Optimal Maintenance Scheduling of Power Systems using an Algorithm Inspired by Swarm Intelligence and Quantum Evolution

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Abstract

This research work applies the techniques of particle swarm optimization (PSO) and the quantum evolution algorithm (QEA) in solving the complex power systems maintenance scheduling (PSMS) problem. The algorithm is applied for 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. Modified discrete particle swarm optimization (MDPSO) algorithm is proposed in the first instance to solve the maintenance scheduling problem to evolve optimal and feasible solutions. The concept of quantum-inspired evolutionary algorithm (QEA) is incorporated into the MDPSO algorithm to form a powerful hybrid quantum-inspired evolutionary discrete particle swarm optimization (QEDPSO) algorithm. The effectiveness and comparisons of the performance of the MDPSO and QEDPSO algorithms for the GMS problem on the Nigerian grid system are presented in this report.

I. Introduction

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

Utilities spend billions of Dollars per year for maintenance. 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.

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

II. **Problem Description**

Generally, there are two main categories of objective functions in generator maintenance scheduling (GMS) namely, based on reliability and economic cost [2]. The latter based on reliability criteria of leveling reserve generation for the entire period of study is considered in this project.

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 load, crew or resource constraints. The penalty value for each constraint violation is proportional to the amount by which the constraint is violated.

$$\sum_c \omega_c V_c \tag{6}$$

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

III. **CI Approach Description**

The concept of quantum-inspired evolutionary algorithm (QEA) is incorporated into the MDPSO algorithm to form a powerful hybrid quantum-inspired evolutionary discrete particle swarm optimization (QEDPSO) algorithm as shown in Fig. 1.

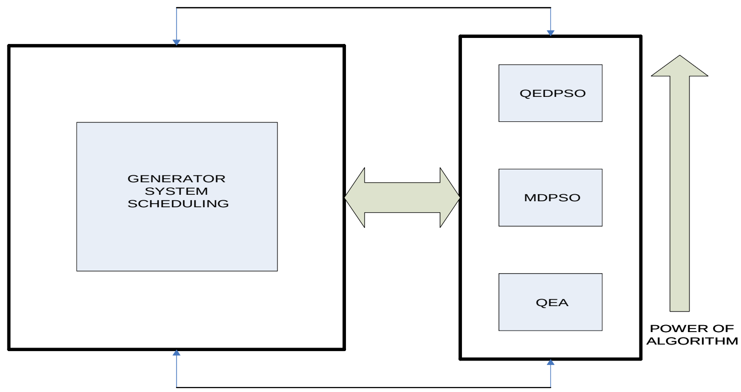

Fig. 1 QEA, MDPSO and QEDPSO for generator system scheduling

Modified Discrete PSO

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 [3]. The following subsections describe the DPSO and proposed enhanced DPSO algorithm (MDPSO).

A. Discrete PSO (DPSO)

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 [4]. 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 [4]. 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}. Thus, V_{id} always lies in the range [- V_{max}, V_{max}]. The new velocity and position for each particle's dimension is determined according to the velocity and position update equations given by (7) and (8).

$$V_{id}(k) = round(w \cdot V_{id}(k-1) + c_1 \cdot rand_1 \cdot (P_{ibd} - X_{id}(k-1)) + c_2 \cdot rand_2 \cdot (P_{gd} - X_{id}(k-1))) \quad (7)$$

$$X_{id}(k) = X_{id}(k-1) + V_{id}(k) \quad (8)$$

Where c_1 and c_2 are cognitive and social acceleration constants respectively, $rand_1$ and $rand_2$ are two random numbers with uniform distribution in the range of [0, 1], and w is the inertia weight constant which is a fixed value, linearly decreasing or dynamically changing.

B. Modified DPSO (MDPSO)

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 DPSO is a variant of the original formulation to solve discrete optimization problems. In this project, 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 collide or converge prematurely to local optima. This in turn improves the DPSO search performance. Supposing $X = (X_1, X_2, \ldots X_N)$ 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 (9).

$$X_n = P_{g_n} + (randn() \cdot P_{g_n} / 2) \qquad n = 1,2,\ldots N \quad (9)$$

where P_{gn} is the *n-th* dimension coordinate of the global best position (P_g). *randn*() is a Gaussian distributed random number with a zero mean and a variance of 1. The flowchart for the MDPSO algorithm applied to GMS problem is illustrated in Fig. 2.

