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Mid Term Unit Commitment Using Modified Particle Swarm Optimization

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Abstract
This paper presents a new approach to unit commitment (UC) problems using a particle swarm optimization (PSO) technique. The mid term UC problem has a cost function with equality and inequality constraints that make the problem of finding the global optimum difficult by using any mathematical approach. In this paper, a modified PSO (MPSO) mechanism is suggested to deal with the equality and inequality constraints in the UC problems. The proposed MPSO is applied to a 10-unit test system and the results of the MPSO are compared with the results of conventional numerical methods such as mixed integer nonlinear programming (MINLP).

Keywords: Unit commitment, constrained optimization, particle swarm optimization (PSO)

1. INTRODUCTION

Unit commitment (UC) in power systems involves the proper scheduling of the on/off states of all the units in the systems. In addition to fulfill a large number of constraints, the optimal UC should meet the load demand plus the reserve requirements at every interval so that the total cost is minimum. The UC is a combinatorial optimization problem with both binary and continuous variables. The number of combinations of 0–1 variables grows exponentially as being a large-scale problem. Therefore, UC is one of the most difficult problems in the power systems.

The UC problem is commonly a nonlinear, large-scale, mixed integer combinatorial problem. The exact solution of the UC problem can be obtained by complete enumeration of all feasible combinations of the generations of units, which is impossible for realistic power systems [1]. The needs for practical UC solutions encouraged the development of various methods providing sub-optimal but efficient scheduling for real sized power systems consisting of hundreds of generators.

Because of the large economic benefits that could result from the unit scheduling improvement, a considerable attention has been devoted to develop problem solution methods. Various mathematical programming and heuristic based approaches such as the dynamic programming [2], the neural networks [3], the simulated annealing [4], the evolutionary programming [5], the genetic algorithms [6], the Lagrangiane relaxation [7], the branch and bound algorithm [8] and the tabu search [9] approaches have been devoted to solve the UC problem.

The rest of this paper is organized as follows. In Section II, the problem formulation and the constraints of the mid term UC are discussed. The PSO method for solving this prob-

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lem in power systems is proposed in Section III. In section IV, the 10-unit system was used and the optimization problem was solved using the PSO method and the results have been compared with the conventional method (mixed integer nonlinear programming). At last, the conclusion is drawn in Section V.

3. MIDE TERM UC PROBLEM FORMULATION

From the definition of UC mentioned above, the objective function of the mid term UC problem is to minimize the production cost over the scheduling time horizon (e.g., 12 month). The mid term UC problem can be formulated mathematically as an optimization problem as follows:

Object Function -- total generation cost including fuel and operation costs:

$$\min J = \sum_{t=1}^{T}\sum_{g=1}^{G}\{F(P_{GD}(g,t))\cdot n(t)\}\cdot U(g,t) + \sum_{t=1}^{T}\sum_{g=1}^{G}\{(P_{GD}(g,t)+P_{GR}(g,t))\cdot O\&MVC(g)\cdot n(t)\}\cdot U(g,t) + \sum_{t=1}^{T}\sum_{g=1}^{G}\{P_{Gg,\max}(g)\cdot O\&MFC(g)\cdot n(t)/8760\} \quad (1)$$

Where

$$F(P_{GD}(g,t)) = a_g + b_g\cdot P_{GD}(g,t) + c_g\cdot(P_{GD}(g,t))^2 \quad (2)$$

System-wide Constraints

-- System demand

$$\sum_{g=1}^{G} P_{GD}(g,t)\cdot U(g,t) = P_d(t) \quad (3)$$

$$t = 1,2,...,T$$

-- Reserve requirement

The reserve requirement is assumed to equal a percent of the total system load (e.g. %5). Thus, the operating reserve must be greater than this reserve requirement.

