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Optimal maintenance scheduling of generators using multiple swarms-MDPSO framework

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ABSTRACT

In this paper, a challenging power system problem of effectively scheduling generating units for maintenance is presented and solved. The problem of generator maintenance scheduling (GMS) is solved in order to generate optimal preventive maintenance schedules of generators that guarantee improved economic benefits and reliable operation of a power system, subject to satisfying system load demand, allowable maintenance window, and crew and resource constraints. A multiple swarm concept is introduced for the modified discrete particle swarm optimization (MDPSO) algorithm to form a robust algorithm for solving the GMS problem. This algorithm is referred to by the authors as multiple swarms-modified particle swarm optimization (MS-MDPSO). The performance and effectiveness of the MS-MDPSO algorithm in solving the GMS problem is illustrated and compared with the MDPSO algorithm on two power systems, the 21-unit test system and 49-unit Nigerian hydrothermal power system. The GMS of the two power systems are considered and the results presented shows great potential for utility application in their area control centers for effective energy management, short and long term generation scheduling, system planning and operation.

1. Introduction

Maintenance scheduling of generating units is an important task in power system and plays important role in the operation and planning activities of the electric power utility. The simultaneous solution of all aspects of the operation and planning scheduling problems in the presence of system complexity at different time-scales, different order of uncertainties and problems dimensionality is required for the efficient economic operation of the utility system.

Power system equipment are made to remain in good 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. Modern power systems have witnessed increased demand for electrical energy with a related expansion in system size, which leads to higher number of generators and lower reserve margins. The resultant effect is the increased complexity of the constrained generator maintenance scheduling (GMS) optimization problem for such large power system. Present research efforts toward solving the GMS constrained optimization problem can be categorized based on the objective function and the type of the problem hyper space (Marwali and Shahidehpour, 2000; Dahal and Chakpitak, 2007; Edwin and Curtius, 1990; Yamayee and Sidenblad, 1983; Dopaz and Merrill, 1975; Yamayee, 1982; Kim et al., 1997; Chen and Toyoda, 1991; Billinton and Abdulwhab, 2003; Satoh and Nara, 1991). Optimization methods such as branch and bound technique (Edwin and Curtius, 1990), dynamic programming (Yamayee and Sidenblad, 1983) and integer programming (Dopaz and Merrill, 1975) were few early techniques that were used to solve simple optimization problems. Approximate solution to the constrained GMS problem can be obtained using new problem optimization concepts (Billinton and Abdulwhab, 2003; Satoh and Nara, 1991; Yellen et al., 1992; Firma and Legey, 2002). Some of these optimization methods include but not limited to applications of probabilistic approach (Billinton and Abdulwhab, 2003), simulated annealing (Satoh and Nara, 1991), decomposition technique (Yellen et al., 1992) and genetic algorithm (GA) (Firma and Legey, 2002).

Bio-inspired and evolutionary techniques have been shown to be very effective optimization tools in solving power system problems (Lee and El-Sharkawi, 2008). Hence their application in

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Nomenclature

AM_t	available manpower at period t
c_1 & c_2	cognitive constant and social acceleration constants, respectively
d	dimension of the problem
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
GA	genetic algorithm
GMS	generator maintenance scheduling
i	index of generating units
I	set of generating unit indices
l_i	latest period for maintenance of unit i to end
j	index of n multiple swarms
k	discrete time step
l	index of particle in a swarm
L_t	anticipated load demand for period t
m	population size of each swarm
MDPSO	modified discrete particle swarm optimization
MS-MDPSO	multiple swarms-modified discrete particle swarm optimization
M_{it}	manpower needed by unit i at period t
M_r	mutation rate
N	total number of generating units
N_c	number of constraint violation
n	number of multiple swarms
P_j^t	jth swarm population in time t
P_{jgd}	jth swarm global best position for dimension d
P_{jlbd}	lth particle best position in jth Swarm for dimension d
P_{ik}	generating capacity for unit i in start time period k
P_{it}	generating capacity of unit i in period t
PSO	particle swarm optimization
R	spinning reserve
$rand$, $rand_1$ and $rand_2$	random numbers for a uniform distribution in the range of [0,1]
$randn$	Gaussian distributed random number with a zero mean and a variance of 1
S_{it}	set of start time period
t	index of period
T	set of indices of periods in planning horizon
T_i	set of periods when maintenance of unit i may start
$\|V_1\|,\|V_2\|$ & $\|V_3\|$	amount of violations of load, maintenance window and crew constraints, respectively
V_c	amount of violation of constraint c
V_{jld}	lth particle velocity in jth swarm for dimension d
w_{iner}	inertia weight constant which is a fixed value, linearly decreasing or dynamically changing
ω_c	weighting coefficient
ω_1, ω_2 & ω_3	weighting coefficients of load, maintenance window and crew constraints, respectively
X_{ik}	maintenance start indicator for unit i in start time period k
X_{it}	maintenance start indicator for unit i in period t
X_{jld}	lth particle position in jth swarm for dimension d

solving power system optimization problems, such as GMS, unit commitment and economic dispatch problems. The multi-species particle swarm optimizer presented in Iwamatsu (2006) extends the original PSO by dividing the particle swarm spatially into a multiple cluster called a species in a multi-dimensional search space. Each species explores a different area of the search space and tries to find out the global or local optima of that area, hence can be used to locate all the global minima of multi-modal functions in parallel (Iwamatsu, 2006). Particle population is split into a set of interacting swarms (Blackwell and Branke, 2006). These swarms interact locally by an exclusion parameter and globally through a new anti-convergence operator (Blackwell and Branke, 2006). Cooperative particle swarm optimizer is presented in Van den Bergh and Engelbrecht (2004) where cooperative behavior is used to significantly improve the performance of the original PSO algorithm, achieved by using multiple swarms to optimize different components of the solution vector cooperatively. Three sub-swarm discrete particle swarm optimization algorithm is presented in Xu et al. (2006), where particles are divided into three sub-swarms. One sub-swarm flies toward global best position, the second sub-swarm flies in the opposite direction, while the third sub-swarm flies randomly around the global best position (Xu et al., 2006). A strategy that allocates an appropriate number of swarms as required to support convergence and diversity criteria among the swarms is presented in Yen and Leong (2009). The multiple swarms in Yen and Leong (2009) are encouraged to explore different regions, and their collective efforts and knowledge are shared among the swarms, thus the diversity is preserved. PSO approaches based on some form of implicit or explicit grouping of particles into sub-swarms is presented in Engelbrecht (2005). Two main approaches of sub-swarms PSO algorithms in Engelbrecht (2005) are the cooperative and competitive PSO algorithms. The cooperative PSO algorithm has some form of cooperation existing between sub-swarms. The cooperation is mainly in terms of exchanging information about best positions found by the different groups. On the other hand, the competitive PSO algorithm is where the particles are in direct competition with other particles. Multi-phase PSO algorithm presented in Al-Kazemi and Mohan (2002a, 2002b) divides the main swarm of particles into subgroups, where each subgroup performs a different task, or exhibits a different behavior. The behavior of a group, or a task performed by a group usually changes over time in response to the group's interaction with the environment, different groups of particles have trajectories that proceed along trajectories with different goals in different phases of the algorithm (Al-Kazemi and Mohan, 2002a, 2002b).

Capabilities of discrete particle swarm optimization (DPSO) algorithm have been enhanced with evolutionary strategies (ESs) to produce a modified discrete particle swarm optimization (MDPSO) in Yare et al. (2008). Detail comparison of three algorithms – DPSO, MDPSO and GA and their application to solving the power system GMS problem are also presented in Yare et al. (2008), which showed that MDPSO produced better results compared with DPSO and GA on similar benchmark test systems.

The primary contributions of this paper are:

- Solving the challenging GMS problem for 21-unit test system and 49-unit Nigerian hydrothermal power system using enhanced swarm-evolutionary hybrid algorithms.
- Improving the quality of the maintenance schedules generated during GMS in terms of reliability and energy cost over what was achieved by MDPSO (Yare et al., 2008) algorithm. This improvement is achieved through the use of the multiple swarms concept and an MDPSO algorithm referred to by the authors as the multiple swarms-modified discrete particle swarm optimization (MS-MDPSO). The MS-MDPSO algorithm takes advantage of maximizing benefits arising from a balanced trade-off of both the exploitation abilities of each n

multiple swarms of population sizes $m_1, m_2, \ldots, m_j, \ldots, m_n$ (where $m_1 = m_2 = \cdots = m_j = \cdots = m_n = m$ is been used for this study) and the exploration of the n multiple swarms put together, and then evolving a single global best solution from a set of n global best solutions obtained from n multiple swarms.

- The performance of the MS-MDPSO algorithm is illustrated and compared with the MDPSO (Yare et al., 2008) algorithm for solving the GMS problem of the two practical power systems.

The rest of the paper is organized as follows: The mathematical problem formulation is presented in Section 2. Section 3 describes the concept of the multiple swarms-MDPSO algorithm. Implementation of MS-MDPSO for GMS and typical results are presented in Section 4. Finally, the conclusions are presented in Section 5.

2. Problem formulation

The purpose of maintenance operation is to extend equipment lifetime, or at least the mean time to the next failure whose repair may be costly. It is expected that effective maintenance policies can reduce the frequency of service interruptions and the many undesirable consequences of such interruptions. Maintenance clearly affects components and system reliability: if too little is done, this may result in an excessive number of costly failures and poor system performance, and hence reliability is degraded, when done too often, reliability may improve but the cost of maintenance will sharply increase. In a cost-effective scheme, reliability and cost of maintenance must be balanced.