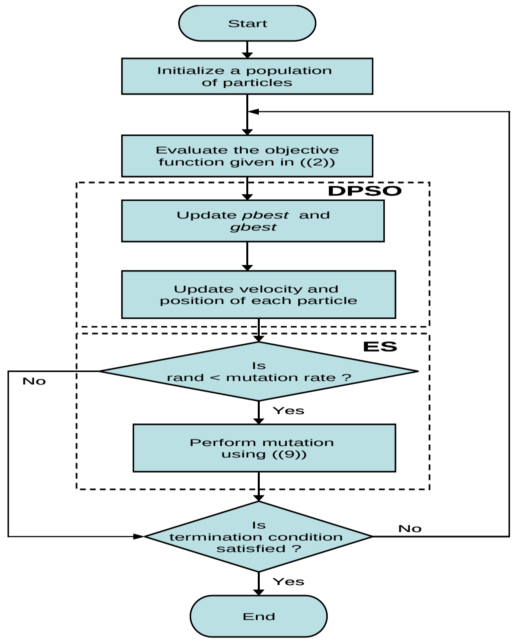

Fig. 2. Flowchart of MDPSO algorithm for GMS problem.

Quantum-Inspired Evolutionary Algorithm

The concepts of quantum computing, the representation of the Q-bit individual, the QEA algorithm and the modified QEA are presented in the following subsections:

A. Quantum computing

The concept of quantum computing utilizes the special non-local properties of quantum phenomena [5]. Ordinary computers are based on bits, which always take one of the two values 0 or 1. Quantum computers are based instead on what are called Q-bits (or qubits). A Q-bit may be simply considered as the spin state of an electron. An electron can have spin Up or spin Down; or three quarters Up and one quarter Down. A Q-bit contains more information than a bit. The state of a Q-bit can be represented as:

$$|\varphi\rangle = \alpha|0\rangle + \beta|1\rangle \tag{10}$$

Where α and β are complex numbers that specify the probability amplitudes of the corresponding states. $|\alpha|^2$ gives the probability of finding the Q-bit in state "0" and $|\beta|^2$ gives the probability of finding the it in state "1". Since the Q-bit can only be in these two states, it should satisfy the following condition:

$$|\alpha|^2 + |\beta|^2 = 1 \tag{11}$$

The state of a Q-bit can be changed by the operation with a quantum gate. A quantum gate is a reversible gate and can be represented as a unitary operator *U* acting on the qubit basis states. The defining property of a unitary matrix is that its conjugate transpose is equal to its inverse. There are several quantum gates, such as the NOT gate, controlled NOT gate, rotation gate, Hadamard gate, etc [6].

B. Individual Representation

The representation of individuals is usually done in the form of bit-strings, real-valued vectors, symbols etc. QEA uses a Q-bit representation based on the concept of Q-bits in Quantum computing. Each Q-bit is defined as a pair of numbers (α , β). A Q-bit individual is defined as a string of *m* Q-bits as shown below:

$$\left[\begin{array}{c|c|c|c} \alpha_1 & \alpha_2 & \cdots & \alpha_m \\ \beta_1 & \beta_2 & \cdots & \beta_m \end{array}\right] \tag{12}$$

Where $|\alpha_i|^2 + |\beta_i|^2 = 1$, for *i* =1, 2,…, *m*.

Evolutionary computing with Q-bit representation has a better characteristic of population diversity than other representations, since it can represent linear superposition of states probabilistically [7]. Here, only one Q-bit individual with m Q-bits is enough to represent 2^m states whereas in binary representation, 2^m individuals will be required for the same.

C. QEA Algorithm

The flowchart for the QEA algorithm proposed by HAN and Kim in [7] is shown in Fig. 3.