$$\sum_{g=1}^{G} P_{GR}(g,t)\cdot U(g,t) \ge P_R(t) \quad (4)$$

$$t = 1,2,...,T$$

-- Maximum and minimum generation limits

$$P_{Gg,\min} \le P_{GD}(g,t) + P_{GR}(g,t) \le P_{Gg,\max}$$

2. IMPLEMENTATION OF PSO METHOD

A. Overview of the PSO

Particle Swarm Optimization (PSO) was first proposed by Kennedy and Eberhart [10] in 1995. This technique was inspired by the choreography of a bird flock and can be seen as a distributed behavior algorithm that performs the multidimensional search. According to PSO, either the best local or the best global particle to help it fly through a hyperspace affects the behavior of each particle. Moreover, a particle can learn from its past experiences to adjust its flying speed and direction. Therefore, by observing the behavior of the flock and memorizing their flying histories, all the particles in the swarm can quickly converge to *near-optimal* geographical positions with well-preserved population density distribution.

Bird flocking optimizes a certain objective function. Each agent knows its best value so far ($pbest$) and its position. Moreover, each agent knows the best value so far in the group ($gbest$) among $pbest$. Namely, each agent tries to modify its position using the following information:

- The distance between the current position and its best position so far,

Unit Constraints

- The distance between the current position and the best position of the group.

Suppose that the search space is *D*-dimensional, then the *i*th particle of the swarm can be represented by a *D*-dimensional vector, $X_i = (x_{i1}, x_{i2}, ..., x_{iD})$. The *velocity* (position change) of this particle can be represented by another *D*-dimensional vector

$V_i = (v_{i1}, v_{i2}, ..., v_{iD})$. The best previously visited position of the *i*th particle is denoted as $pbest_i = (p_{i1}, p_{i2}, ..., p_{iD})$. Defining $gbest$ as the best particle in the swarm, then the swarm is updated according to the following equation:

$$v_{id}^{k+1} = w \cdot v_{id}^{k} + c_1 r_1^k (pbest_{id}^k - x_{id}^k) + c_2 r_2^k (gbest_d^k - x_{id}^k) \qquad (6)$$

Where

$d = 1, 2, . . ., D$;

$i = 1, 2, . . . , N$,

$k = 1, 2, . . .$, the iteration number,

In this velocity updating process, the values of parameters such as w, $c1$ and $c2$ should be determined in advance. In general, the weighting function (w) of the equation (6) is set to the following equation:

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{\max iter} \times iter \qquad (7)$$

The model using (7) is called "inertia weights approach (IWA)" [11].By using the above equation, the diversification characteristic is gradually decreased and a certain velocity, which gradually moves the current searching point close to $pbest$ and $gbest$ can be calculated. The current position (the searching point in the solution space) can be modified by the following equation:

$$x_{id}^{k+1} = x_{id}^{k} + v_{id}^{k+1} \qquad (8)$$

Fig. 1 shows a concept of modification of a searching point by PSO using the modified velocity and the position of the individual particle *i* based on (6) and (8) if the values of w, r_1, r_2, c_1 and c_2 are one.

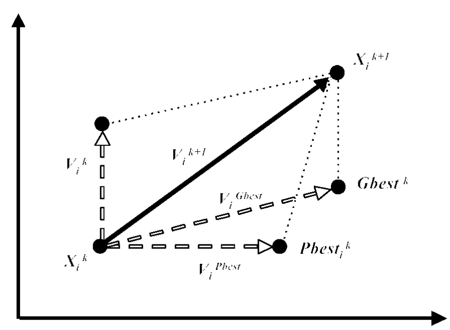

Fig. 1. Concept of modification of a searching point by PSO

B.Modified PSO for Mid Term UC Problem

In this section, a new approach to implement the PSO algorithm will be described in solving the UC problems. Especially, a suggestion will be given on how to deal with the equality and inequality constraints of the UC problems when modifying each particle search point in the PSO algorithm. The process of the modified PSO algorithm can be summarized as follows:

1. The initialization of a group at random while satisfying constraints.
2. The velocity and position updates while satisfying constraints.
3. The update of *Pbest* and *Gbest*.
4. Go to Step 2 until satisfying stopping criteria.

In the subsequent sections, the detailed implementation strategies of the MPSO are described.

