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Optimal Scheduling of Generator Maintenance using Modified Discrete Particle Swarm Optimization

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Abstract

This paper presents a modified discrete particle swarm optimization (PSO) based technique 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. While GA and other analytical methods might suffer from premature convergence and the curse of dimensionality, heuristics based swarm intelligence can be an efficient alternative. PSO is known to effectively solve large scale multi-objective optimization problems. Here, a modified discrete PSO approach is proposed for the GMS optimization problem in order to overcome the limitations of the conventional methods and come up with a feasible and an optimal solution.

Introduction

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 in the electric utility 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 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 solution is found. Power system components are made to remain in operating conditions by regular preventive maintenance. The purpose of maintenance scheduling is to find the sequence of scheduled outages of generating units over a given period of time such that the level of energy reserve is maintained. This type of schedule is important mainly because other planning activities are directly affected by such decisions. In modern power systems the demand for electricity has greatly increased with related expansions in system size, which has resulted in higher number of generators and lower reserve margins making the generator maintenance scheduling **(**GMS) problem more complicated. The eventual aim of the GMS is the effective allocation of generating units for maintenance while maintaining high system reliability, reducing production cost, prolonging generator life time subject to some unit and system constraints [1]-[3].

The GMS is an optimization problem. Various methods exist in the literature that addresses optimization problems under different conditions. Different optimization techniques are classified based on the type of the search space and the objective function. The simplest method is linear programming (LP) which concerns the case where the objective function is linear [4]. For a special case, where some or all variables are constrained to take on integer values, the technique is referred to as integer programming [4]. In general, the objective function or the constraints or both may contain nonlinearities, which raise the concept of nonlinear programming (NLP) [5]. This type of optimization technique has been extensively used for solving problems, such as power system voltage security [6], optimal power flow [7]-[10], power system operation and planning [11]-[12], dynamic security [13], reactive power control [14], capacitor placement [15], power quality [16] and optimizing controller parameters [17]. Even though deterministic optimization problems are formulated with known parameters, real world problems almost invariably include some unknown parameters. This necessitates the introduction of dynamic programming (DP) [18]. Although the DP technique has been mathematically proven to find an optimal solution, it has its own drawbacks. Solving the dynamic programming algorithm in most of the cases is not feasible and numerical solution requires extensive computational effort, which increases exponentially as the size of the problem increases. The complexity is even further increased when moving from finite horizon to infinite horizon problems, while also considering the stochastic effects, model imperfections and the presence of the external disturbances [18].

Genetic algorithm (GA) can provide solution to GMS and the above optimization problems. GA represents a particular class of evolutionary algorithms that uses techniques inspired by evolutionary biology such as inheritance, mutation, natural selection and crossover. While it can rapidly locate good solutions, it may have a tendency to converge towards local optima rather than the global optimum of the problem [19].

Particle swarm optimization (PSO) is a computational intelligence based technique inspired by the social behavior of bird flocking or fish schooling. It has its roots in artificial life and social psychology as well as in engineering and computer science. This technique is not largely affected by the size and nonlinearity of the problem, and can converge to the optimal solution in many problems where most analytical methods fail to converge. It can therefore be effectively applied to the GMS problem to evolve optimal sequence of maintenance of generating units having different specifications subject to practical constraints [20].

This paper presents a modified discrete particle swarm optimization (MDPSO) based technique for obtaining optimal preventive maintenance schedule of generating units for economical and reliable operation of a power system while satisfying system load demand and crew constraints.

GMS Problem Formulation

Generator maintenance schedule is a preventive outage schedule for generating units in a power system within a specified time horizon. Maintenance scheduling becomes a complex optimization problem when the power system contains a number of generating units with different specifications, and when numerous constraints have to be taken into consideration to obtain an optimal, practical and feasible solution. It is done for a time horizon of different durations. A planning horizon of half year (that is 26 weeks) for 13 generating units of different capacities is considered in the GMS problem presented in this paper. The GMS over this planning period is important for resource management and future planning.