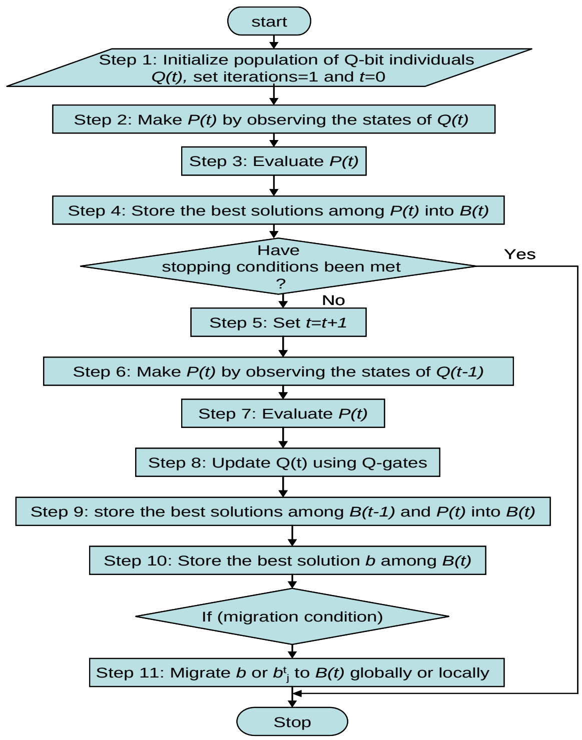

Fig. 3. QEA flowchart.

In QEA, the population of Q-bit individuals at time 't' can be represented as $Q(t)=\{q_1^t, q_2^t, ..., q_n^t\}$ where n is the size of the population. A Q-gate is defined as a variation operator of QEA, by which operation the updated Q-bit should satisfy the normalization condition, $|\alpha'|^2+|\beta'|^2=1$, where α' and β' are the values of the updated Q-bit. The following rotation gate is used as a Q-gate in QEA, such as

$$U(\Delta\theta_i)=\begin{bmatrix}\cos(\Delta\theta_i) & -\sin(\Delta\theta_i)\\ \sin(\Delta\theta_i) & \cos(\Delta\theta_i)\end{bmatrix} \tag{13}$$

Where $\Delta\theta_i$, i=1, 2, …, m is a rotation angle of each Q-bit toward either 0 or 1 state depending on its sign. $\Delta\theta_i$ should be designed in compliance with the application problem. Where the delta step size has not had theoretical basis till now, even though it usually is set a small value [8].

Quantum Angle

A quantum angle is defined as an arbitrary angle θ and a Q-bit is presented as $[\theta]$. Then $[\theta]$ is equivalent to the original Q-bit as $\begin{bmatrix}\sin(\theta)\\ \cos(\theta)\end{bmatrix}$. It satisfies that $|\sin(\theta)|^2+|\cos(\theta)|^2=1$. Then an m Q-bits $\left[\begin{array}{c|c|c|c}\alpha_1 & \alpha_2 & \cdots & \alpha_m\\ \beta_1 & \beta_2 & \cdots & \beta_m\end{array}\right]$ could be replaced by $[\theta_1|\theta_2|\cdots|\theta_m]$ [8].

Quantum swarm evolutionary algorithm

The concept of swarm intelligence of the PSO is used, and regard all m-Q-bits in the population as an intelligent group, which is named quantum angle and the global best value from the local ones. Then according to these values, we update quantum angles by Q-gate. The proposed procedure is shown to perform better than the QEA [8]. The quantum swarm evolutionary algorithm flowchart is shown in fig. 4.

$$Q(t) = \{q_1^t, q_2^t, ..., q_n^t\} \tag{14}$$

$$q_j^t = \left[\theta_{j1}^t \middle| \theta_{j2}^t \middle| \cdots \middle| \theta_{jm}^t \right] \tag{15}$$

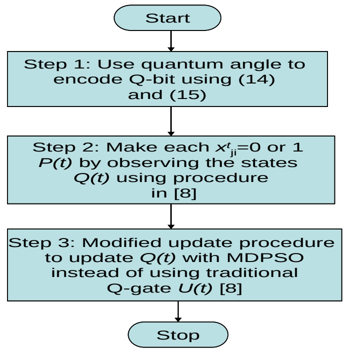

Fig. 4. Quantum swarm evolutionary algorithm flowchart.