1) Initialization and Structure of Particles: In the initialization process, a set of particles is created at random. In this paper, the structure of a particle for mid term UC problem is composed of a set of elements (i.e., generation and reserve outputs in each interval). Therefore, the particle i position at the iteration 0 can be represented as the vector of

$$X_i^0 = (P_{GDi1,t}^0, P_{GDi2,t}^0, ..., P_{GDiG,t}^0, P_{GRi1,t}^0, P_{GRi2,t}^0, ..., P_{GRiG,t}^0)$$

where G is the number of generators and $t = 1,2,...,T$ is the index of time period (e.g. $T = 12$ for 12 month). Thus, the dimension of each particle is $2*G*T$ in this study. In other words, the particle has T sections for all units power generation and reserve.

The velocity of the particle i (i.e., $V_i^0 = (v_{i1}^0, v_{i2}^0, ..., v_{iD}^0)$) corresponds to the generation update quantity covering all the generators. The elements of position and velocity have the same dimension, i.e., MW in this case. Note that it is very important to create a group of individuals satisfying the equality constraint (3) and inequality constraints (4) and (5). That is, summation of all elements of the particle i (i.e., $\sum_{g=1}^{G} P_{GDig,t}^0$) should be equal to the total system demand $P_d(t)$ at any time interval and the created element g of the particle i at random (i.e., $P_{GDig,t}^0$ or $P_{GRig,t}^0$) should be located within its boundary. Although we can create the element g of the particle i at random satisfying the inequality constraint by mapping [0,1] into $[P_{Gg,\min}, P_{Gg,\max}]$ when the unit is on. Also, it is necessary to develop a new strategy to handle the equality constraint. To do this, the following procedure is suggested for any particle in a group:

Step 1. Set P_{GDig}^0 of each section of the particle i to modeling the on/off state of the unit at random by this equation:

$$P_{GDig,t}^0 = \begin{cases} rand \cdot \left[P_{Gg,\max} - P_{Gg,\min}\right] + P_{Gg,\min} & if \quad rand_1 < rand_2 \\ 0 & elsewhere \end{cases} \tag{9}$$

$g = 1,2,...,G$

Step 2. Set $g = 1$.

Step 3. The value of each element of the particle is determined by the sharing principle method from the total system demand ($PureLoad = P_d(t)$) in each time period.

$$(P_{GDig,t}^0)_{new} = PureLoad \cdot \frac{(P_{GDig,t}^0)_{old}}{\sum_{\forall g \in \{\Psi\}} (P_{GDig,t}^0)_{old}} \tag{10}$$

Where Ψ is the set of units which power is not reached to the upper/lower bound limits. If the $(P_{GDig}^0)_{new}$ is in the range of operating region of the unit g then go to Step 6; otherwise go to Step 4.

Step 4. If $(P_{GDig}^0)_{new}$ is lower than $P_{Gg,\min}$, then $(P_{GDig}^0)_{new} = P_{Gg,\min}$. If $(P_{GDig}^0)_{new}$ is greater than $P_{Gg,\max}$, then $(P_{GDig}^0)_{new} = P_{Gg,\max}$.

Step 5. $PureLoad = PureLoad - (P_{GDig}^0)_{new}$ and $\{\Psi\}_{new} = \{\Psi\}_{old} - g$.

Step 6. If $g > G$ then go to step 7, otherwise $g = g + 1$ and go to step 3.

Step 7. If the $\sum_{g=1}^{G} (P_{GDig}^0)_{new} = P_d(t)$ then go to step 8, otherwise go to step 1.

Step 8. . Set the reserve power of each unit (P_{GRig}^0) for each individual i by this equation:

$$P_{GRig}^0 = \begin{cases} rand \cdot (P_{Gg,\max} - (P_{GDig}^0)_{new}) & if \quad (P_{GDig}^0)_{new} \neq 0 \\ 0 & otherwise \end{cases} \tag{11}$$

$g = 1,2,...,G$

Step 9. If the $\sum_{g=1}^{G} P_{GRig}^0 \geq P_R(t)$ then go to step 10, otherwise go to step 8.

Step 10. Stop the initialization process.

The above procedure must be repeated for all of the time periods. After creating the initial position of each individual, the velocity of each individual is also created at random. The initial of individual is set as the initial position of individual and the initial *Gbest* is determined as the position of an individual with minimum payoff of (1).