Generally, there are two main categories of objective functions in GMS, namely, based on reliability and economic cost [2]. This study applies the reliability criteria of leveling reserve generation for the entire period of study. This can be realized by minimizing the sum of squares of the reserve over the entire operational planning period. The problem has a series 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 reliability constraints - total capacity of the units running at any interval should be not less than predicted load at that interval. The load demand on the power system is considered during the scheduling period.

- Spinning reserve - in order to maintain the electric power supply normally, there must be a spinning reserve to meet unexpected load demand.

Suppose $T_i \subset T$ is the set of periods when maintenance of unit i may start,

$$T_i = \{t \in T : e_i \le t \le l_i - d_i + 1\} \text{ for each } i.$$

Define

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

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 is to minimize the sum of squares of the reserve generation given by (1). In this paper, modified discrete particle swarm optimization (MDPSO) is applied to minimize (1) subject to the constraints given by (2), (3) and (4).

$$\underset{X_{it}}{Min}\left\{ \sum_t \left(\sum_i P_{it} - \sum_{i \in I_t} \sum_{k \in S_{it}} X_{ik} \cdot P_{ik} - L_t \right)^2 \right\} \qquad (1)$$

subject to the maintenance window constraint

$$\sum_{t \in T_i} X_{it} = 1 \qquad \forall i , \qquad (2)$$

the crew constraint

$$\sum_{i \in T_t} \sum_{k \in S_{it}} X_{ik} \cdot M_{ik} \le AM_t \qquad \forall t, \qquad (3)$$

and the load constraint

$$\sum_i P_{it} - \sum_{i \in I_t} \sum_{k \in S_{it}} X_{ik} \cdot P_{ik} \ge L_t \qquad \forall t, \qquad (4)$$

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

Penalty cost given by (5) is added to the objective function ((1)) if the schedule cannot meet the load or the crew and resource constraints.

$$\sum_t Penalty\ Cost \qquad (5)$$

Modified Discrete PSO

The PSO is a population based evolutionary computation technique introduced in 1995 by Russell Eberhart and James Kennedy [20]. PSO has been proposed recently and proved to be a powerful competitor in the field of optimization. PSO, inspired by social behavior of bird flocking or fish schooling, is an algorithm for finding optimal regions of complex search spaces through the interaction of individuals in a population of particles. In PSO, the potential solutions, called particles, fly through the problem space by following the current optimum particles. PSO has been recently applied to several power system problems, such as reactive power and voltage control, optimal power flow, dynamic security border identification and state estimation , and has been shown to perform well [21]-[23].

The PSO has some advantages over other similar heuristic optimization techniques, namely:

- PSO is easier to implement and there are fewer parameters to adjust.
- In PSO, every particle remembers its own previous best value as well as the neighborhood best; therefore, it has a more effective memory capability.
- PSO is more efficient in maintaining the diversity of the swarm [8], (more similar to the ideal social interaction in a community), since all the particles use the information related to the most successful particle in order to improve themselves.

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.

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 [21]. Discrete particle swarm optimization (DPSO) 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_i always lies in the range [$-V_{max}$, V_{max}]. The new velocity and position for each particle $X_i(t) \in R^n$ are determined according to the velocity and position update equations given by (6) and (7).

$$V_i(t) = round(w \cdot V_i(t-1) + c_1 \cdot rand_1 \cdot (P_b - X_i(t-1)) + c_2 \cdot rand_2 \cdot (P_g - X_i(t-1))) \quad (6)$$

$$X_i(t) = X_i(t-1) + V_i(t) \quad (7)$$

where c_1 and c_2 are cognitive and social constants respectively, $rand_1$ and $rand_2$ are two random numbers with uniform distribution in the range of [0.0, 1.0], and w is the inertia weight constant which can be implemented as a fixed value, linearly decreasing or dynamically changing.