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 two main categories of objective functions in solving GMS problem are based on reliability and economic cost (Dahal and Chakpitak, 2007; Yare et al., 2008; Dahal et al., 2000; Wang and McDonald, 1994). The reliability criterion of optimizing generation over the entire operational period of study is considered for solving the GMS problem in this paper. The net reserve of the system during any period t is the total installed capacity from all generating units $\left(\sum_{i \in I_t} P_{it}\right)$ minus the reserve loss due to the pre-scheduled outages as a result of planned generator maintenance $\left(\sum_{i \in I_t} \sum_{k \in S_{it}} X_{ik} P_{ik}\right)$ and the peak load forecast for that maintenance period (L_t). Hence the component $\left(\sum_{i \in I_t} P_{it} - \sum_{i \in I_t} \sum_{k \in S_{it}} X_{ik} P_{ik} - L_t\right)$ represents the net reserve level in time period t. Minimizing the sum of the squares of the reserves over the entire operational planning period enhances reduction in large variations of reserve and better long-term reserve capacity planning in the presence of unit maintenance. Therefore, the objective function to be minimized can be expressed by

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

The objective function in (2) is minimized subject to the following unit and system constraints given by (3), (4) and (5). Transmission loss and network limitations constraints are not considered for simplicity, but could be flexibly incorporated.

- Load and spinning reserve constraints – this specifies that the total capacity of the units running at any interval should not be less than forecasted load and spinning reserve for that interval:

$$\sum_{i \in I_t} P_{it} - \sum_{i \in I_t} \sum_{k \in S_{it}} X_{ik} P_{ik} \ge L_t + R \quad \forall t \tag{3}$$

- Maintenance window and sequence constraints – this defines the starting of maintenance at the beginning of an interval and finishing at the end of the same interval. The maintenance cannot be aborted or finished earlier than scheduled:

$$\sum_{t \in T_i} X_{it} = 1 \quad \forall i \tag{4}$$

- Crew and resource constraints – this specifies that for each maintenance period, the number of people to perform maintenance schedule cannot exceed the available crew. It also defines manpower availability and the limits on the resources/tools needed for maintenance activity at each time period:

$$\sum_{i \in T_t} \sum_{k \in S_{it}} X_{ik} M_{ik} \le AM_t \quad \forall t \tag{5}$$

Penalty cost given by (6) is added to the objective function in (2) if the schedule cannot satisfy the load, maintenance window and crew constraints. The penalty value for each constraint violation $|V_1|$, $|V_2|$ and $|V_3|$ is proportional to the amount by which the constraint is violate:

$$Penalty\ \text{cost} = \sum_{c=1}^{N_c} \omega_c |V_c| = \omega_1 |V_1| + \omega_2 |V_2| + \omega_3 |V_3| \tag{6}$$

The weighting coefficients ω_1, ω_2 and ω_3 are chosen in such a way that the violation of harder constraints gives a greater penalty value than for softer constraints. Typically the weighting coefficients are in the range 0.2–1.2.

3. Multiple swarms-MDPSO algorithm

Section 3.1 presents the MDPSO algorithm, while Section 3.2 presents the design details of the MS-MDPSO algorithm whose flowchart is shown in Fig. 1(a) and (b).

3.1. MDPSO

The modified discrete particle swarm optimization (MDPSO) algorithm presented in Engelbrecht (2005) and Yare et al. (2008) is an enhancement of DPSO algorithm with the inclusion of an evolutionary strategy based mutation operator similar to the one used in genetic algorithm. The MDPSO algorithm is applied in the update procedure of the velocities and positions of the particles (Yare et al., 2008).

Let X and V denote a particle's coordinates (position) and its corresponding flight speed (velocity) in a search space, respectively. Therefore, the lth particle is represented as $X_{ld} = (X_{l1}, X_{l2}, \ldots, X_{lN})$ in the d-dimensional space. The best previous position of the lth particle, referred to as *pbest*, is recorded and represented as $P_{lbd} = (P_{lb1}, P_{lb2}, \ldots, P_{lbN})$. The index of the best particle among all the *pbest* in the swarm is referred to as the *gbest* and is represented by P_{gd}. The rate of the velocity for particle lth is represented as $V_{ld} = (V_{l1}, V_{l2}, \ldots, V_{lN})$. The new velocity and position for each particle i in dimension d is determined according to the velocity and position update equations given by (7) and (8), respectively. The inertia weight w_{iner} is updated

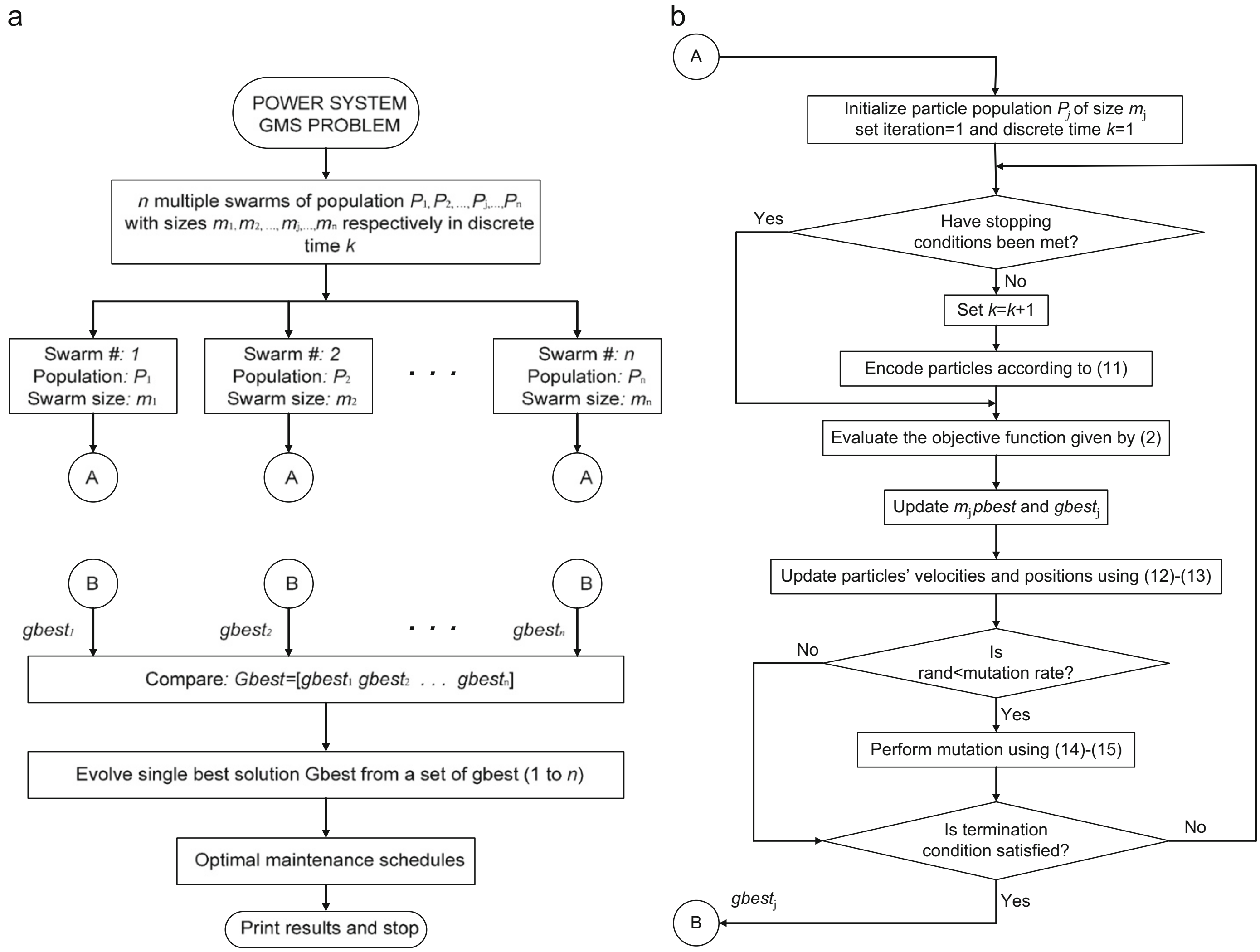

Fig. 1. MS-MDPSO algorithm framework for power system GMS problem: (a) n multiple swarms-MDPSO and (b) MDPSO implementation for multiple swarms application.

according to (9):

$$V_{ld}(t)=round\Big(w_{iner}V_{ld}(t-1)+c_1\,rand_1(P_{lbd}(t-1)-X_{ld}(t-1))\\ +c_2\,rand_2(P^*_{gb}(t-1)-X_{ld}(t-1))\Big) \tag{7}$$

$$X_{ld}(t)=X_{ld}(t-1)+V_{ld}(t) \tag{8}$$

$$w_{iner}=w_{iner}^{\max}-\left(\frac{w_{iner}^{\max}-w_{iner}^{\min}}{iter_{\max}}\right)\times iter \tag{9}$$

A mutation operator is introduced into the DPSO algorithm above, so that the swarm's best position in dimension d is updated according to (10). Supposing P^*_{gd} is the particle chosen with a random number less than a predefined mutation rate (for $0<$ mutation rate <0.3), then the mutation equation is given by

$$P^*_{gd}=P_{gd}+(randn()\times P_{gd}/2) \tag{10}$$

$d=1,\ 2,\ \ldots,N$ is the problem dimension.