2) Velocity Update: To modify the position of each individual, it is necessary to calculate the velocity of each individual in the next stage, which is obtained from (6). In this velocity updating process, the values of parameters such as w, c_1 and c_2 should be determined in advance. In this paper, the weighting function is defined as the equation (7).

3) Position Modification Considering Constraints: The position of each individual is modified by (8). The resulting position of an individual is not always guaranteed to satisfy the equality/inequality constraints due to the over/under velocity. If any element of an individual violates its inequality constraint due to the over/under speed then the position of the individual is fixed to its maximum/ minimum operating point. To do this, the following procedure is suggested for any individual in a group:

Step 1. P_{GDig}^{k+1} and P_{GRig}^{k+1} for each particle i are calculated by the equation (8).

Step 2. $g = 1$.

Step 3. If the P_{GDig}^{k+1} is in the range of its operating region of the unit g then go to Step 4; otherwise go to Step 5.

Step 4. If P_{GDig}^{k+1} is lower than $P_{Gg,\min}$, then $P_{GDig}^{k+1} = 0$. If P_{GDig}^{k+1} is greater than $P_{Gg,\max}$, then $P_{GDig}^{k+1} = P_{Gg,\max}$ and $P_{GRig}^{k+1} = 0$. Also, if $P_{GDig}^{k+1} = 0$ or $P_{GRig}^{k+1} \le 0$ then $P_{GRig}^{k+1} = 0$. If $P_{GRig}^{k+1} \ge P_{Gg,\max} - P_{GDig}^{k+1}$ then $P_{GRig}^{k+1} = P_{Gg,\max} - P_{GDig}^{+1}$.

Step 5. If $g > G$ then go to step 6, otherwise $g = g + 1$ and go to step 3.

Step 6. The ratio $P_d(t) \Big/ \sum_{g=1}^{G} (P_{GDig}^{k+1})$ is calculated. If this ration is greater than 1 then go to step 7, otherwise go to step 12.

Step 7. The value of each element of an individual is determined by the sharing principle method from the total system demand $PureLoad = P_d(t) - \sum_{\forall g \in \Phi} (P_{GDig}^{k+1})$ in each time period.

$$(P_{GDig}^{k+1})_{new} = PureLoad \cdot \frac{(P_{GDig}^{k+1})_{old}}{\sum_{\forall g \notin \{\Phi\}} (P_{GDig}^{k+1})_{old}} \qquad \forall g \notin \{\Phi\} \tag{12}$$

Where Φ is the set of units that its power is reached to upper bound limit.

Step 8. If the $(P_{GDig}^{k+1})_{new}$ is in the range of its operating region of the unit g then go to Step 7 for the next unit; otherwise go to Step 9.

Step 9. If $(P_{GDig}^{k+1})_{new}$ is greater than $P_{Gg,\max}$, then $(P_{GDig}^{k+1})_{new} = P_{Gg,\max}$.

Step 10. $PureLoad = PureLoad - (P_{GDig}^{k+1})_{new}$ and $\{\Phi\}_{new} = \{\Phi\}_{old} - g$.

Step 11. If $g > G$ then go to step 17, and otherwise go to step 7 for the next unit.

Step 12. The value of each element of an individual is determined by the sharing principle method from the total system demand $PureLoad = P_d(t) - \sum_{\forall g \in \Psi} (P_{GDig}^{k+1})$ in each time period.

$$(P_{GDig}^{k+1})_{new} = PureLoad \cdot \frac{(P_{GDig}^{k+1})_{old}}{\sum_{\forall g \notin \{\Psi\}} (P_{GDig}^{k+1})_{old}} \qquad \forall g \notin \{\Psi\} \tag{13}$$

Where Ψ is the set of units that its power is reached to lower bound limit.

Step 13. If the $(P_{GDig}^{k+1})_{new}$ is in the range of its operating region of the unit g then go to Step 12 for the next unit; otherwise go to Step 14.

Step 14. If $(P_{GDig}^{k+1})_{new}$ is lower than $P_{Gg,\min}$, then $(P_{GDig}^{k+1})_{new} = P_{Gg,\min}$.

