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Adaptive PSO based Hybrid Algorithm for Unit Commitment

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Abstract: This paper presents a new hybrid algorithm based on adaptive PSO and enhanced Lagrangian relaxation technique for unit commitment. The intelligent generation of initial population, on/off decision criterion and identical unit decommiting scheme attempt to enhance the optimal solution and reduce the overall computation time. The algorithm adoptively adjusts the inertia weight and the acceleration coefficients in order to enhance the search process. Numerical results on systems up to 100 generating units demonstrate the effectiveness of the proposed strategy.

Key words: Unit commitment, particle swarm optimization, lambda iteration method, Lagrangian Relaxation.

Nomenclature:

ACT	Average Computation Time
ED	Economic Load Dispatch
EPM	EP based Method
ELRM	Enhanced LRM
FLAPC	Full Load Average Production Cost
GAM	GA based Method
LRM	Lagrangian Relaxation Method
LRGAM	combined LR and GA based method
PSO	Particle Swarm Optimization
PHM	Proposed Hybrid Method
UC	Unit Commitment
a, b, c	fuel cost coefficients
C	dynamic coefficient
CST_i	cold start up cost of unit-i (\$)
$D(\lambda, \mu)$	dual function
c_1 & c_2	acceleration coefficients
$F(P_i^t)$	generator fuel cost function (\$/hr)
G	relative duality gap
HST_i	hot start up cost of unit-i (\$)
$J(P, U)$	primal function
K^{max}	iteration counter
$L(P, U, \lambda, \mu)$	Lagrangian function
N	number of generating units
n	number of particles in the population
P_i^{min} & P_i^{max}	minimum and maximum real power generation of unit i respectively
P_i^t	real power generation of unit-i at hour-t
P^t_{load}	load demand at hour-t

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(P^*, U^*)	optimal solution of the primal problem
R^t	spinning reserve at hour-t
r_1 & r_2	uniformly distributed random numbers in the range of [0,1]
ST_i^t	startup cost of unit-i at hour-t
T	total number of hours
T_i^{cold}	cold start hour of unit-i (hours)
T_i^{down}	minimum down time of unit-i (hours)
T_i^{off}	continuously off time of unit-i (hours)
T_i^{on}	continuously on time of unit-i (hours)
T_i^{up}	minimum up time of unit-i (hours)
$U_{i,t}$	on/off status of unit-i at hour-t
$V_i(k)$	velocity of i^{th} moving particle
$V^{j,\max}$	velocity limiter of the j^{th} dimension of the particle
$w(k)$	inertia weight
$X_i(k)$	candidate solution of the i^{th} particle
$X^{j,\min}, X^{j,\max}$	minimum and maximum of the j^{th} dimension of the particle
$X^*(k)$	particle best
$X^{**}(k)$	global best
α	decrement constant smaller than but close to 1
ε	a small positive number
λ and μ	Lagrange multipliers
$\Phi(P, U)$	cost function to be minimized over the scheduling period
(λ^*, μ^*)	optimal solution of the dual problem
superscripts *ini* & *fin*	initial and final values respectively

INTRODUCTION

Unit Commitment (UC) has significant influence on secure and economic operation of power systems. Optimal commitment scheduling can save huge amount of costs to electric utilities and improve reliability by keeping proper spinning reserves. The UC problems involve scheduling on/off states of generating units, which minimizes the operating cost, start-up cost and shut-down cost for a given horizon under various operating constraints. In the UC problem, the decisions are the selection of the time for each unit to be on and/or offline as well as the unit's economic generation level. Thus, the UC problem can be formulated as a non-linear, large-scale, mixed-integer combinatorial optimization problem, which is quite difficult due to its inherent high dimensional, non-convex, discrete and nonlinear nature (Wood, 1996). Over the years numerous methods with various degrees of near-optimality, efficiency, ability to handle difficult constraints and heuristics, have been suggested in the literature. At one end of the spectrum, there are simple and fast but highly heuristic priority list (Happ, 1971; Baldwin, 1960) methods. At the other end, there are dynamic programming (Snyder, 1987; Hobbs, 1982) and branch-and bound (Dillon 1978; Cohen, 1983), which are in general flexible but often prone to the curse of dimensionality. Between the two extremes, there are Lagrangian relaxation methods (LRM) (Lee, 1989; Cheng, 2000), which are efficient and appear to be a desirable compromise, and well suited for large-scale UC. However, they take a large computation time when using single-unit dynamic programming to find the optimal path of each unit over the planning period. Moreover, they are not effective when identical units exist. In addition the solution quality heavily depends on the initial Lagrangian multipliers and the procedure of updating them. An enhanced adaptive LRM (EALRM) and heuristic search has been proposed (Weerakorn Ongsakul, 2004).