The velocity update equation in (6) has three major components [21]:

- The first component is sometimes referred to as inertia, momentum or habit. It models the tendency of the particle to continue in the same direction it has been traveling.
- The second component is a linear attraction towards the best position ever found by the given particle P_i (whose corresponding fitness value is called the particle's best, p_{best} or P_b). This component serves as the memory or self-knowledge.
- The third component of the velocity update equation is a linear attraction towards the best position found by any particle whose fitness value is called global best, g_{best} or P_g. This component is referred to as cooperation, social knowledge or group knowledge.

Integer or discrete PSO has a high success rate in solving integer programming problems even when other methods, such as branch and bound fail [24].

Modified DPSO (MDPSO)

The modified discrete particle swarm optimization (MDPSO) is a combination of DPSO and an evolutionary algorithm 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 discrete PSO is a variant of the original formulation to solve discrete optimization problems.

The proposed MDPSO overcomes the premature convergence phenomenon experienced with the original PSO formulation by introducing a mutation operator. A natural evolution of the particle swarm algorithm can be achieved by incorporating methods that have already been tested in other evolutionary computation techniques. In this paper mutation operator often used in GA [25]-[26] is introduced into the discrete PSO 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 (8).

$$X_n = P_{g_n} + 0.5 \cdot randn() \cdot P_{g_n} \quad (8)$$
$$n=1, 2, \ldots N$$

Where P_{gn} is the n-th dimension coordinate of the global best position (P_g). $randn()$ is a Gaussian distributed random number with zero mean and variance 1.

GMS with MDPSO

The flowchart for the application of MDPSO algorithm for GMS problem is shown in Figure 1.

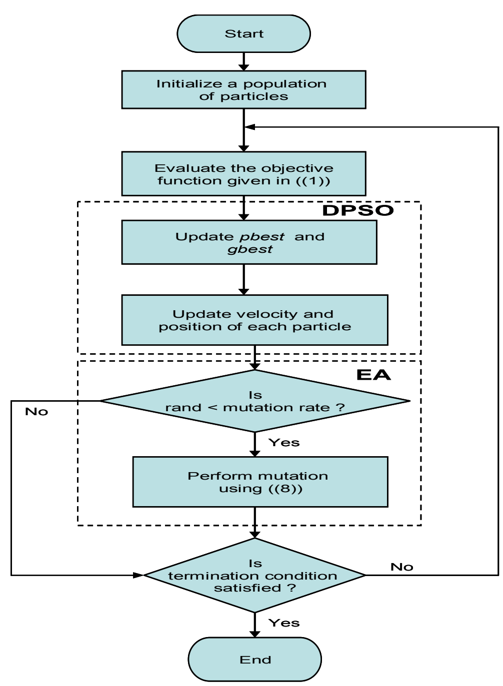

Fig. 1. Flowchart of MDPSO algorithm for GMS problem.

GMS problem is addressed by first finding the starting period, which is the time the maintenance should begin for each generating unit. The integer encoding approach consists of a string of integers, each of which indicates the maintenance start period of a unit and the string length is equal to the number of units. Since the maintenance period varies for every unit, the start period is selected within the specified maintenance window of 26 weeks. In order to investigate the performance of the proposed algorithm for the GMS, a test system comprising 13 units over a planning period of 26 weeks, which is obtained from the example presented in [2]. During this period, 13 units need to undergo maintenance, and Table 1 lists the generator ratings, maintenance duration of each unit and crew required weekly for each unit.

Table1
Data for the 13 units test system

Unit	Capacity (MW)	Maintenance Duration (weeks)	Manpower required for each week
1	555	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

The maintenance outages for the generating units are scheduled to minimize the sum of squares of reserves and satisfy the following constraints:

- Maintenance window - each unit must be maintained exactly once within time duration without interruption.
- Load constraint and spinning reserve - the system's peak load including 6.5% spinning reserve [27]-[28] is 2500MW.
- Crew constraint - there are only 40 crew available for the maintenance work each week.