IV. Implementation of the CI approach to the Problem

A. Nigerian Power System

The Nigerian power system consists of a total of 49 units positioned in 7 generating plants located in distinct areas (AFAM, DELTA, EGBIN, SAPELE, JEBBA, KAINJI and SHIRORO plants). AFAM, DELTA and 8 units of EGBIN thermal plants are gas fired, while SAPELE and 6 units of EGBIN thermal plants are steam driven. JEBBA, KAINJI and SHIRORO hydro plants are water driven.

B. Kainji Lake

The Kainji lake that services the three Nigerian hydro plants, namely Jebba, Kainji and Shiroro hydro plants is located between 9^0 51\`N to $10^0$ 57\`N and $4^0$20\`E to $4^0$ 50\`E in Northwestern Nigeria with water-level variation and rainfall distribution shown in Fig. 5 [9]. The variation in the lake water-level is controlled mainly by the inflow into the lake, rainfall at the lake, outflow through turbines and irrigation water supply. This water-level variation has significant impact on the generated output of the hydro plants, and also influences the allowed periods for the maintenance of the three hydro plants. At high water-level, the three plants operate at their best generating maximum power possible, and none of these plants is allowed to be shut down for maintenance. But when the water level is low, they operate at their worst condition and could be scheduled for maintenance.

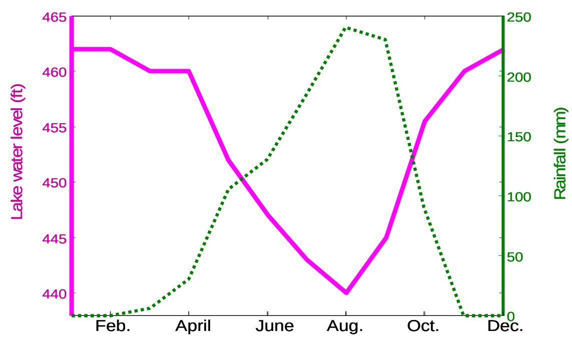

Fig. 5. Lake-water level variation and rainfall distribution.

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

C. MDPSO-a and QEDPSO-a

The Nigerian data comprises 49 units to be scheduled for maintenance over a planning period of 52 weeks. Thermal and steam turbines could be shut down for maintenance only when the hydro plants are operating at their maximum generation as dictated by the lake water level variation in Fig. 5. This corresponds to the months of January to April and November to December each year. The hydro plants can be scheduled for maintenance during low water level corresponding to the months of May to October. Within these months no thermal plant should be shut down for maintenance. 5% increased load variation is considered during the hot season of March to July every year.

D. MDPSO-b and QEDPSO-b

In these case studies, 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 are 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.

V. **Tests, Results and Discussion**

Table A.1 of the Appendix presents the generator schedules obtained by MDPSO-a and MDPSO-b, while Table A.2 of the same Appendix shows the schedules produced by QEDPSO-a and QEDPSO-b. Fig. 6 shows the available generation for MDPSO-a, MDPSO-b, QEDPSO-a and QEDPSO-b during maintenance, the maximum generation and a 5% varying load within the hot season of March to July each year. For MDPSO-a and QEDPSO-a, between the months of May and October when the hydro plants are undergoing maintenance, the bulk of the generation comes in from the thermal plants as non of them is scheduled for maintenance within this period. It leads to an uneven generation over the entire maintenance period, resulting to an unpredictable energy profile, sharp and large variations in load shedding. MDPSO-b and QEDPSO-b however, produce better and more even generation throughout the year under maintenance, with an average generation and standard deviation of 3130.557±79.781MW and 3130.692±78.125 respectively. MDPSO-a and QEDPSO-a produce average generation and standard deviation of 3130.500±121.075MW and 3130.610±119.559 respectively.

