The problem studied here is solved by minimizing the sum of squares of the reserve over the entire operational planning period [16]-[17]. 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

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

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

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

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

$$Penalty\ \cos t = \omega_1 |V_1| + \omega_2 |V_2| + \omega_3 |V_3| \tag{6}$$

IV. DIFFERENTIAL EVOLUTION

Differential evolution is an optimization algorithm that solves real-valued problems based on the principles of natural evolution [18]-[19]. 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 [20]-[22]. Design principles in DE are [20]-[21]:

- 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 [20]-[22]. 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:

$$P_3' = P_3 + F * (P_1 - P_2) \tag{7}$$

F is typically ($0 \leq F \leq 1.2$) and a value 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).

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

C_R is typically ($0 \leq C_R \leq 1.0$) and a value 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.

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

V. Modified Discrete PSO

Particle swarm optimization (PSO) is an algorithm inspired by the social behavior of bird flocking or fish schooling which is used for finding optimal regions of complex search spaces through the interaction of individuals in a population of particles [23]. The following subsections describe the DPSO and enhanced modified DPSO (MDPSO) algorithms. Statistical evaluations and comparison between DPSO algorithm and the improved MDPSO algorithm are presented in [14]-[15].

A. Discrete PSO

The general concepts behind optimization techniques initially developed for problems defined over real-valued vector spaces, such as PSO, can also be applied to discrete-valued search spaces where either binary or integer variables have to be arranged into particles [24]-[25]. When integer solutions (not necessarily 0 or 1) are needed, the optimal solution can be determined by rounding off the real optimum values to the nearest integer [24]-[25]. Discrete particle swarm optimization has been developed specifically for solving discrete problems. DPSO allows discrete steps in velocity and thus in position. In this version of PSO, the velocity is limited to a certain range [- V_{max}, V_{max}] such that V_{id} always lies in that range. The new velocity and position for each particle i in dimension d is determined according to the velocity and position update equations given by (10) and (11).

$$\begin{aligned} V_{id}(k) = round(& w \cdot V_{id}(k-1) + c_1 \cdot rand_1 \cdot (P_{ibd} - X_{id}(k-1)) \\ & + c_2 \cdot rand_2 \cdot (P_{gd} - X_{id}(k-1))) \end{aligned} \tag{10}$$

$$X_{id}(k) = X_{id}(k-1) + V_{id}(k) \tag{11}$$

B. Modified DPSO

The modified discrete particle swarm optimization is a combination of DPSO and an evolutionary strategy enhancing the algorithm to perform optimal search under complex environments such as the case of the constrained GMS optimization problem considered in this paper. This version of MDPSO is a variant of the original formulation of the DPSO to solve discrete optimization problems. Supposing $X = (X_1, X_2, \dots X_N)$ is the particle chosen with a random number less than a predefined mutation rate (for 0 < mutation rate < 0.3) then the mutation result of this particle is given by (12).

$$X_{id} = P_{gd} + (randn() \cdot P_{gd} / 2) \qquad d = 1, 2, \dots N \qquad (12)$$

Herein, the mutation operator is introduced into the DPSO algorithm. The main goal is to increase the diversity of the population by preventing the particles from moving too close to each other, thus converging prematurely to local optima. This in turn improves the DPSO's search performance. The flowchart for the MDPSO algorithm applied to GMS problem is illustrated in Fig. 1.