3.2. MS-MDPSO

The concept of multiple swarms with modified discrete particle swarm optimization (MDPSO) to explore the problem space together for the purpose of finding optimal solutions is considered in this paper. Multiple swarms in MDPSO select their own global best leaders to lead and influence their movement toward the best solution found so far. Information shared within a swarm and among swarms is portrayed in the multiple swarms' movement. This concepts produce an improved and efficient hybrid algorithm referred to in this paper, as the multiple swarms-modified discrete particle swarm optimization (MS-MDPSO) algorithm and is applied to solving the GMS problem as illustrated in the flowchart of Fig. 1(a) and (b).

The MS-MDPSO algorithm takes advantage of maximizing benefits arising from a balanced trade-off of both the exploitation abilities of each n multiple swarms of population sizes $m_1,\ m_2,\ \ldots,m_j,\ \ldots,m_n$ (where $m_1=m_2=\cdots=m_j=\cdots=m_n=m$ has been used for this study) and the exploration of the n multiple swarms put together, and then evolving a single global best solution from a set of n global best solutions obtained from n multiple swarms. It is this newly found single global best solution that is used to generate the optimal solution (optimal maintenance schedules) for this GMS problem as depicted in Fig. 1(a) and (b).

Particle X^k_{jl} (where $j=1,\ 2,\ \ldots,n$, and $l=1,\ 2,\ \ldots,m$) in each of the n multiple swarms of population $P^k_1,P^k_2,\ldots P^k_j,\ldots,P^k_n$ with sizes $m_1,\ m_2,\ \ldots,m_j,\ \ldots,m_n$, respectively can be modeled at discrete time k by

$$P_1^k=\left[X_{11}^k\middle|X_{12}^k\middle|\cdots\middle|X_{1m_1}^k\right],\quad P_2^k=\left[X_{21}^k\middle|X_{22}^k\middle|\cdots\middle|X_{2m_2}^k\right],$$
$$P_j^k=\left[X_{j1}^k\middle|X_{j2}^k\middle|\cdots\middle|X_{jm_j}^k\right],\quad P_n^k=\left[X_{n1}^k\middle|X_{n2}^k\middle|\cdots\middle|X_{nm_n}^k\right] \tag{11}$$

where $m_1=m_2=\cdots=m_j=\cdots=m_n=m$ for this study.

The MDPSO velocity and position update equations given by (7) and (8), respectively are modified and used in the MS-MDPSO algorithm to update the particles' velocities and positions in each n multiple swarms as shown in

$$V_{jld}(k)=round(w_{iner}V_{jld}(k-1)+c_1\,rand_1(P_{jlbd}(k-1)-X_{jld}(k-1))+c_2\,rand_2(P^*_{jgb}(k-1)-X_{jld}(k-1))) \tag{12}$$

$$X_{jld}(k)=X_{jld}(k-1)+V_{jld}(k) \tag{13}$$

With $w=0.8$, $c_1=2$ and $c_2=2$, the particles have good global searching abilities and converge to the global optimal position.

For mutation rate that lies within the range $(0<M_r<0.3)$, the mutation equation of the chosen particle is modified from (10) and given by

If rand < M_r

$$P^*_{jgd}(k-1)=P_{jgd}(k-1)+ceil(randn\times P_{jgd}(k-1)/\beta_{gb}) \tag{14}$$

else

$$P^*_{jgd}(k-1)=P_{jgd}(k-1) \tag{15}$$

endwhere β_{gb} can be either dynamically changing or fixed, and controls the mutation process. The mutation operation increases the diversity of the population by preventing the particles from moving too close to each other, thus converging prematurely to local optima.

4. Implementation of MS-MDPSO for GMS and results

Two cases studies are presented in this section to demonstrate the application and performance of the MS-MDPSO algorithm compared with MDPSO algorithm for solving the GMS problem of two practical power systems.

4.1. GMS implementation with MS-MDPSO

The global best solution is the evolved single best solution from a set of n global best solutions of the n multiple swarms. The performances of the n global best solutions are measured by comparing their fitness evaluations against each other. The resultant solution with the best fitness emerges as the single global best solution of the n multiple swarms. The global best solution is then used to generate the optimal maintenance schedules for all the generating units. It is also used to determine the optimal maintenance start period X_{ik} for each generating unit i, and when applied to (3) and (5) it produces the optimal available generation from all running units during maintenance and crew requirement for generators undergoing maintenance, respectively, over a maintenance period of 52 weeks.

4.2. 21-Unit test system

A test system comprising twenty one generating units (Dahal and Chakpitak, 2007, Yamayee and Sidenblad, 1983; Yare et al., 2008; Dahal et al., 2000; Wang and McDonald, 1994) with installed capacity, units' maintenance duration (weeks) and anticipated manpower requirement over a maintenance planning period of 52 weeks is used to demonstrate the performance of the MS-MSPSO algorithm for the GMS problem. Table 1 shows the unit rating, allowed maintenance period, maintenance duration and technical manpower/crew requirement by generating units during each maintenance week. The maintenance outages for the generating units are scheduled to minimize the sum of squares of reserves and meet the maintenance window constraint (each unit must be maintained exactly once every 52 weeks without interruption), the system peak load demand (4739 MW), and manpower/crew requirements to carry out maintenance tasks (there is maximum of 35 in total of technical manpower/crews available each week for the maintenance work).

Table 1
Data for the 21-unit test system.

Unit	Capacity (MW)	Allowed maintenance period	Maintenance duration (weeks)	Manpower required by units for each maintenance week
1	555	1–26 weeks	7	10+10+5+5+5+5+3
2	180		2	15+15
3	180		1	20
4	640		3	15+15+15
5	640		3	15+15+15
6	276		10	3+2+2+2+2+2+2+2+2+3
7	140		4	10+10+5+5
8	90		1	20
9	76		2	15+15
10	94		4	10+10+10+10
11	39		2	15+15
12	188		2	15+15
13	52		3	10+10+10
14	555	27–52 weeks	5	10+10+10+5+5
15	640		5	10+10+10+10+10
16	555		6	10+10+10+5+5+5
17	76		3	10+15+15
18	58		1	20
19	48		2	15+15
20	137		1	15
21	469		4	10+10+10+10

4.2.1. Test, results and discussion

Fig. 2(a) and (b) shows typical available generation and maintenance crew plots, respectively, for the 21-unit test system using the MDPSO and MS-MDPSO algorithms. It can be deduced from these figures and the typical maintenance schedules presented in Table A1 of the Appendix that using the MDPSO algorithm, weeks 23 and 35 indicate periods with low maintenance task (no unit is scheduled for maintenance) resulting in comparatively high available generation on same weeks 23 and 35. Similarly, using the MS-MDPSO algorithm, weeks 30 and 36 indicate periods with low maintenance activity (no unit is scheduled for maintenance) resulting in comparatively high available generation on same weeks 30 and 36. The weekly manpower requirement depicted in Fig. 2(b) using the MS-MDPSO algorithm clearly satisfies the crew constraint expressed in (5). This is not the case with the MDPSO algorithm, the 8th week experienced lowest drop in available generation (shown in Fig. 2(a)) due to heightened maintenance activities carried out simultaneously on units 3, 6 and 11 (shown in Table A1 of the Appendix), which also violated the manpower/crew constraint in (5). However, both the MDPSO and MS-MDPSO algorithms produced available generation that satisfies the constraint given by (3) as shown in Fig. 2(a).

Fig. 2(c) shows typical convergence of the objective function given in (2) for the 21-unit test system using MDPSO and MS-MDPSO algorithms, obtained after 100 iterations. The figure shows that the minimization of the objective function converged to 13,863,021.02 and 13,749,264.32 using the MDPSO and MS-MDPSO algorithms, respectively. A lower value of the objective function is preferable for better economic benefit, and is also a guarantee for more effective maintenance schedules produced by the MS-MDPSO algorithm.

Table 2 presents the statistical comparison of convergence of the objective function for the 21-unit test system using the MDPSO and MS-MDPSO algorithms, obtained after 100 iterations of 5000 trials. The table shows optimal numerical values of the objective function produced by MDPSO and MS-MDPSO to be 13,863,021.02 and 13,749,264.32, respectively, representing 113,756.70 (0.82%) reduction. This indicates improvement in minimizing the objective function given by (2) using MS-MDPSO compared with MDPSO algorithm, especially in cases with large variations of system net reserve. It also represents improvement in the quality of maintenance schedules generated by the MS-MDPSO algorithm compared with the MDPSO algorithm. The statistical results presented in Table 2 for the 21-unit test system shows, generally, that the MS-MDPSO algorithm produced better maintenance schedules compared with the MDPSO algorithm for the same GMS problem.

Table 3 and Fig. 2(d)–(f) further illustrates the design and application of MS-MDPSO algorithm for solving the GMS problem by presenting typical evolution of single global best solution (*Gbest*) from a set of five global best solutions ($gbest_1$, $gbest_2$, $gbest_3$, $gbest_4$ and $gbest_5$) obtained from five multiple swarms (n=5) over five trials for the 21-unit test system presented in Section 4.2. Table 3 and Fig. 2(e) shows that for the 21-unit test system, the *Gbest* (consisting of an array of 100 global best solutions) obtained for 100 iterations over the first trial is primarily composed of $gbest_1$ (33 global best solutions from swarm #1), $gbest_2$ (28 global best solutions from swarm #2), $gbest_3$ (22 global best solutions from swarm #3), $gbest_4$ (14 global best solutions from swarm #4) and $gbest_5$ (2 global best solutions from swarm #5). Further, Gbest feasible solutions obtained over five trials are presented in Table 3 and depicted in Fig. 2(f).