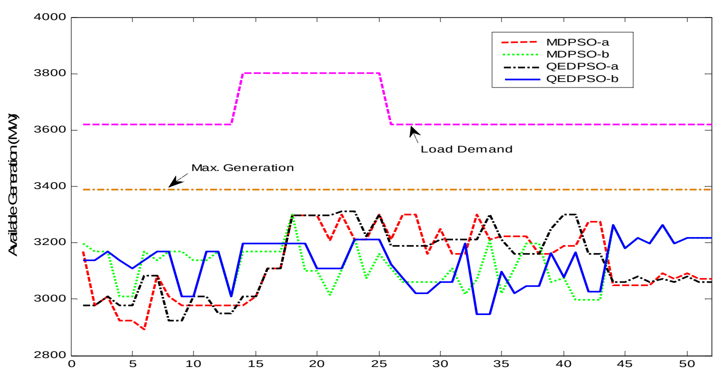

Fig. 6. Generation plots during maintenance.

Fig. 7 shows the corresponding crew availability for MDPSO-a, MDPSO-b, QEDPSO-a and QEDPSO-b during maintenance. MDPSO-b and QEDPSO-b scheduling produce better crew distribution over the maintenance period than MDPSO-a and QEDPSO-a. Both cases are seen to have satisfied the crew constraint. MDPSO-a and QEDPSO-a generate average crew requirement and standard deviation of 12±4.769 and 12±5.438 respectively, while MDPSO-b and QEDPSO-b produce 12±3.658 and 12±3.567 respectively.

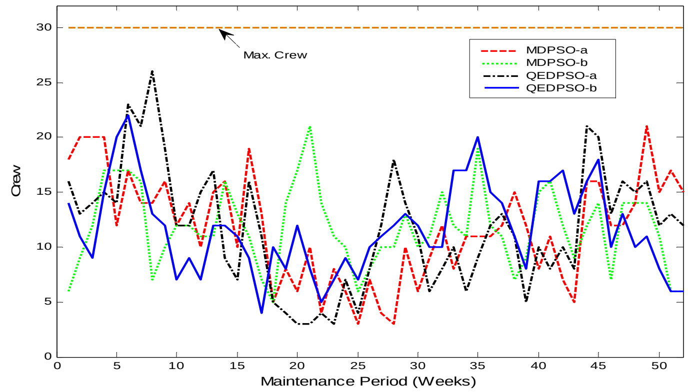

Fig. 7. Crew plots during maintenance.

Fig. 8 presents the reliability indices for MDPSO-a, MDPSO-b, QEDPSO-a and QEDPSO-b during maintenance period, compared against the system reliability index without maintenance. The plot shows that QEDPSO-b produces better system reliability of 0.772 while MDPSO-a generate the worst reliability index of 0.752 after 100 iterations.

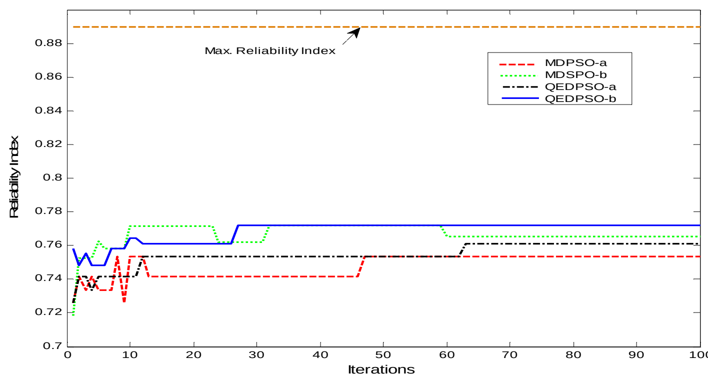

Fig. 8. Reliability index plots.

Fig. 9 shows the plots of costs of purchasing energy versus the reliability indices with the solutions obtained for MDPSO-a, MDPSO-b, QEDPSO-a and QEDPSO-b. It can be seen from the figure that at any system reliability index, the corresponding energy costs for MDPSO-a, MDPSO-b and QEDPSO-a solutions are higher than that for QEDPSO-b solution. Similarly, at any energy cost, QEDPSO-b gives better reliability than MDPSO-a, MDPSO-b and QEDPSO-a. Without maintenance, the system has much higher reliability index than the two cases considered with maintenance, and there is no need to purchase energy as a result of maintenance activities.