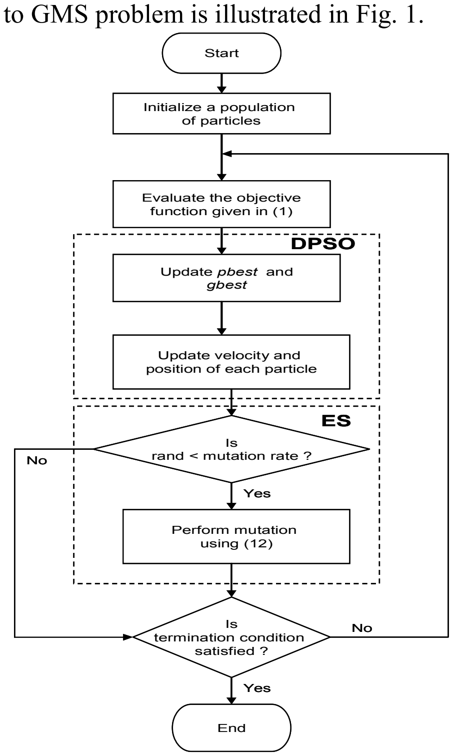

Fig. 1. Flowchart of MDPSO algorithm for GMS problem

VI. Case Studies on Nigerian Power System

The Nigerian power system consists of a total of 49 functional units distributed among 7 generating stations at the following locations: AFAM, DELTA, EGBIN, SAPELE, JEBBA, KAINJI and SHIRORO. Table I summarizes the units' base case ratings. Note that all the units at AFAM and DELTA stations as well as 8 units at EGBIN station are gas turbines, whilst all units at SAPELE station and other 6 units at EGBIN station are steam driven. The JEBBA, KAINJI and SHIRORO hydro stations are all sited in Northwestern Nigeria. Over 25 years of operational experience and available historical data on hydrological conditions reveal that inflow variation profile at each hydro station location, significantly impacts the generated power output of each hydro plant. This inflow profile also dictates the allowed periods for the maintenance of the three hydro plants.

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

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

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

A. Case I: DE-a and MDPSO-a

Table I present the data for the Nigerian power system used to investigate the performance of the proposed DE and MDPSO algorithms. All the hydrothermal units feeding the Nigerian national grid are to be scheduled for maintenance over a planning horizon of 52 weeks. The table shows the allowed periods for which planned preventive maintenance of generating units should be carried out. In this case study, GTs and steam turbines are to be shut down for maintenance only when the hydro plants are operating at their maximum generation. This corresponds to the months of January to April and November to December each year. The hydro plants can then be scheduled for maintenance during low inflow period corresponding to the months of May to October of each year. Within these months no thermal plant is allowed to be shut down for maintenance. The maintenance duration of each unit and crew required weekly for each unit are shown in Table 2. A maximum power demand of 3625MW plus 5% load increase is considered during the hot season of March to July every year.

B. Case II: DE-b and MDPSO-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 proposed maintenance scenario in DE-b and MDPSO-b deviates from the current practice of the Nigerian power utility, wherein the thermal plants are expected to be operated at optimum generation during low inflows at all the hydro stations, the results of this comparison are noteworthy for good energy management and planning.

C. 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 Independent Power Producers (IPPs) or possibly the West African Power Pool (WAPP) 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 by a zero generation output. This means that there will be persistent load shedding to be carried out by the utility throughout the year.

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

	Annual generation - without maintenance	Annual generation - with maintenance	Annual load demand	Annual suppressed load - without maintenance	Annual suppressed load - with maintenance	Increase in suppressed load due to maintenance
Case DE-a						
Mega Watt hour (MWh)	29,601,936.00	27,348,720.00	31,990,896.00	2,388,960.00	4,647,168.00	94.52%
Cost of purchasing energy (X 1000 Naira/year)			191,945,376.00	14,333,760.00	27,883,056.00	13,549,296.00
Case MDPSO-a						
Mega Watt hour (MWh)	29,601,936.00	27,347,930.40	31,990,896.00	2,388,960.00	4,643,182.66	94.36%
Cost of purchasing energy (X 1000 Naira/year)			191,945,376.00	14,333,760.00	27,859,095.96	13,525,335.96
Case DE-b						
Mega Watt hour (MWh)	29,601,936.00	27,350,064.00	31,990,896.00	2,388,960.00	4,646,664.00	94.50%
Cost of purchasing energy (X 1000 Naira/year)			191,945,376.00	14,333,760.00	27,879,992.00	13,546,232.00
Case MDPSO-b						
Mega Watt hour (MWh)	29,601,936.00	27,348,720.00	31,990,896.00	2,388,960.00	4,642,465.67	94.33%
Cost of purchasing energy (X 1000 Naira/year)			191,945,376.00	14,333,760.00	27,854,794.02	13,521,034.02

Cost of energy in Nigeria: 6 Naira/kWh and 118 Naira is equivalent to 1 US Dollar

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 MDPSO-a produce result that shows not only a slightly better annual generation as seen in Fig. 3, but also an improved energy management as there is 0.16% decline in suppressed load during maintenance due to 0.16% 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. For the MDPSO-b, there is 0.17% decline in suppressed load during maintenance due to 0.17% increase in annual generation, and an equivalent reduction in the cost of energy to be purchased when compared to the results obtained by DE-b. Generally from Table III, the MDPSO-b shows improved performance over DE-b, MDPSO-a and DE-a. Though these percentages are small, it shows that better energy management is achievable with proper scheduling of the generating units.