Step 15. $PureLoad = PureLoad - (P_{GDig}^{k+1})_{new}$ and $\{\Psi\}_{new} = \{\Psi\}_{old} - g$.

Step 16. If $g > G$ then go to step 17, and otherwise go to step 12 for the next unit.

Step 17. If the $\sum_{g=1}^{G}(P_{GDig}^{k+1})_{new} = P_d(t)$ then go to step 18, otherwise we must create a new particle from initialization process.

Step 18. Set the reserve power of each unit (P_{GRig}^{k+1}) for each individual i by this equation:

$$P_{GRig}^{k+1} = \begin{cases} rand \cdot (P_{Gg,\max} - (P_{GDig}^{k+1})_{new}) & if \quad (P_{GDig}^{k+1})_{new} \neq 0 \\ 0 & otherwise \end{cases} \qquad (14)$$

$g = 1,2,...,G$

Step 19. If the $\sum_{g=1}^{G} P_{GRig}^{k+1} \geq P_R(t)$ then go to step 20, otherwise go to step 18.

Step 20. The above procedure must be repeated for all of the time periods and then stop the updating process.

4) Update of Pbest and Gbest: The *Pbest* of each individual at iteration and the *Gbest* is updated with respect to the cost function.

5) Stopping Criteria: The MPSO is terminated if the iteration approaches to the predefined maximum iteration.

4. NUMERICAL TESTING RESULTS

The proposed optimization algorithm is applied to a model system to verify its effectiveness. This approach is applied to the test system, which has 10 generators. The input data for a 10-generator system are given in table 1 [9]. The annual peak load is 1500 MW and the percent of each interval time period is shown in table 2.

TABLE 1.*GENERATOR COST AND EMISSION COEFFICIENTS*

Coeff.	**Unit 1**	**Unit 2**	**Unit 3**	**Unit 4**	**Unit 5**
$P_{G,\max}$ (MW)	455	455	130	130	162
$P_{G,\min}$ (MW)	150	150	20	20	25
Fixed O&M Cost ($/Mw-yr)	5000	5000	7000	7000	7000
Variable O&M Cost ($/Mwh)	0.3	0.3	0.8	0.8	0.8
A ($/hr)	1000	970	700	680	450
B ($/Mwh)	16.19	17.26	16.6	16.5	19.7
C ($/Mwh)	0.00048	0.00031	0.002	0.00211	0.00398
Coeff.	Unit 6	Unit 7	Unit 8	Unit 9	Unit 10
$P_{G,\max}$ (MW)	80	85	55	55	55
$P_{G,\min}$ (MW)	20	25	10	10	10
Fixed O&M Cost ($/Mw-yr)	8500	10000	10000	10000	10000
Variable O&M Cost ($/Mwh)	0.9	0.8	0.9	0.9	0.9
a	370	480	660	665	670
b	22.26	27.74	25.92	27.27	27.79
c	0.00712	0.00079	0.00413	0.00222	0.00173

To assess the efficiency of the proposed MPSO, it has been applied to UC problems where the objective functions can be either smooth or non-smooth. The results obtained from the MPSO are compared with the results that are obtained by the mixed integer nonlinear programming (MINLP).

TABLE2. ***LOAD PATTERN AND RESERVE REQUIREMENT***

Period (Month)	Load (%)	Reserve Requirement(MW)	Period (Month)	Load (%)	Reserve Requirement (MW)
1	87.8	65.85	7	88	66
2	88	66	8	80	60
3	75	56.25	9	78	58.5
4	83.7	62.775	10	88.1	66.075
5	90	67.5	11	94	70.5
6	89.6	67.2	12	100	75

Tables 3 and 4 show the results of optimal generator scheduling (mid term UC) that is obtained by MINLP. The total cost of the test system in this annual scheduling is 268.98 million dollars per year. Also, figure 2 presents the results of the mid term UC of the test system.