Experimental Study and Results

To implement the MDPSO, a population size of 30 particles was chosen to provide sufficient diversity into the population taking into account the dimensionality and complexity of the problem. This population size ensured that the domain is examined in full, and on the other hand it would mean increasing the running time. The experiment is conducted for 5000 and 10000 iterations over 100 trials.

Table 2 shows fitness values, ((1)), for three different PSO parameters obtained after 10000 iterations. The MDPSO performs better than the DPSO. The two algorithms produced best results when w=0.8 and c_1=c_2=2, and the worst result is with linearly decreasing w.

Table 2
Fitness values (10000 iterations)

	DPSO		MDPSO	
	Mean fitness and standard deviation ($\times 10^6$)	Ranking	Mean fitness and standard deviation ($\times 10^6$)	Ranking
w=0.8, c_1=2, c_2=2	1.083 ± 0.10	1	1.073 ± 0.091	1
Linearly decreasing w (0.9 to 0.4), c_1=2, c_2=2	1.096 ± 0.09	3	1.093 ± 0.105	3
Constriction factor [29] w=0.729 c_1=1.49, c_2=1.49	1.092 ± 0.12	2	1.090 ± 0.107	2

Table 3 presents best schedules evolved by the DPSO and the MDPSO after 5000 iterations. During the 26-week maintenance period, every week is productively utilized to maintain generation that meets peak demand while satisfying manpower availability.

Table 3
Best generator maintenance schedules obtained by DPSO and MDPSO

Week no.	Generating units scheduled for maintenance		Week no.	Generating units scheduled for maintenance	
	DPSO	MDPSO		DPSO	MDPSO
1	4	4	14	10, 11	7, 10
2	4	4	15	12	7
3	4	4	16	12	7, 8
4	6	6	17	5	5
5	6, 7	2, 6, 13	18	5	5
6	6, 7	2, 6, 13	19	5	5
7	2, 6, 7	6, 13	20	1	1
8	2, 6, 7	3, 6	21	1	1
9	3, 6, 13	6, 12	22	1	1
10	6, 13	6, 11, 12	23	1	1
11	6, 10	6, 10, 11	24	1, 8	1
12	6, 10	6, 10	25	1, 9	1, 9
13	6, 10, 11	6, 7, 10	26	1, 9	1, 9

Figure 2 shows optimal maintenance schedules obtained from the best results in Table III. Within the maintenance window, a minimum of 2500MW was sustained to meet the peak demand, while the crew was limited to maximum of 40. It is important to note from this figure that the crew demand inversely related with the load availability over the entire maintenance period. When maintenance activities are intensified in a particular week, more generators are shut down which translates to reduced generation. The opposite happens when the tempo on maintenance is reduced. It can be observed also that there is maintenance activity on every week through out the 26 weeks without any interruption.

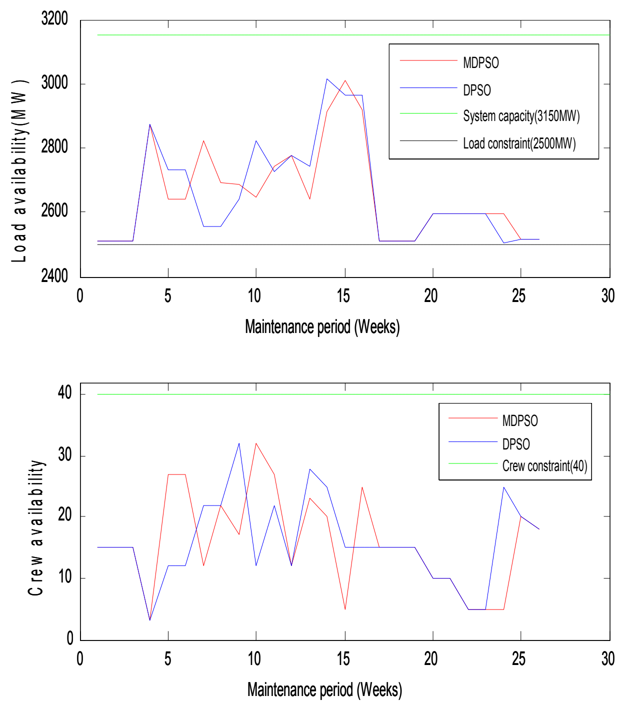

Fig. 2. Load availability and crew curves during maintenance period

Figure 3 shows the performance graph of the best MDPSO and DPSO for w=0.8 and c_1=c_2=2. The results show that the DPSO is likely to be stuck in a local optimum whereas MDPSO has a higher chance of escape from the local attraction.