Methods such as genetic algorithms (Kazarlis, 1996; Senjyu, 2003) simulated annealing (Simopoulos, 2006), evolutionary programming (Juste, 1999) and particle swarm optimization (PSO) (Yun-Won Jeong, 2010; Zhao, 2006; Yuan, 2009) have been applied in solving UC. Having in common processes of natural evolution, these algorithms share many similarities; each maintains a population of solutions that are evolved through random alterations and selection. The differences between these procedures lie in the representation techniques they utilize to encode candidates, the type of alterations they use to create new solutions, and the mechanism they employ for selecting the new parents. The algorithms have yielded satisfactory results across a great variety of power system problems. The main difficulty is their sensitivity to the choice of the parameters, such as temperature in SA, the crossover and mutation probabilities in GA and the inertia weight, acceleration coefficients and velocity limits in PSO. There exists a need for evolving simple and effective methods for obtaining optimal solution for the UC problem.

An adaptive PSO based hybrid algorithm involving EALRM to solve UC problem efficiently with a view to enhance the search process and the computational speed has been suggested in this paper. The developed strategy has been tested to demonstrate the performance on systems up to 100 generating units and the results presented.

2. Problem Description:

The main objective of UC problem is to minimize the overall system production cost over the scheduled time horizon under the spinning reserve and operational constraints of generator units. This constrained optimization problem is formulated as

Minimize

$$\Phi(P,U) = \sum_{t=1}^{T}\sum_{i=1}^{N}\left\{F_i(P_i^t) + ST_i^t\left(1-U_{i,t-1}\right)\right\}U_{i,t} \tag{1}$$

where

$$F_i(P_i^t) = a_i P_i^{t2} + b_i P_i^t + c_i$$

Subject to

Power balance constraint

$$P^t{}_{load} - \sum_{i=1}^{N} P_i^t\, U_{i,t} = 0 \tag{2}$$

Spinning reserve constraint:

$$P^t{}_{load} + R^t - \sum_{i=1}^{N} P_i^{\max}\, U_{i,t} \le 0 \tag{3}$$

Generation limit constraints:

$$P_i^{\min} U_{i,t} \le P_i^t \le P_i^{\max} U_{i,t} \tag{4}$$

$$i = 1, 2, \cdots, N$$

Minimum up and down time constraints:

$$U_{i,t} = \begin{cases} 1 & if \;\; T_i^{on} < T_i^{up} \\ 0 & if \;\; T_i^{off} < T_i^{down} \\ 0 \; or \; 1 & otherwise \end{cases} \tag{5}$$

Startup Cost:

$$ST_i = \begin{cases} HST_i & if \;\; T_i^{down} \le T_i^{off} \le T_i^{cold} + T_i^{down} \\ CST_i & if \;\; T_i^{off} > T_i^{cold} + T_i^{down} \end{cases} \tag{6}$$

3. Adaptive Particle Swarm Optimization:

PSO was introduced by Kennedy and Eberhart as a modern heuristic optimizer. It is a population-based stochastic optimization technique modeled on swarm intelligence. Swarm-intelligence, also referred to as collective intelligence, is based on social-psychological principles and provides insights into social behavior, as well as contributing to engineering applications. The PSO system combines a social-only model and a cognition-only model (Kennady, 1995).

In this approach, a population of *m*-individuals, called particles *(X)k*, is initialized with random guesses in the problem space. Each particle represents a candidate solution to the problem at hand. These particles fly around in a multidimensional search space with a velocity, *V(k)*.