Table III shows the cost of improving the 'reliability index' (RI) for DE-a, MDPSO-a, DE-b and MDPSO-b without and under maintenance. The RI given by (13) 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. It is computed by taking the minimum of the ratio of available generation to load demand over 5000 trials and the entire operational period of 52 weeks.

$$RI = \underset{\substack{(over\,5000\\ trials)}}{Min}\left(\underset{\substack{(over\,52\\ weeks)}}{Min}\left(\begin{array}{ll}\frac{Avail.Gen.}{Load} & if\ Avail.Gen. \le Load\\ 1 & otherwise\end{array}\right)\right) \quad (13)$$

TABLE III
COST OF IMPROVING RELIABILITY

	Without maintenance		With maintenance		
	Case DE-a				
Reliability index	0.89	1	0.679	0.89	1
Cost (x1000 Naira)	0	14,333,760.00	0	13,549,296.00	27,883,056.00
	Case MDPSO-a				
Reliability index	0.89	1	0.76	0.89	1
Cost (x1000 Naira)	0	14,333,760.00	0	13,525,335.96	27,859,095.96
	Case DE-b				
Reliability index	0.89	1	0.72	0.89	1
Cost (x1000 Naira)	0	14,333,760.00	0	13,546,232.00	27,879,992.00
	Case MDPSO-b				
Reliability index	0.89	1	0.775	0.89	1
Cost (x1000 Naira)	0	14,333,760.00	0	13,521,034.02	27,854,794.02

Without maintenance for the two cases, there is 14,333,760.00 Naira to be expended on purchase of energy if RI of 1 is to be achieved. For zero cost, there is slight improvement in the RI for MDPSO-a compared to DE-a under maintenance. Similarly, the result shows MDPSO-b having better RI than DE-b under maintenance. The costs for 0.89 and 1 reliability indices under maintenance is seen to be higher for DE-a when compared with MDPSO-a, and also higher for DE-b when compared with MDPSO-b.

Figs. 2 and 3 shows the available generation for the case DE-a and MDPSO-a, and case DE-b and MDPSO-b respectively during maintenance, the maximum generation and a 5% varying load within the hot season of March to July each year.

For case DE-a and MDPSO-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. Fig. 2 shows MDPSO-a producing slightly better and more even generation compared with DE-a over the planning period under maintenance. In Fig. 3, the MDPSO-b similarly compared favorably over DE-b. The uneven generation produced by both DE-a and DE-b compared to MDPSO-a and MDPSO-b respectively results in an unpredictable energy profile, sharp and large variations in load shedding. MDPSO-b produce an average generation and standard deviation of 3130.53±75.72MW compared to 3130.51±226.68MW generated by DE-b. MDPSO-a and DE-a produce average generation and standard deviation of 3130.52±118.67MW and 3130.50±232.41 MW respectively.

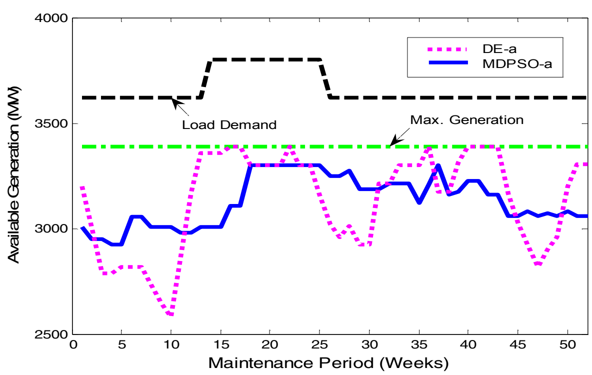

Fig. 2. Generation plots for DE-a and MDPSO-a during maintenance period.

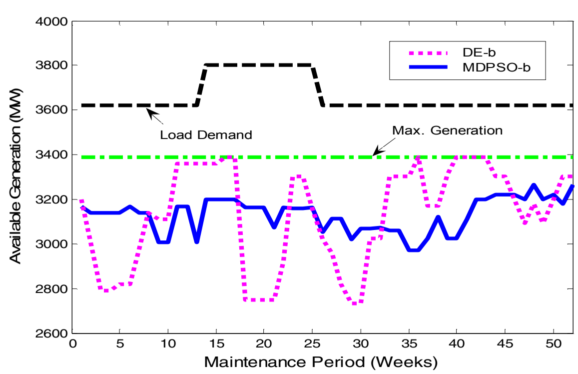

Fig. 3. Generation plots for DE-b and MDPSO-b during maintenance period.

Figs. 4 and 5 shows the corresponding crew availability for case DE-a and MDPSO-a, and case DE-b and MDPSO-b respectively during maintenance. MDPSO-a and MDPSO-b scheduling produce better crew distribution over the entire maintenance period than DE-a and DE-b respectively.