4.3. Nigerian grid system

Table 4 presents data of the Nigerian grid system comprising a total of 49 functional generating units spread across seven generating stations located at: AFAM, DELTA, EGBIN, SAPELE, JEBBA, KAINJI and SHIRORO (Yare et al., 2008) as depicted in Fig. 3. The table shows the type of power station, name of power station, plant number, name of turbine unit, type of turbine, unit's actual base case rating, allowed maintenance period, maintenance duration and technical manpower/crew requirement by generating unit for each maintenance week. All the generating units at AFAM and DELTA stations as well as eight generating units at EGBIN station are gas turbines (GTs), while all generating units at SAPELE station and other six generating units at EGBIN

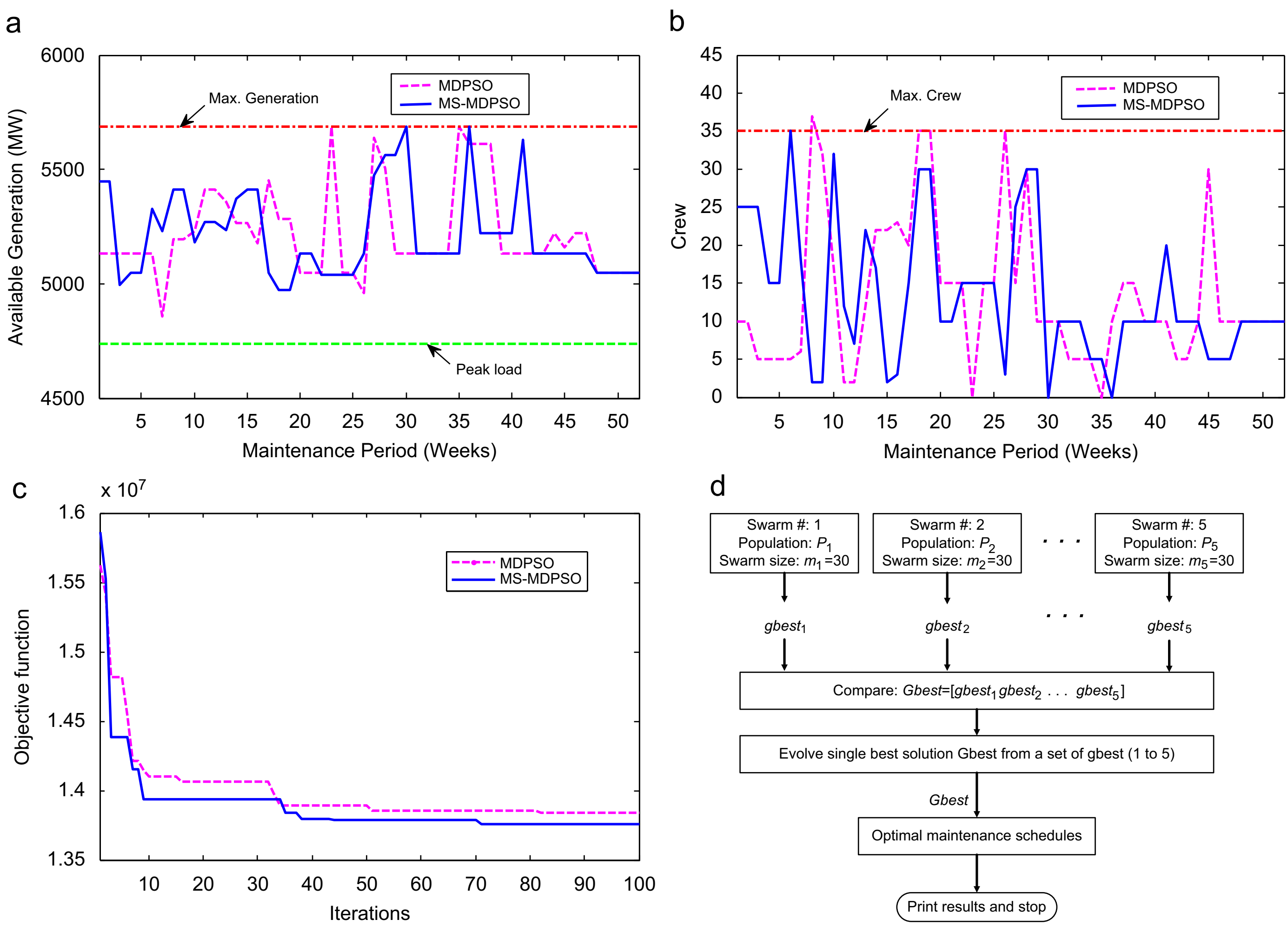

Fig. 2. Generation, technical crew, typical convergence, five multiple swarms and Gbest plots for the 21-unit test system using MDPSO and MS-MDPSO algorithms: (a) Available generation versus maintenance period for MDPSO and MS-MDPSO, (b) crew requirement versus maintenance period for MDPSO and MS-MDPSO, (c) typical convergence of the objective function given by (2), (d) five multiple swarms-MDPSO, (e) gbest versus iterations for five multiple swarms (trial #1) and (f) gbest versus iterations for five multiple swarms (five different trials).

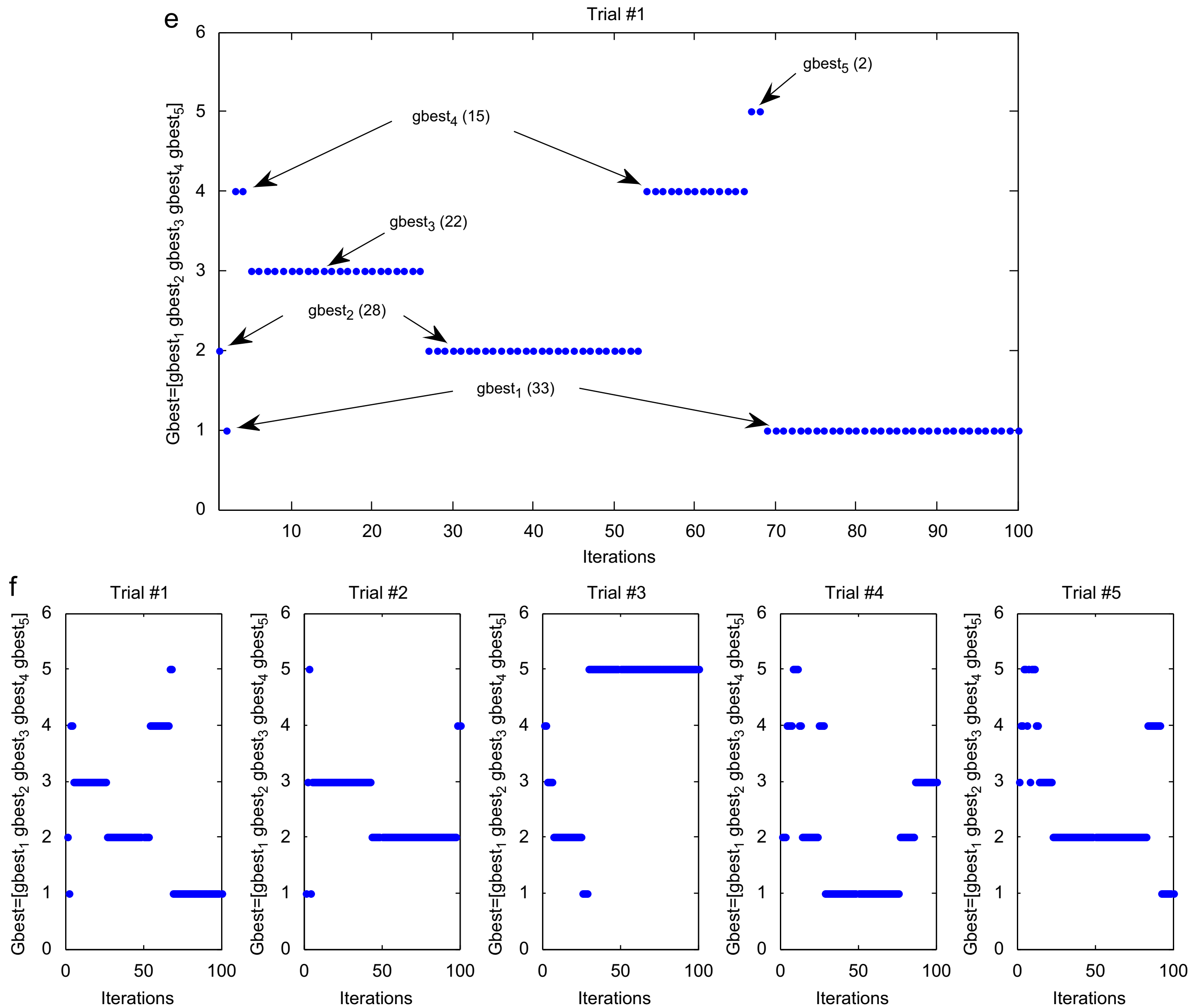

Fig. 2. (*Continued*)

station are steam turbines (STs). Also the four thermal plants utilize natural gas supplied from the Nigerian Gas Company (NGC) as their raw material input. The three hydrostations (Hs) namely JEBBA, KAINJI and SHIRORO are located in Northwestern Nigeria. Well over two decades of operational experience and available historical data on hydrological conditions reveal that inflow variation profile at each hydrostation location, by and large affects the generated power output of each hydroplant (Yare et al., 2008). The maintenance window and sequence constraints of the three hydroplants are greatly influenced by the trend of the inflow into these hydrological areas. This result in two distinct case studies namely, case a: MDPSO-a and MS-MDPSO-a and case b: MDPSO-b and MS-MDPSO-b described below.