TABLE3. ***OPTIMAL RESULT FOR MINLP SOLUTION***

Period (Month)	Contribution of Units in Load Supplying (MW)				
	1	2	3	4	5
1	455	455	130	130	127
2	455	455	130	130	130
3	455	455	130	0	85
4	455	455	130	130	85.5
5	455	455	130	130	135
6	455	455	130	130	149
7	455	455	130	130	130
8	455	455	130	130	30
9	455	430	130	130	25
10	455	455	130	130	131.5
11	455	455	130	130	162
12	455	455	130	130	162
Period (Month)	**Contribution of Units in Load Supplying (MW)**				
	6	7	8	9	10
1	20	0	0	0	0
2	20	0	0	0	0
3	0	0	0	0	0
4	0	0	0	0	0
5	20	25	0	0	0
6	0	25	0	0	0
7	20	0	0	0	0
8	0	0	0	0	0
9	0	0	0	0	0
10	20	0	0	0	0
11	53	25	0	0	0
12	80	25	53	10	0

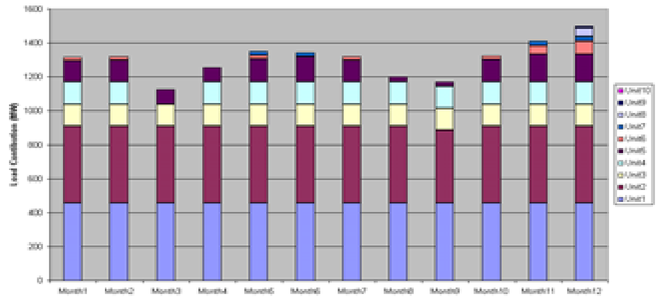

Fig. 2. Mid Term Unit Commitment Results (MINLP Solution)

TABLE4. ***OPTIMAL RESULT FOR MINLP SOLUTION***

Period (Month)	Contribution of Units in Reserve Supplying (MW)				
	1	2	3	4	5
1	0	0	0	0	35
2	0	0	0	0	32
3	0	0	0	0	56.25
4	0	0	0	0	62.775
5	0	0	0	0	7.5
6	0	0	0	0	7.2
7	0	0	0	0	32
8	0	0	0	0	60
9	0	25	0	0	33.5
10	0	0	0	0	30.5
11	0	0	0	0	0
12	0	0	0	0	0
Period (Month)	**Contribution of Units in Reserve Supplying (MW)**				
	6	7	8	9	10
1	30.85	0	0	0	0
2	34	0	0	0	0
3	0	0	0	0	0
4	0	0	0	0	0
5	0	60	0	0	0
6	0	60	0	0	0
7	34	0	0	0	0
8	0	0	0	0	0
9	0	0	0	0	0
10	35.575	0	0	0	0
11	10.5	60	0	0	0
12	0	60	2	13	0

There are several parameters to be determined for the implementation of the MPSO such as in (7) and (10) as well as in (13). In this paper these parameters have been determined through the experiments.

1) The values of $w_{\max}$ and $w_{\min}$ are assumed 1.0 and 0.1.

2) The values of c_1 and c_2 are varied from 0.1 to 1.0.

3) The value of the $\max iter$ is assumed to 50.

This study is repeated for five different sizes of population (20, 40, 60, 80 and 100). Table 5 shows the best solution of PSO at different values of constants. The best optimal solution of MPSO method is obtained at $c_1 = 0.8$, $c_2 = 0.7$ and $N = 40$. Total cost of the test system in this annual scheduling is 271.21 million dollars per year. Tables 6 and 7 show the mid term UC results of these conditions.

TABLE5. ***BEST RESULTS OF PSO FOR DIFFERENT VALUES OF CONSTANTS***

Population	c_1	c_2	Total Cost (M$)
20	0.3	0.1	272.07
40	0.8	0.7	271.21
60	0.1	0.7	271.37
80	0.7	0.1	271.6
100	0.2	0.7	271.22

5. CONCLUSIONS

This paper presents a new approach to the mid term UC problems based on the PSO algorithm. A new position adjustment strategy is incorporated in the PSO method to provide the solutions which satisfy the constraints. The equality constraint in the UC problem is resolved by the principle sharing method between the generating units. This problem is applied to a 10-unit test system and is solved using the Mixed Integer Non Linear Programming (MINLP) and the PSO methods. Numerical testing results clearly show the trade-off between minimizing cost and satisfying constraints. For a given desired cost, the particle swarm optimization method can generate a near optimal schedule.