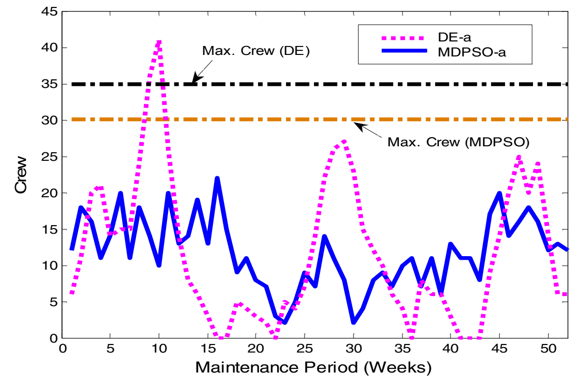

Fig. 4. Crew plots for DE-a and MDPSO-a during maintenance.

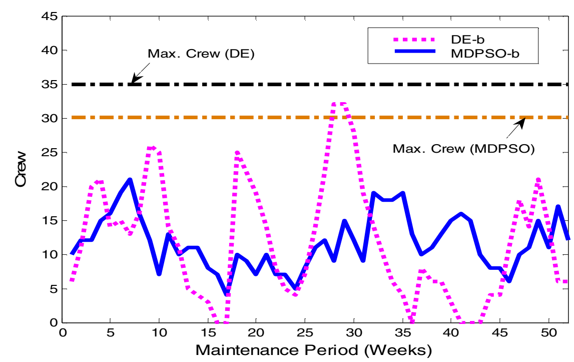

Fig. 5. Crew plots for DE-b and MDPSO-b during maintenance.

Figs. 6 and 7 present the reliability indices for case DE-a and MDPSO-a, and case DE-b and MDPSO-b respectively during maintenance period, compared against the RI of 0.89 without maintenance. The figures also show that the DE algorithm displays premature convergence compared to the MDPSO algorithm for this GMS problem.

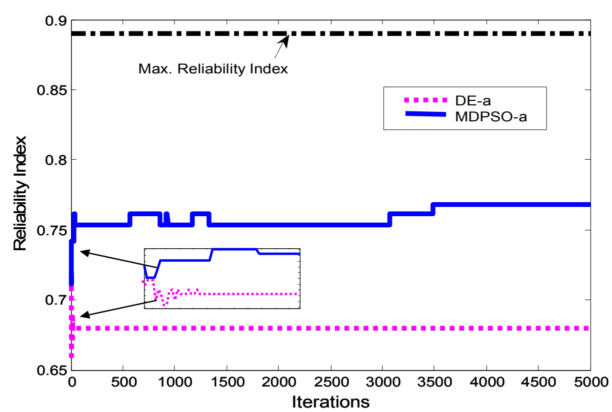

Fig. 6. Reliability index plots for DE-a and MDPSO-a.

It is seen from Figs. 6 and 7 that DE-a produce 0.679 RI compared to 0.76 RI generated by MDPSO-a, while DE-b and MDPSO- b produce 0.72 RI and 0.775 RI respectively after 5000 iterations of 5000 trials. The result clearly shows the superior performance of the MDPSO algorithm over the DE algorithm for this GMS problem.

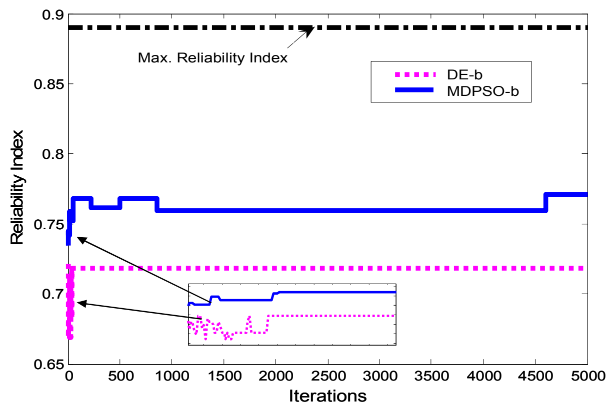

Fig. 7. Reliability index plots for DE-b and MDPSO-b.

Figs. 8 and 9 shows the plots of costs of purchasing energy versus the reliability indices for case DE-a and MDPSO-a, and case DE-b and MDPSO-b respectively obtained using the data presented in Table III. It can be seen from Fig. 8 that at any RI, the corresponding energy cost for DE-a solution is higher than that produced by MDPSO-a solution. Similarly, at any energy cost MDPSO-a gives better RI than DE-a. Without maintenance, the system has much higher RI than the case considered with maintenance, and there is no need to purchase energy as a result of maintenance activities. The same analogy follows for the case DE-b and MDPSO-b shown in Fig. 9.