4.3.1. *Case a: MDPSO-a and MS-MDPSO-a*

The operational data for the Nigerian grid system used to illustrate the effectiveness and performance of the proposed MS-MDPSO algorithm and compared with MDPSO algorithm is shown in Table 4. The 49 generating units of the Nigerian data

Table 2
Statistical comparison of convergence of the objective function for the 21-unit test system.

	Algorithm	
	MDPSO	MS-MDPSO
Minimum	13,863,021.02	13,749,264.32
Maximum	14,132,336.49	14,015,289.69
Mean	13,984,883.84	13,870,778.81
Standard deviation	± 11,943	± 11,429

need to be scheduled for maintenance over a 52 week maintenance planning period. The allowed period for maintenance, maintenance duration and the manpower required for each maintenance week are also shown in Table 4. Thermal and steam turbines could be shut down for maintenance only when the hydroplants are operating at their maximum generation, which tallies with the months of January–April and November–December each operational year. On the other hand, the hydroplants

Table 3
Gbest solution for the 21-unit test system using MS-MDPSO.

	21-unit test system Number of trials					
	#1 (iterations)	#2 (iterations)	#3 (iterations)	#4 (iterations)	#5 (iterations)	Total (%)
$gbest_1$	33	2	4	48	8	95 (19.0%)
$gbest_2$	28	55	19	24	61	187 (37.4%)
$gbest_3$	22	40	4	14	16	96 (19.2%)
$gbest_4$	15	2	2	10	12	41 (8.2%)
$gbest_5$	2	1	71	4	3	81 (16.2%)
Gbest	100	100	100	100	100	500 (100%)

Table 4
Power station, maintenance and manpower data for the 49 generating units in the Nigerian grid system.

Type of power station	Power station						Allowed maintenance period	Maintenance duration (Weeks)	Manpower required by units for each maintenance week
	Name of power station	S/N	Plant number	Name of turbine unit	Type of turbine	Base case rating (MW)			
Thermal	EGBIN PS	1	3	EGBINST1	ST	190.0	January–April (1–17 weeks)	5	6+5+5+4+2
		2	3	EGBINST2	ST	190.0		5	6+5+5+4+2
		3	3	EGBINST3	ST	190.0		5	6+5+5+4+2
		4	3	EGBINST4	ST	190.0		5	6+5+5+4+2
		5	3	EGBINST5	ST	190.0		5	6+5+5+4+2
		6	3	EGBINST6	ST	190.0		5	6+5+5+4+2
		7	4	EGBINGT1	GT	220.0		2	4+3
		8	4	EGBINGT2	GT	30.0		2	4+3
		9	4	EGBINGT3	GT	30.0		2	4+3
		10	4	EGBINGT4	GT	30.0		2	4+3
		11	4	EGBINGT5	GT	30.0		2	4+3
		12	4	EGBINGT6	GT	30.0		2	4+3
		13	4	EGBINGT7	GT	30.0		2	4+3
		14	4	EGBINGT8	GT	30.0		2	4+3
	SAPELE PS	15	5	SAPELST1	ST	0.0		4	4+3+3+2
		16	5	SAPELST2	ST	0.0		4	4+3+3+2
		17	5	SAPELST3	ST	0.0		4	4+3+3+2
		18	5	SAPELST4	ST	0.0		4	4+3+3+2
		19	5	SAPELST5	ST	0.0		4	4+3+3+2
		20	5	SAPELST6	ST	85.3		4	4+3+3+2
Hydro	JEBBA PS	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
	KAINJI PS	27	7	KAING05	H	112.5		4	5+5+4+3
		28	7	KAING06	H	0.0		4	5+5+4+3
		29	7	KAING07	H	0.0		3	4+3+2
		30	7	KAING08	H	0.0		3	4+3+2
		31	7	KAING09	H	0.0		3	4+3+2
		32	7	KAING10	H	76.5		3	4+3+2
		33	7	KAING11	H	90.0		4	5+4+3+3
		34	7	KAING12	H	0.0		4	5+4+3+3
	SHIRORO PS	35	8	SHIRGH1	H	249.0		2	4+3
		36	8	SHIRGH2	H	249.0		2	4+3
		37	8	SHIRGH3	H	140.0		2	4+3
		38	8	SHIRGH4	H	249.0		2	4+3
Thermal	AFAM PS	39	1	AFAMGT19	GT	138.0	November–December (44–52 weeks)	5	5+5+4+3+3
		40	1	AFAMGT20	GT	138.0		5	5+5+4+3+3
	DELTA PS	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	0.0		4	4+4+3+3
		46	2	DELTAG15	GT	85.0		4	4+4+3+3
		47	2	DELTAG16	GT	85.0		4	4+4+3+3
		48	2	DELTAG17	GT	85.0		4	4+4+3+3
		49	2	DELTAG18	GT	85.0		4	4+4+3+3

PS – power station, GT – gas turbine, ST – steam turbine, H – hydro.

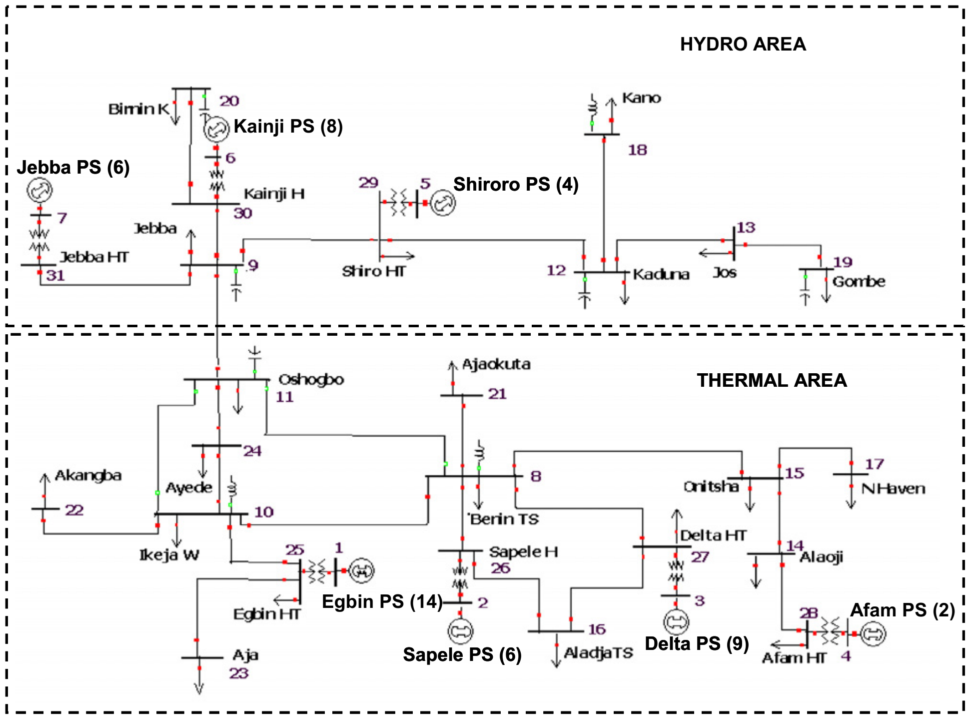

Fig. 3. Nigerian 330 kV grid showing seven power generating stations.

Table 5
Annual generation, load demand and cost of purchasing energy.

	Annual generation – without maintenance	Annual generation – with scheduled shutdown maintenance	Annual load demand	Annual suppressed load – without maintenance	Annual suppressed load – with scheduled shutdown maintenance	Increase in suppressed load due to maintenance
Case MDPSO-a						
Mega watt hour (MWh)	29,601,936.00	27,348,048.00	31,990,896.00	2,388,960.00	4,643,016.00	94.35%
Cost of purchasing energy (× 1000 Naira/year)			191,945,376.00	14,333,760.00	27,858,096.00	13,524,336.00
Case MS-MDPSO-a						
Mega watt hour (MWh)	29,601,936.00	27,349,056.00	31,990,896.00	2,388,960.00	4,641,840.00	94.30%
Cost of purchasing energy (× 1000 Naira/year)			191,945,376.00	14,333,760.00	27,851,040.00	13,517,280.00
Case MDPSO-b						
Mega watt hour (MWh)	29,601,936.00	27,348,552.00	31,990,896.00	2,388,960.00	4,642,344.00	94.32%
Cost of purchasing energy (× 1000 Naira/year)			191,945,376.00	14,333,760.00	27,854,064.00	13,520,304.00
Case MS-MDPSO-b						
Mega watt hour (MWh)	29,601,936.00	27,349,728.00	31,990,896.00	2,388,960.00	4,641,168.00	94.27%
Cost of purchasing energy (× 1000 Naira/year)			191,945,376.00	14,333,760.00	27,847,008.00	13,513,248.00

Cost of energy in Nigeria: 6 Naira/kWh and 150 Naira is equivalent to 1 US Dollar.

can be scheduled for maintenance during low water level corresponding to the months of May–October, the thermal plants supports the hydrogeneration within these periods and should therefore not be scheduled for shutdown maintenance. 5% increased load variation is allowed during the hot season of March to July each operational year.