These particles share their information with each other and run toward best trajectory to find optimal solution in an iterative process. In each iteration, the velocity and the position of particles are updated by

$$\begin{aligned} V_i(k) = w(t).V_i(k-1) + \\ c_1 r_1 \left\{ X_i^*(k-1) - X_i(k-1) \right\} + \\ c_2 r_2 \left\{ X^{**}(k-1) - X_i(k-1) \right\} \end{aligned}$$

$$i = 1, 2, \cdots, n \tag{7}$$

$$X(k) = X(k-1) + V(k) \tag{8}$$

The inertia weight *w(k)* is gradually decreased during the iterative process using the relation

$$w(k) = \alpha \cdot w(k-1) \tag{9}$$

The iterative process of updating the particle positions and velocities based on the objective function values is continued until the desired conditions are satisfied.

The time varying inertia weight that is linearly reduced during the iterations in order to enhance the computational efficiency is suggested in (Chaturvedi, 2008) instead of using Eq. (9).

$$w(k) = \left(w^{fin} - w^{ini} \right) \times \left(\frac{K^{\max} - k}{K^{\max}} \right) + w^{ini} \tag{10}$$

The time-varying acceleration coefficients are introduced in (Ratnaweera, 2004) with a view to efficiently control the search process and convergence to the global solution. A large cognitive component and small social component at the beginning allows particles to move around the search space instead of prematurely moving towards the population best. A small cognitive component and a large social component during the latter stage allow the particles to converge to the global optimum.

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$$c_1 = \left(c_1^{fin} - c_1^{ini}\right)\left(\frac{k}{K^{\max}}\right) + c_1^{ini}, \quad c_1^{fin} < c_1^{ini}$$
$$c_2 = \left(c_2^{fin} - c_2^{ini}\right)\left(\frac{k}{K^{\max}}\right) + c_2^{ini}, \quad c_2^{fin} > c_2^{ini} \tag{11}$$

In the conventional PSO, a fixed velocity limiter, which prevents particles moving too rapidly from one region in search space to another, for each dimension is usually considered as a proportion of the allowable position range. However selecting a proper velocity limiter is difficult, especially for complex problems. A higher velocity limiter is usually required for initial stages of the search process so that the particles can search different regions of the solution space. On the other hand, a lower velocity limiter is preferred for the final stages of the search process in order to obtain a better convergence. The selection of this value is nontrivial and very important in view of obtaining better overall performance of the algorithm. The following velocity limiter that adaptively sets the maximum allowable velocity (Nma Amjady, 2010) offers good exploration capability and convergence behavior.

$$V^{j,\max} = R \times (X^{j,\max} - X^{j,\min}) \tag{12}$$

where

$$R = R^{ini} + (R^{fin} - R^{ini})\left(\frac{k}{K^{\max}}\right), \qquad R^{ini} > R^{fin} \tag{13}$$

In the proposed formulation, the inertia weight, acceleration coefficients and maximum velocity limiter are adaptively changed with a view of enhancing the computational efficiency, improving the search capabilities and obtaining the global optimal solution.

4. Proposed Algorithm:

LR solves the UC problem by ignoring the coupling constraints temporarily and solving the problem as if they did not exist. The LR decomposition procedure, based on dual optimization procedure, generates a separable problem, known as dual and primal sub-problems, by integrating the coupling constraints into the objective function through functions of the constraint violation with Lagrange multipliers, while minimizing with respect to UC control variable. The Lagrangian function can be formulated as

$$L(P,U,\lambda,\mu) = \Phi(P,U) \quad + \sum_{t=1}^{T} \lambda^t \left[P^t{}_{load} - \sum_{i=1}^{N} P_i^t U_{i,t} \right]$$
$$+ \sum_{t=1}^{T} \mu^t \left[P^t{}_{load} + R^t - \sum_{i=1}^{N} P_i^{\max} U_{i,t} \right] \tag{14}$$

Where λ and μ are Lagrange multipliers defined as

$$\lambda = [\lambda^1, \lambda^2, \lambda^3 \cdots, \lambda^T], \quad \mu = [\mu^1, \mu^2, \mu^3 \cdots, \mu^T] \tag{15}$$