Table IV shows the summary and comparison table between the performances of the DE and MDPSO algorithms. The table presents different comparison criteria on the basis of which the superior performance of the MDPSO algorithm over the DE algorithm has been established for this GMS problem. The MDPSO algorithm effectively and optimally allocates generators for maintenance without any unutilized maintenance week compared to the DE algorithm as shown in Table IV, and Tables A and B of the appendix.

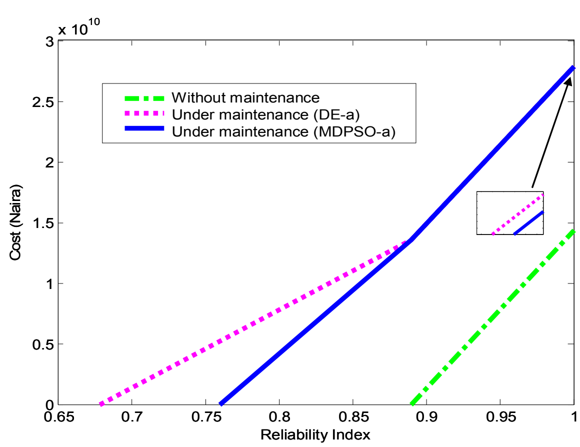

Fig. 8. Cost versus reliability index plots for DE-a and MDPSO-a.

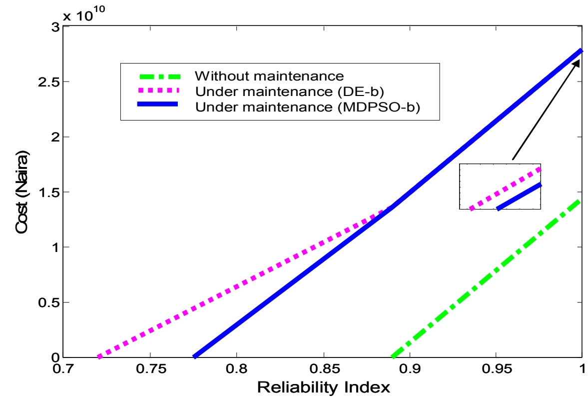

Fig. 9. Cost versus reliability index plots for DE-b and MDPSO-b.

TABLE IV
COMPARISON AND PERFORMANCE TABLE BETWEEN DE AND MDPSO ALGORITHMS

		Algorithm			
		DE-a	MDPSO-a	DE-b	MDPSO-b
Without maintenance	Annual suppressed load (MWh)	2,388,960.00	2,388,960.00	2,388,960.00	2,388,960.00
	Cost of purchasing energy (X1000 Naira/year)	14,333,740.00	14,333,740.00	14,333,740.00	14,333,740.00
	Reliability index (RI)	0.89	0.89	0.89	0.89
Under maintenance	Annual suppressed load (MWh)	4,647,168.00	4,643,182.66	4,646,664.00	4,642,465.67
	% increase in suppressed load	94.52%	94.36%	94.50%	94.33%
	Cost of purchasing energy (X1000 Naira/year)	27,883,056.00	27,859,095.96	27,879,992.00	27,854,794.02
	Reliability index (RI)	0.679	0.76	0.72	0.775
	Ave generation and standard dev. (MW)	3130.50±232.41	3130.52±118.67	3130.51±226.69	3130.53±75.72
	Ave crew reqirement and standard dev.	12±9.89	12±4.82	12±8.77	11±4.00
	Utilized maintenance weeks out of 52 weeks	45 weeks utilized	52 weeks utilized	46 weeks utilized	52 weeks utilized

VII. CONCLUSION

This paper has shown the application of differential evolution (DE) and modified discrete particle swarm optimization (MDPSO) algorithms for solving the GMS problem, featuring the advantages of well 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 investigated using the DE and the MDPSO algorithms. Several results obtained and analyses carried out were presented from the standpoints of their practical applications.

The proposed methods evolved an intelligent maintenance unit scheduling framework for the Nigerian power utility that achieved better utilization of available energy generation with improved reliability and reduction in energy cost. The proposed method can be flexibly modified to accommodate the maintenance unit requirements of emerging independent power producers and future generation additions as well as network constraints not considered in this paper.

APPENDIX

TABLE A

TYPICAL GENERATOR MAINTENANCE SCHEDULES OBTAINED BY DE-A AND MDPSO-A AFTER 5000 ITERATIONS OF 5000 TRIALS

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

TABLE B

TYPICAL GENERATOR MAINTENANCE SCHEDULES OBTAINED BY DE-A AND MDPSO-A AFTER 5000 ITERATIONS OF 5000 TRIALS

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

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