4.3.2. *Case b: MDPSO-b and MS-MDPSO-b*

The economic implication in terms of reduced energy cost and increased reliability is enhanced by a logical and appropriate combination of thermal and hydroplants for maintenance within the period of low water level from May to October. These are investigated in this case study. Only five of the thermal plants, namely AFAMG 19, AFAMG 20, EGBINST 1, EGBINST 2 and SAPELEST 6 are allowed to be scheduled for maintenance along with the hydroplants within the period of low water level. There is 5% increased load variation allowed during the hot season of March–July each operational year.

4.3.3. *Test, results and discussion*

Table A2 in the Appendix presents the generator schedules obtained by case a: MDPSO-a and MS-MDPSO-a, while the schedules produced by case b: MDPSO-b and MS-MDPSO-b are shown in Table A3. Notice that both MDPSO-b and MS-MDPSO-b of case b in Table A3 generate similar maintenance schedules for weeks 14, 15, 16 and 17.

Table 5 presents the annual generation, load demand and the cost in Nigerian Naira for purchasing energy form Independent Power Producers (IPPs). The resultant suppressed loads as a consequence of scheduled maintenance work are also shown in

Table 5. The suppressed loads can be catered for by purchase of additional energy from IPPs, or other sources. The annual base case generation for Nigeria cannot meet the annual load demand due to inadequate generation from some generating units. These units' energy contributions to the national grid are marginally low and are represented with a zero generation as shown in Table 4. This scenario translates to frequent load shedding over the entire maintenance planning period of 52 weeks. Table 5 shows 94.35% and 94.30% increases in suppressed loads due to scheduled maintenance planning using MDPSO-a and MS-MDPSO-a, respectively. These translates to 13,524,336,000.00 and 13,517,280,000.00 Naira/year as costs of purchasing additional energy from IPPs to supplement and meet the rising energy demand occasioned by the increases in suppressed loads due to scheduled maintenance. Table 5 shows that case MS-MDPSO-a produces a 0.05% reduction in suppressed load increase compared to case MDPSO-an under scheduled shutdown maintenance.

Similarly, Table 5 also shows 94.32% and 94.27% increases in suppressed load occasioned by scheduled maintenance planning using MDPSO-b and MS-MDPSO-b, respectively. These infer 13,520,304,000.00 and 13,513,248,000.00 Naira/year as costs of purchasing additional energy from IPPs to satisfy the rising energy demand caused by increases in suppressed loads due to scheduled maintenance. Case MS-MDPSO-b produces a 0.05% reduction in suppressed load increase compared to case MDPSO-b under scheduled maintenance. These reductions translate to a huge annual savings of energy to be purchased in order to service the suppressed loads. The percentages may be small, but they are worth noting considering their impacts over an entire operational year, and could form basis for good planning and better energy management. Saved cost of fuel for units scheduled for maintenance was not considered in this study.

Fig. 4(a) shows the available generation for case a: MDPSO-a and MS-MDPSO-a, while the available generation for case b: MDPSO-b and MS-MDPSO-b are presented in Fig. 4(b). Presented in the two figures are also the maximum generation of 3388MW and a 5% load variation within the hot season of March to July each year. For cases MDPSO-a and MS-MDPSO-a, between the months of May and October when the hydroplants are undergoing maintenance, the major energy generation is supplied from the thermal plants since they are not scheduled for maintenance within this period. Their energy generation curves are not spread evenly over the entire

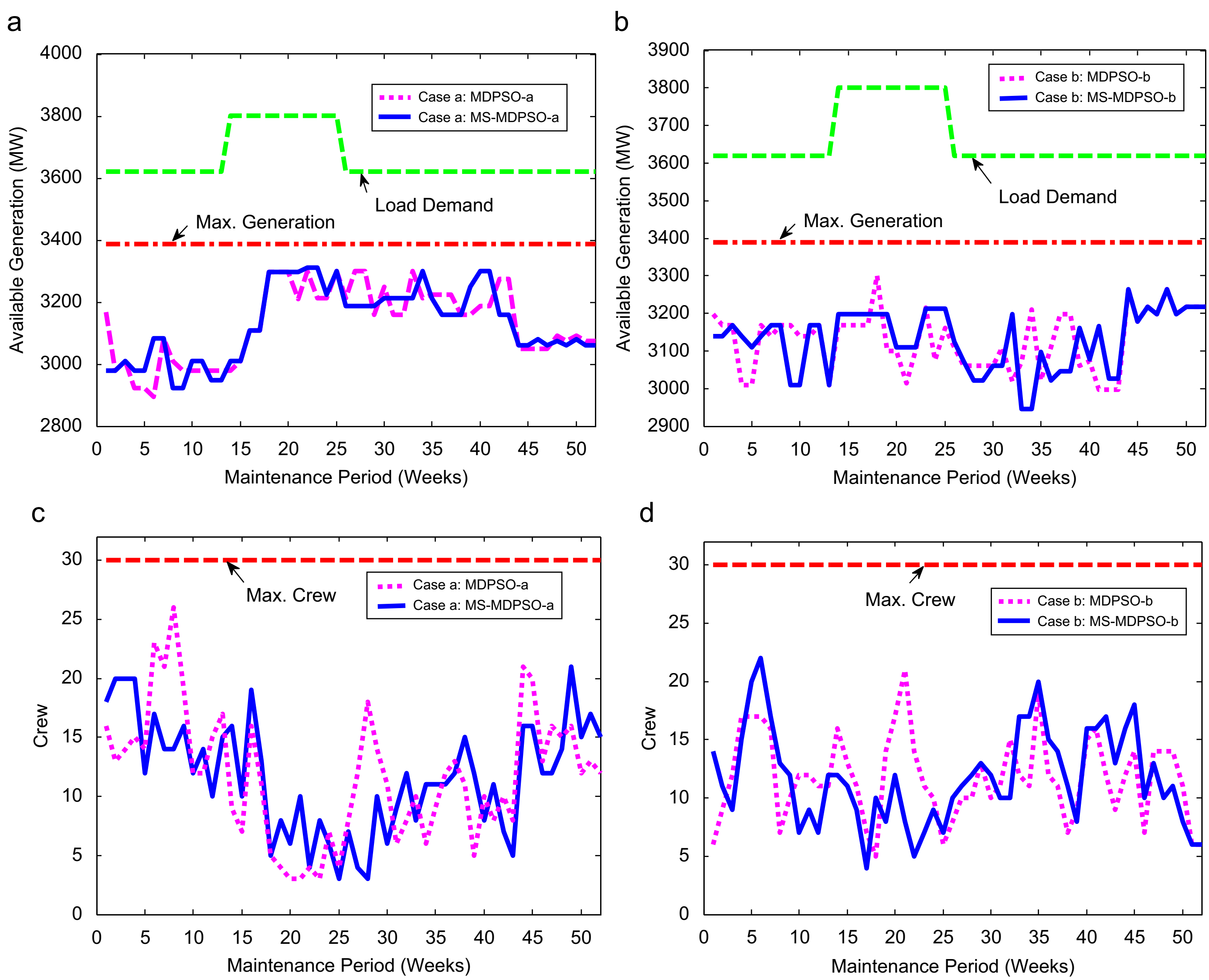

Fig. 4. Generation and crew plots during maintenance period: (a) available generation versus maintenance period for case a: MDPSO-a and MS-MDPSO-a, (b) available generation versus maintenance period for case b: MDPSO-b and MS-MDPSO-b, (c) crew requirement versus maintenance period for case a: MDPSO-a and MS-MDPSO-a and (d) crew requirement versus maintenance period for case b: MDPSO-b and MS-MDPSO-b.

maintenance period, which is interpreted as resulting to an unpredictable energy profile which causes large and sudden variations in loads requiring shedding. Cases MDPSO-b and MS-MDPSO-b however, generate evenly distributed generation throughout the year under maintenance, with an average generation and standard deviation of 3130.557 ± 79.781 MW and 3130.692 ± 78.125 MW, respectively. While cases MDPSO-a and MS-MDPSO-a produce average generation and standard deviation of 3130.500 ± 121.075 MW and 3130.610 ± 119.559 MW, respectively.

Fig. 4(c) and (d) presents the corresponding crew availability needed to carryout the scheduled shutdown maintenance of the generating units for case a: MDPSO-a and MS-MDPSO-a, and case b:

Table 6
Cost of improving the reliability index.