The primal function is defined as

$$J(P,U) = \underset{P,U}{Min}\, \Phi(P,U) \tag{16}$$

and the dual function is defined as

$$D(\lambda,\mu) = \underset{P,U}{Min}\, L(P,U,\lambda,\mu) \tag{17}$$

Then the dual problem is to find

$$D^*(\lambda,\mu) = \underset{\mu\geq 0,\lambda}{Max}\, D(\lambda,\mu) \tag{18}$$

Suppose that (P^*, U^*) and (λ^*, μ^*) are the optimal solutions to the primal and dual problems respectively, then it holds the following.

$$D(\lambda^*,\mu^*) \leq J(P^*,U^*) \tag{19}$$

Besides it satisfies

$$G = \frac{J(P^*,U^*) - D(\lambda^*,\mu^*)}{J(P^*,U^*)} \leq \varepsilon \tag{20}$$

Though LRM provides a fast solution, it suffers from convergence and solution quality problems. Besides, it requires good initial estimate and skillful updating procedure for Lagrangian multipliers in order to obtain optimal solution.

The PSO algorithm provides global solution but is a time consuming process as it is initialized with random starting values. Recently hybrid methods involving LR approaches and evolutionary algorithms such as GA and PSO (Cheng, 2000; Balci, 2004) are suggested to solve the UC problem. The optimal Lagrange multipliers are obtained by evolutionary algorithms, while the Lagrange function is solved by dynamic programming for UC control variables. They suffer from the drawbacks of random generation of initial population and the problems associated LR approaches. This paper proposes an adaptive PSO based hybrid approach involving the enhanced LR (Weerakorn Ongsakul, 2004) that uses a new scheme for generating initial population, a novel on/off decision criterion, unit classification and identical marginal unit decommitment, with a view to over come the drawbacks of the existing approaches.

4.1 Unit Classification:

The generation units can be classified into three types.

1. Base load units with low operation cost, high startup costs and long up/down times.
2. Intermediate load units with medium operating cost, medium startup costs and medium up/down times.
3. Peak load units with high operating cost, low startup costs and short up/down times

The base load units should not be shut down. Intermediate units could be committed during on-peak and decommitted during off-peak periods. Finally peak load units could be frequently turned on/off.

4.2 Representation of PSO Variables:

The dual variables λ & μ are considered as the PSO variable. Each particle is therefore represented as shown in Fig. 1

λ^1	λ^2	λ^3	- - -	λ^3	μ^1	μ^2	μ^3	- - -	μ^T

Fig. 1: Representation of a particle.

4.3 Generating Initial Population:

It is difficult to generate feasible solution when initial population is generated at random. The procedure (Weerakorn Ongsakul, 2004) described below, intends to create a good starting solution, is used to form the initial population.

1. Sort the generating units in ascending order of full load average production cost (FLAPC) and commit the groups of identical units with least FLAPC one by one unit until the power balance constraint is satisfied for each interval. Then carry out ED to obtain equal lambda, λ^t, at each interval.

2. Compute μ_i^t for each committed unit at every interval

$$\mu_i^t = Max\left(0, \frac{1}{P_i^{\max}}\left[F_i(P_i^t) + \frac{CST_i}{T_i^{up}} - \lambda^t P_i^t\right]\right)$$

3. Obtain the highest μ^t among the committed units.

$$\mu^t = Max[\mu_1^t, \mu_2^t, \mu_3^t \cdots, \mu_N^t]$$

4. Use the values obtained in steps (i) and (iii) for λ & μ to form a particle and then perturb them randomly to generate the remaining particles in the initial population.

4.4 On/Off Decision Criterion:

The computation time of conventional LR method, while solving dynamic programming to obtain dual solution, increases linearly with N and T. The following on/off decision criterion to solve the unit sub problem enhances the computational speed.

1. Solve $P_i^t = \dfrac{\lambda^t - b_i}{2c_i}$ subject to $P_i^{\min} \le P_i^t \le P_i^{\max}$

2. Compute A_i^t for each unit-*i*.

$$A_i^t = \left[F_i(P_i^t) + ST_i^t\left(1 - U_{i,t-1}\right)/T_i^{up} - \lambda^t P_i^t - \mu^t P_i^{\max}\right]$$

3. If $A_i^t \le 0$, commit the unit-*i*, $U_{i,t} = 1$.

Else decommit the unit-*i*, $U_{i,t} = 0$.