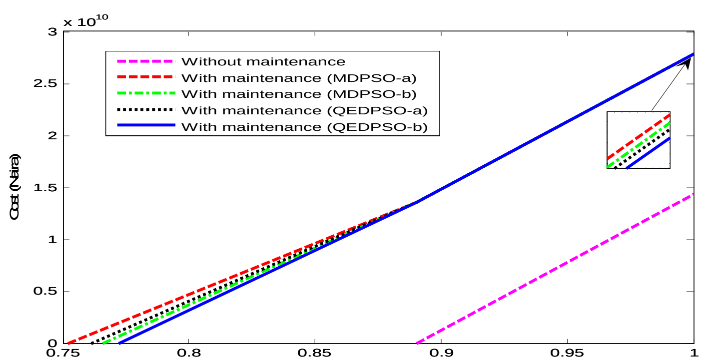

Fig. 9. Cost versus reliability index plots.

VI. **Conclusion**

The problem of generating optimal preventive maintenance schedule of generating units, in the first instance, for economical and reliable operation of a power system while satisfying system load demand and crew constraints over one year period, has been presented for the Nigerian power system comprising 49-units. Two Cases-a and -b of the Nigerian power system have been investigated. The appropriate placements of some thermal plants for maintenance along with hydro plants during low water level have also been studied using the MDPSO and QEDPSO algorithms, and their results compared. The algorithms are successfully applied in solving the maintenance scheduling problem of the Nigerian grid system, and the results show a promising future for the Nigerian power utility in terms of better energy management, improving system reliability and energy cost curtailment through proper maintenance scheduling. These investigation and analysis provides planning opportunities for implementing other short-term scheduling measures such as solving the unit commitment, load flow and optimal power flow problems. Future work will investigate system stability issues that could result as a consequence of carrying out scheduled maintenance.

APPENDIX

TABLE A.1
TYPICAL GENERATOR MAINTENANCE SCHEDULES OBTAINED BY MDPSO-A AND MDPSO-B

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

TABLE A.2
TYPICAL GENERATOR MAINTENANCE SCHEDULES OBTAINED BY QEDPSO-A AND QEDPSO-B

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

VII. **Acknowledgement**

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VIII. **References**

[1] M. K. C. Marwali and S. M. Shahidehpour, "Coordination between long – term and short – term generation scheduling with network constraints," *IEEE Transactions on Power Systems*, vol. 15, pp.1161-1167, August 2000.

[2] K. P. Dahal and J. R. McDonald, "Generator maintenance scheduling of electric power systems using genetic algorithms with integer representation," *IEEE Conference on Genetic Algorithms in Engineering Systems: Innovations and Applications*, pp. 456-461, September 2-4 1997.

[3] J. Kennedy and R. Eberhart, "Particle swarm optimization," *IEEE International Conference on Neural Networks*, vol. 4, pp. 1942-1948, Nov. 27 – Dec. 1 1995.

[4] Y. D. Valle, G. K. Venayagamoorthy, S. Mohagheghi, J. Hernandez and R. G. Harley, "Particle swarm optimization basic concepts, variants and applications in power system," *IEEE Transactions on Evolutionary Computation*, in press.

[5] G. K. Venayagamoorthy and G. Singhal, "Quantum-inspired evolutionary algorithms and binary particle swarm optimization for training MLP and SRN neural networks," *Journal of Computational and Theoretical Nanoscience*, vol. 2, 1-8, 2005.

[6] T. Hey, *Computing and Control Engineering Journal*, 10, 105, 1999.

[7] K. Han and J. kim, "Quantum-inspired evolutionary algorithm for a class of combinatorial optimization," *IEEE Transactions on Evolutionary Computation*, vol. 6, no. 6, December 2002.

[8] Y. Wang, X. Feng. Y. Huang, D. Pu, W. Zhou, Y. Liang, C. Zhou, "A novel quantum swarm evolutionary algorithm and its applications," *ScienceDirect*, , pp. 633-640, 2006.

[9] Nigeria–Kainji lake draw-down areas , soil and land evaluation report, *United Nations Development Programme and the Food and Agriculture Organization (FAO) of the United Nations.* November 1973. Available: http://www.fao.org/docrep/