	Without maintenance		With scheduled shutdown maintenance		
Case MDPSO-a					
Reliability index	0.89	1	0.752	0.89	1
Cost (× 1000 Naira)	0	14,333,760.00	0	13,524,336.00	27,858,096.00
Case MS-MDPSO-a					
Reliability index	0.89	1	0.761	0.89	1
Cost (× 1000 Naira)	0	14,333,760.00	0	13,517,280.00	27,851,040.00
Case MDPSO-b					
Reliability index	0.89	1	0.766	0.89	1
Cost (× 1000 Naira)	0	14,333,760.00	0	13,520,304.00	27,854,064.00
Case MS-MDPSO-b					
Reliability index	0.89	1	0.772	0.89	1
Cost (× 1000 Naira)	0	14,333,760.00	0	13,513,248.00	27,847,008.00

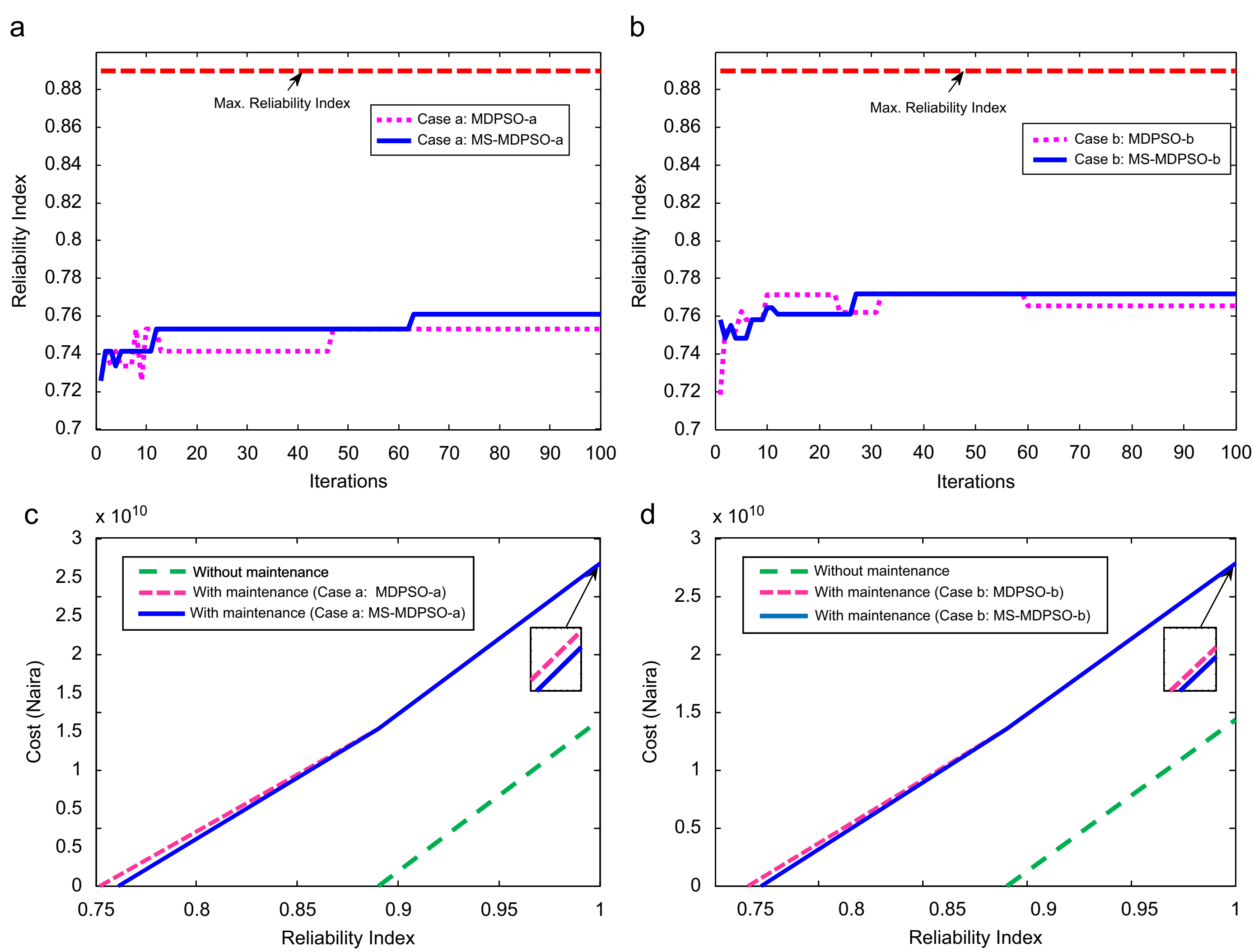

Fig. 5. Reliability index and cost of energy plots: (a) reliability index versus iterations for case a: MDPSO-a and MS-MDPSO-a, (b) reliability index versus iterations for case b: MDPSO-b and MS-MDPSO-b, (c) cost requirement versus reliability index for case a: MDPSO-a and MS-MDPSO-a and (d) cost requirement versus reliability index plots for case b: MDPSO-b and MS-MDPSO-b.

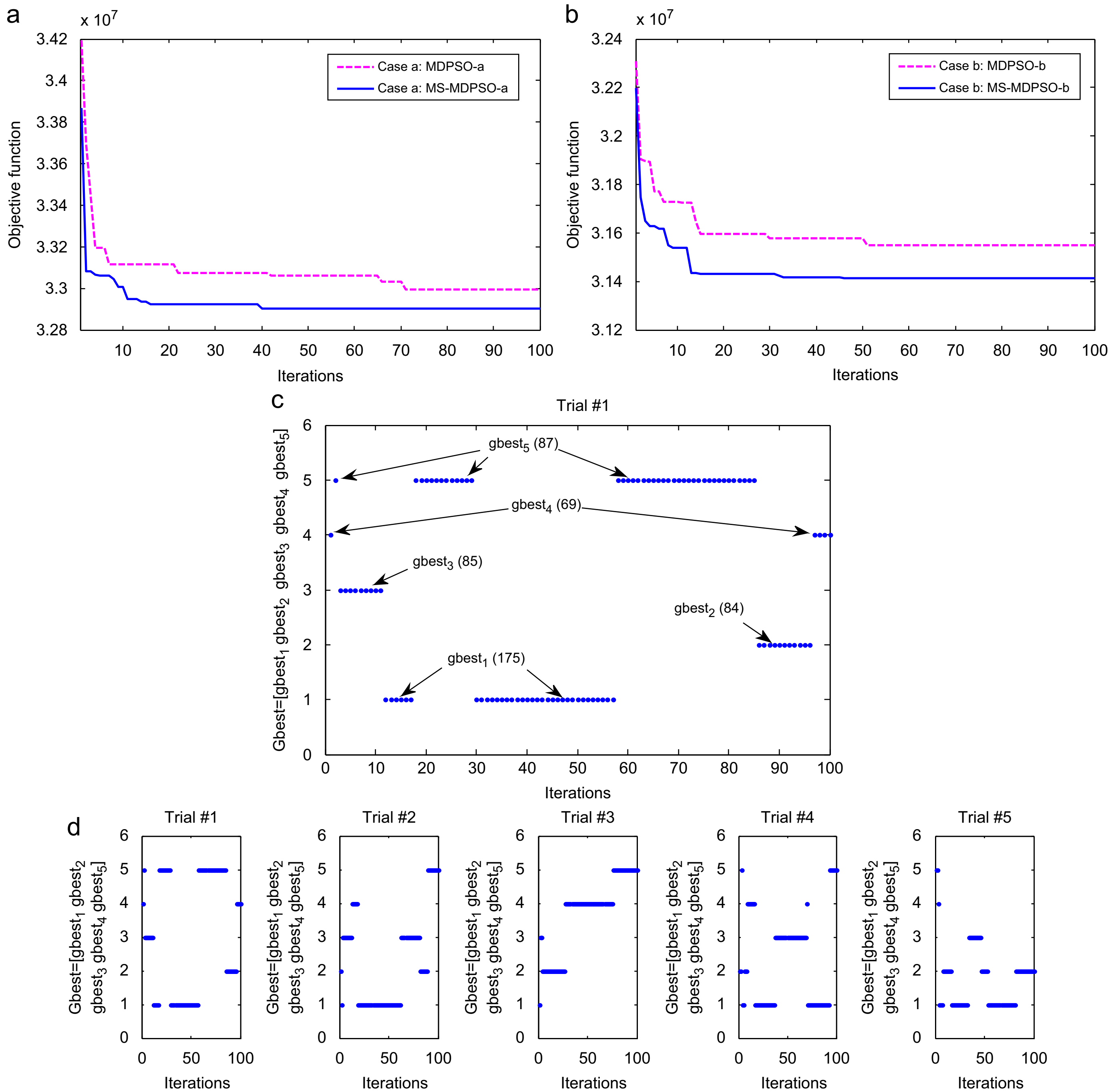

Fig. 6. Typical convergence of the objective function given by (2) and Gbest plots for the 49-unit Nigerian power system using MDPSO and MS-MDPSO algorithms (a) typical convergence of the objective function given by (2) for case a: MDPSO-a and MS-MDPSO-a, (b) typical convergence of the objective function given by (2) for case b: MDPSO-b and MS-MDPSO-b, (c) gbest versus iterations for five multiple swarms (trial #1) and (d) gbest versus iterations for five multiple swarms (five different trials).

MDPSO-b and MS-MDPSO-b, respectively. Case b: MDPSO-b and MS-MDPSO-b scheduling generate more even crew distribution over the maintenance period compared with case a: MDPSO-a and MS-MDPSO-a. Both cases however satisfied the crew constraint placed at 30. Cases MDPSO-a and MS-MDPSO-a have an average crew requirement and standard deviation of 12 ± 5.438 and 12 ± 4.769, respectively, while cases MDPSO-b and MS-MDPSO-b require 12 ± 3.658 and 12 ± 3.567, respectively.