TABLE6. ***OPTIMAL RESULT FOR PSO SOLUTION***

Period (Month)	Contribution of Units in Load Supplying (MW)				
	1	2	3	4	5
1	458.4	453.4	130	130	68.9
2	455	308	130	130	162
3	445.7	446	128.9	92.4	0
4	454.7	454.4	129.9	129.1	87.4
5	451.3	452	129.7	129.1	89.1
6	453.3	453.5	118.7	129.5	61.6
7	436.1	446.5	129.6	129.6	44.4
8	454.1	452.9	129.9	122.1	41
9	453.7	454.8	96.6	128.9	36
10	455	455	130	130	71.5
11	452.1	454.5	100.3	127.5	156.5
12	455	455	130	130	162
Period (Month)	**Contribution of Units in Load Supplying (MW)**				
	6	7	8	9	10
1	80	0	0	0	0
2	80	0	0	0	55
3	0	0	12	0	0
4	0	0	0	0	0
5	77.2	0	21.6	0	0
6	77.6	49.8	0	0	0
7	79.7	0	0	0	54
8	0	0	0	0	0
9	0	0	0	0	0
10	80	0	0	0	0
11	65.4	0	15.6	0	38.2
12	63.8	34.7	34	35.5	0

TABLE7. *OPTIMAL RESULT FOR PSO SOLUTION*

Period (Month)	Contribution of Units in Load Supplying (MW)				
	1	2	3	4	5
1	458.4	453.4	130	130	68.9
2	455	308	130	130	162
3	445.7	446	128.9	92.4	0
4	454.7	454.4	129.9	129.1	87.4
5	451.3	452	129.7	129.1	89.1
6	453.3	453.5	118.7	129.5	61.6
7	436.1	446.5	129.6	129.6	44.4
8	454.1	452.9	129.9	122.1	41
9	453.7	454.8	96.6	128.9	36
10	455	455	130	130	71.5
11	452.1	454.5	100.3	127.5	156.5
12	455	455	130	130	162

Period (Month)	Contribution of Units in Load Supplying (MW)				
	6	7	8	9	10
1	80	0	0	0	0
2	80	0	0	0	55
3	0	0	12	0	0
4	0	0	0	0	0
5	77.2	0	21.6	0	0
6	77.6	49.8	0	0	0
7	79.7	0	0	0	54
8	0	0	0	0	0
9	0	0	0	0	0
10	80	0	0	0	0
11	65.4	0	15.6	0	38.2
12	63.8	34.7	34	35.5	0

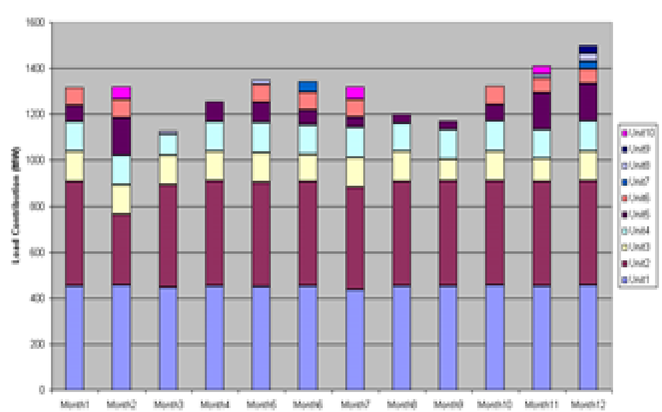

Fig. 3. Mid Term Unit Commitment Results (PSO Solution)

NOMENCLATURE

a_g, b_g, c_g The coefficients of generating unit g

c_1, c_2 Weighting factors called *acceleration constants*

D Dimension of the particle

$gbest_d^k$ Dimension d of the best particle in the swarm group until iteration k

g Index for generator unit

$iter$ Current iteration number

G Number of generator units

k The iteration number

$\max iter$ Maximum iteration

N The size of the swarm

$n(t)$ Number of hours in time t (e.g. 720 hr)