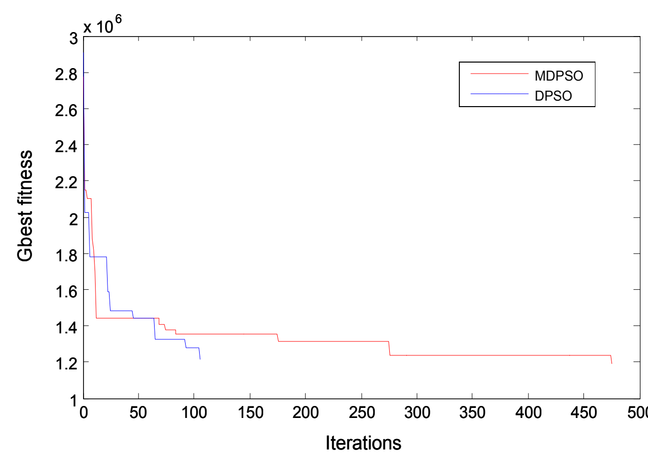

Fig. 3. Convergence rate of best MDPSO and DPSO

Table 4 presents the mean iterations for both the MDPSO and the DPSO when all constraints are satisfied. These results are obtained over five trials. DPSO converged prematurely than the MDPSO. The MDPSO avoided the premature convergence by making the mutated particles enter other region to continue searching for better global optimum solution.

Table 4
Iterations when all constraints are satisfied

	DPSO		MDPSO	
	Mean number of iterations and standard deviation ($\times 10^3$)	Ranking	Mean number of iterations and standard deviation ($\times 10^3$)	Ranking
w=0.8, c_1=2, c_2=2	0.04 ± 0.127	1	0.768 ± 0.868	1
Linearly decreasing w (0.9 to 0.4), c_1=2, c_2=2	0.078 ± 0.12	2	1.732 ± 1.032	2
Constriction factor [29] w=0.729 c_1=1.49, c_2=1.49	0.829 ± 0.828	3	2.732 ± 1.269	3

Table 5 shows the percentage of feasible optimal maintenance schedules obtained after 5000 and 10000 iterations. The result shows the efficiency and better performance of MDPSO over the DPSO. Both algorithms performed best for w=0.8 and c_1=c_2=2 and worst for the constriction factor based PDO for this GMS problem.

Table 5
Fixed number of iterations

	DPSO (Per cent of feasible optimal schedules)		MDPSO (Per cent of feasible optimal schedules)	
	5000 Iterations	10000 Iterations	5000 Iterations	10000 Iterations
w=0.8, c_1=2, c_2=2	43%	58%	58%	79%
Linearly decreasing w (0.9 to 0.4), c_1=2, c_2=2	43%	53%	57%	66%
Constriction factor [29] w=0.729 c_1=1.49, c_2=1.49	37%	50%	50%	62%

Conclusion

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 a half year period has been presented in a 13-unit test system.

The integration of the mutation operator in the MDPSO algorithm improved the particles diversity and avoided the premature convergence problem effectively, and also showed good optimization performance. It copes with continuous and discrete variables conveniently. The results reflect a feasible and practical optimal solution that can be implemented in real time.

Future work is to test on a large test system having different specifications over one year maintenance window, and then to a composite power system. The resulting optimal schedules will form part of overall system planning operation of a power utility. Future work will also seek to make the mutation operation adaptive while other powerful variants could be integrated into the MDPSO algorithm to improve the present performance.

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