Table 6 presents the cost of improving 'reliability index' (RI) for case a: MDPSO-a and MS-MDPSO-a and case b: MDPSO-b and MS-MDPSO-b without maintenance and with scheduled shutdown maintenance. The RI is computed by taking the minimum of the ratio of available generation to load demand over 5000 trials and the entire operational period (Yare et al., 2008) as given by

$$RI = \underset{\substack{(\text{over } 5000 \\ \text{trials})}}{Min} \left(\underset{\substack{(\text{over } 52 \\ \text{weeks})}}{Min} \begin{pmatrix} \dfrac{Avail.Gen.}{Load} & \text{if } Avail.Gen. \le Load \\ 1 & \text{otherwise} \end{pmatrix} \right) \tag{16}$$

Table 6 shows that case MS-MDPSO-a produces schedules with better RI compared with case MDPSO-a, while case MS-MDPSO-b produces improved RI over case MDPSO-b under scheduled shutdown maintenance for 100 iterations of 5000 trials. Further experiments for 5000 iterations of 5000 trials reveals RIs of 0.76, 0.769, 0.78 and 0.786 for cases MDPSO-a, MS-MDPSO-a, MDPSO-b and MS-MDPSO-b, respectively. The costs for 0.89 and 1 RIs under maintenance is seen to be the least for case MS-MDPSO-b and the highest for case MDPSO-a. These numerical RIs suggest that the Nigerian power system is more reliable when this long-term maintenance planning is based on MS-MDPSO algorithm compared with MDPSO algorithm. It also imply enhanced capability of long-term predictability of generation and manpower/crew requirement needed for maintenance over the entire maintenance horizon using MS-MDPSO algorithm compared with MDPSO algorithm.

Fig. 5(a) and (b) shows the plots of RIs versus iterations for case a: MDPSO-a and MS-MDPSO-a, and case b: MDPSO-b and MS-MDPSO-b, respectively, during shutdown maintenance period, compared against the maximum RI of 0.89 representing a case without any ongoing maintenance work taking place over a period of 52 weeks. The plots show that case MS-MDPSO-b generate the best RI of 0.772 while case MDPSO-a produce the worst RI of 0.752 after 100 iterations of 5000 trials.

Fig. 5(c) and (d) presents the plots of cost of purchasing energy versus the RI for case a: MDPSO-a and MS-MDPSO-a, and case b: MDPSO-b and MS-MDPSO-b, respectively. It can be seen from the figure that at any RI, the corresponding energy cost for case MS-MDPSO-a is lower compared with case MDPSO-a, and similarly case MS-MDPSO-b produce lower energy cost to be purchased compared with case MDPSO-b. On the overall, at any energy cost case MS-MDPSO -b gives the best RI compared with either MDPSO-b, MS-MDPSO-a or MDPSO-a. Without maintenance for the two cases, there is 14,333,760,000.00 Naira to be spent on purchase of energy if a RI of 1 is desirable, otherwise the RI simply remains at 0.89 with zero cost with no purchase of energy as shown in Table 6. In the absence of any ongoing maintenance work, the system has higher RI than the two cases considered during scheduled shutdown maintenance, and there may not be need to spend financial resources on energy purchases as a consequence of maintenance actions.

Fig. 6(a) and (b) shows typical convergence of the objective function for the Nigerian power system obtained after 100 iterations of 5000 trials. The converged results clearly present minimization of the objective function given by (2). The minimized objective function produced using Case a: MDPSO-a and MS-MDPSO-a are 33,000,504.15 and 32,913,169.25, respectively, as shown in Fig. 6(a). Similarly, the minimized objective function produced using Case b: MDPSO-b and MS-MDPSO-b are 31,550,689.31 and 31,416,025.42, respectively, as shown in Fig. 6(b). The optimization process demonstrates the capabilities of the MDPSO and MS-MDPSO algorithms in minimizing large variations of system net reserve in case they occur.

Table 7 shows the statistical comparison of convergence of the objective function given by (2) for the Nigerian power system using Case a: MDPSO-a and MS-MDPSO-a and Case b: MDPSO-b and MS-MDPSO-b described in subsections 4.3.1 and 4.3.2, respectively, obtained after 100 iterations of 5000 trials. The table shows that for Case a, the minimized numerical values of the objective function produced by MDPSO-a and MS-MDPSO-a are 33,000,504.15 and 32,913,169.25, respectively, representing 87,334.90 (0.26%) reduction. Similarly, for Case b, the minimized numerical values of the objective function produced by MDPSO-b and MS-MDPSO-b are 31,550,689.31 and 31,416,025.42, respectively, representing 134,663.89 (0.42%) reduction. The results indicate that better and enhanced optimization is achieved with the MS-MDPSO compared with MDPSO for both Cases an and b. The best optimization result of 31,416,025.00 is obtained with the MS-MDPSO-b while the worst optimization result of 33,000,504.00 is obtained with the MDPSO-a. The results also imply that better maintenance schedules are generated by the MS-MDPSO-b. Both MDPSO and MS-MDPSO algorithms however, produce optimal schedules that utilizes every allowable maintenance week of the entire 52 weeks as shown in Tables A2 and A3 of the Appendix. The results presented for this 49-unit Nigerian hydrothermal power system shows, generally, that the MS-MDPSO algorithm produces better maintenance

Table 7
Statistical comparison of convergence of the objective function for the Nigerian power system.

	Algorithm Case a		Case b	
	MDPSO-a	MS-MDPSO-a	MDPSO-b	MS-MDPSO-b
Minimum	33,000,504.15	32,913,169.25	31,550,689.31	31,416,025.42
Maximum	33,163,777.44	33,068,250.25	31,686,766.81	31,591,144.36
Mean	33,106,214.39	32,996,982.49	31,597,889.45	31,477,710.25
Standard deviation	± 45,580	± 42,710	± 42,630	± 41,890

Table 8
Gbest solution for the 49-unit Nigerian power system using MS-MDPSO.

	49-unit Nigerian hydrothermal power system Number of trials					
	#1 (iterations)	#2 (iterations)	#3 (iterations)	#4 (iterations)	#5 (iterations)	Total (%)
$gbest_1$	34	45	1	46	49	175 (35%)
$gbest_2$	11	9	24	5	35	84 (16.8%)
$gbest_3$	9	29	2	32	13	85 (17.0%)
$gbest_4$	5	6	48	9	1	69 (13.8%)
$gbest_5$	41	11	25	8	2	87 (17.4%)
Gbest	100	100	100	100	100	500 (100%)

schedules compared with the MDPSO algorithm for this GMS problem.

Table 8, Figs. 2(d), 6(c) and (d) further illustrate the design and application of MS-MDPSO algorithm for solving the GMS problem by presenting typical evolution of single global best solution (*Gbest*) from a set of five global best solutions ($gbest_1$, $gbest_2$, $gbest_3$, $gbest_4$ and $gbest_5$) obtained from five multiple swarms (n=5) over five trials for the 49-unit Nigerian power system presented in Section 4.3. Table 8 and Fig. 6(c) shows that for the 49-unit Nigerian power system, the *Gbest* (consisting of an array of 100 global best solutions) obtained for 100 iterations over the first trial is composed of $gbest_1$ (34 global best solutions from swarm #1), $gbest_2$ (11 global best solutions from swarm #2), $gbest_3$ (9 global best solutions from swarm #3), $gbest_4$ (5 global best solutions from swarm #4) and $gbest_5$ (41 global best solutions from swarm #5). Gbest feasible solutions obtained over five trials are also presented in Table 8 and depicted in Fig. 6(d).

5. Conclusions

The problem of generating optimal preventive maintenance schedules of generating units for the purpose of maximizing economic benefits and improving reliable operation of a power system, subject to satisfying system load demand, allowable maintenance window, and crew and resource constraints over 52 weeks maintenance and operational period has been presented for 21-unit test system and 49-unit Nigerian hydrothermal grid system.

Improvement in the quality of the maintenance schedules generated by MS-MDPSO algorithm in terms of reliability and energy cost curtailment over what was achieved by MDPSO algorithm has been presented. This improvement is achieved through the use of the multiple swarms' idea on the MDPSO algorithm where the evolution of a single best global solution among the swarms forms the optimal maintenance schedule for respective power system. The better solutions obtained by the MS-MDPSO algorithm for the two GMS problems are achieved at the expense of more computational time, which is not a problem since the simulation is done off-line.

With respect to the 49-unit Nigerian hydrothermal power system, two possible case studies have been investigated and compared. The logical and optimal placements of some thermal plants for maintenance along with hydroplants during low water level have been illustrated using the MDPSO and the proposed MS-MDPSO algorithms, and their results compared. The MS-MDPSO algorithm demonstrates better performance over the MDPSO algorithm for this GMS problem, and produce optimal 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 studies and analysis presented in this paper provides potential for practical implementation and enhancement of effective planning strategies that incorporates other short-term generation scheduling measures, such as unit commitment and economic load dispatch, and the integration of renewable energy resources.

Acknowledgment

The financial support from the National Science Foundation (NSF), USA under the grants ECCS #0348221 and EFRI #0836017 are gratefully acknowledged by the authors.

Appendix

See Tables A1, A2 and A3.

Table A1
Typical generator maintenance schedules obtained by MDPSO and MS-MDPSO for the 21-unit test system.

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

Table A2
Typical generator maintenance schedules obtained by MDPSO-a and MS-MDPSO-a for the Nigerian power system.

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

Table A3
Typical generator maintenance schedules obtained by MDPSO-b and MS-MDPSO-b for the Nigerian power system.

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

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