$O\&MFC(g)$ Operation and maintenance fixed cost of the unit g, in $/Mw-yr

$O\&MVC(g)$ Operation and maintenance variables cost of the unit g, in $/Mwh

$pbest_{id}^k$ Dimension d of the own best position of particle i until iteration k

$P_d(t)$ System demand at time t, in MW

$P_{Gg,\min}$ Lower limit of generation of the unit g, in MW

$P_{Gg,\max}$ Upper limit of generation of the unit g, in MW

$P_{GD}(g,t)$ Load contribution of the unit g at time t, in MW

$P_R(t)$ System reserve requirement at time t, in MW

$P_{GDig,t}^k$ Load contribution of the unit g at the iteration k and the time t in the particle i, in MW

$P_{GRig,t}^k$ Reserve contribution of the unit g at the iteration k and the time t in the particle i, in MW

$P_{GR}(g,t)$ Reserve contribution of the unit g at the time t, in MW

r_1, r_2 Random numbers, uniformly distributed in [0,1]

$rand$ Random number, uniformly distributed in [0,1]

t The index of time

T Number of periods under study (12 Month)

$U(g,t)$ The commitment state of the unit g at the time t (on = 1, off = 0)

v_{id}^k Dimension d of the velocity of the particle i at the iteration k

w Weighting function

$w_{\max}$ The final value of weighting coefficient

$w_{\min}$ The initial value of weighting coefficient

x_{id}^k Dimension d of the current position of the particle i at the iteration k

REFERENCES

[1] A. J. Wood and B. F. Wollenberg, "*Power system generation, operation and control*," 2nd ed., New York: John Wiley, 1996.

[2] Z. Ouyang and S. M. Shahidehpour, "An intelligent dynamic programming for unit commitment application," *IEEE Trans. Power System*, vol. 6, no. 3, pp. 1203–1209, Aug. 1991.

[3] H. Sasaki, *et al.*, "A solution method of unit commitment by artificial neural networks," *IEEE Trans. Power Syst.*, vol. 7, pp. 974–981, Aug. 1992.

[4] U. D. Annakkage, *et al.*, "Unit commitment by parallel simmulated annealing," *Proc. Inst. Elect. Eng., Gen. Transm. Dist.*, vol. 142, pp. 595–600, 1995.

[5] K. A. Juste, *et al.*, "An evolutionary programming solution to the unit commitment problem," *IEEE Trans. Power System*, vol. 14, no. 4, pp. 1452–1459, Nov. 1999.

[7] I. G. Damousis, *et al.*, “A solution to the unit-commitment problem using integer-coded genetic algorithm,” *IEEE Trans. Power System*, vol. 19, no. 2, pp. 1165–1172, May 2004.

[8] W. L. Peterson and S. R. Brammer, “A capacity based Lagrangian relaxation unit commitment with ramp rate constraints,” *IEEE Trans. Power Syst.*, vol. 10, no. 2, pp. 1077–1084, May 1995.

[9] A. I. Cohen and M. Yoshimura, “A branch-and-bound algorithm for unit commitment,” *IEEE Trans. Power App. System*, vol. PAS-102, no. 2, pp. 444–451, Feb. 1983.

[10] H. Mori and O. Matsuzaki, “Application of priority-list-embedded tabu search to unit commitment in power systems,” *Inst. Elect. Eng. Jpn.*, vol. 121-B, no. 4, pp. 535–541, 2001.

[11] J. Kennedy and R. C. Eberhart, “Particle swarm optimization,” *IEEE Int. Conf. Neural Net.*, Australia, pp. 1942–1948, Nov. 1995.

[12] Y. Fukuyama, *et al.*, “A particle swarm optimization for reactive power and voltage control considering voltage security assessment,” *IEEE Trans. Power Syst.*, vol. 15, pp. 1232–1239, Nov. 2000.

[13] K. A. Juste, *et al.*, “An evolutionary programming solution to the unit commitment problem,” IEEE Trans. Power Syst., vol. 14, no. 4, pp. 1452-1459, Nov. 1999.