4.5 Identical Marginal Unit Decommitment:

The conventional LR method simultaneously commits/decommits a group of units that have identical characteristics. This will lead to suboptimal solution because committing one unit at a time will be less expensive than committing a whole group of units. The following procedure decommits one unit at a time to avoid over commitment.

1. Set t = 1.
2. Sort the committed units excluding the base load units in the descending order of the negative value of A_i^t to obtain the sorted set SS^t .
3. Set the first unit in the sorted set be CU^t . If the SS^t has only one unit, go to step-viii.
4. Calculate the excess spinning reserve of the hour-*t*.
5. If the excess spinning reserve is less than maximum generation of CU^t , go to step-viii.
6. If decommitting CU^t violates its minimum uptime constraint, go to step (viii).
7. Decommit CU^t and delete it from the set SS^t and update $\left[U_{i,t}\right]$ and return to step-iii
8. If $t < T$, $t = t + 1$ and return to step-ii.

4.6 Economic Load Dispatch:

The economic load dispatch is an intensive computational part in UC problem. It is solved using lambda iteration method (Wood, 1996) based on the principle of equal incremental cost as the fuel cost is represented by a quadratic cost function. Lambda iteration method is carried out for various generating unit schedules of each particle using the expression.

$$P_i^t = \frac{\lambda^t}{2a_i + b_i} \tag{21}$$

4.7 Cost Function:

The PSO searches for the optimal solution by minimizing a cost function. The relative duality gap, *G*, Eq. (20), is considered as the cost function to be minimized while searching for the best particle in the proposed approach.

4.8 Stopping Criteria:

The process of generating new particles can be terminated either after a fixed number of iterations or if there is no further significant improvement in the global best solution.

4.9 Algorithm:

The flow of the proposed hybrid algorithm (PHA) for solving the UC problem is outlined.

1. Read the input data of the UC problem
2. Choose population size, *m*, and other PSO parameters
3. Initialization
   a Set $k = 0$
   b Classify the units into base, intermediate and peak load units following the procedure described in section 4.1.
   c Generate initial population consisting *m* particles following the scheme outlined in section 4.3.
   d Randomly generate *m* initial velocity values.

4. $k = k + 1$
5. For each particle, perform the following.
   a Solve the unit subproblem using the on/off decision criteria described in section 4.4.
   b Check whether the dual solution is feasible, that is, check for constraint violation of Eqs. 2 and 3. If not feasible, randomly alter the particle till it becomes feasible.
   c Carryout identical marginal unit decommitment procedure explained in section 4.5.
   d Carry out the economic load dispatch.
   e Calculate the primal cost, *J(P, U)*, dual cost, *D(λ, μ)* and relative duality gap, *G*.
6. Search for particle best and global best positions based on the relative duality gap *G*, which is to be minimized and store them.

7. Obtain values for $w(k), c_1 \& c_2$ and $V^{j,\max}$ using Eqs. 10, 11 and 12.

8. Update particle velocity subject to the respective velocity limit and positions using Eqs. 7 and 8.
9. Check for convergence. If converged, stop and print the optimal solution *(P*, U*)* corresponding to the global best position. Otherwise, go to step-4.

Table 1: Comparison of fuel cost

Number of units	Best Fuel Cost ($)					
	LRM [11]	EALRM [10]	GAM [11]	EPM [14]	LRGAM [9]	PHA
10	565825	565508	565825	564551	564800	563938
20	1130660	1126720	1126243	1125494	1122622	1123607
40	2258503	2249790	2251911	2249093	2242178	2245557
60	3394066	3371188	3376625	3371611	3371079	3366676
80	4526022	4494487	4504933	4498479	4501844	4482826
100	5257277	5615893	5627437	5623885	5613127	5602388

5. Simulation Results:

The PHA has been tested on systems with 10, 20, 40, 60, 80 and 100 generating units. The unit data and load demand data for 24 hours for the system with 10 units are given in Table 1 and 2 respectively (Yun-Won Jeong, 2010). The data for other larger systems are obtained by duplicating the data of 10 unit system and adjusting the load demand in proportion to the system size. The population size is chosen as 30 for all the test

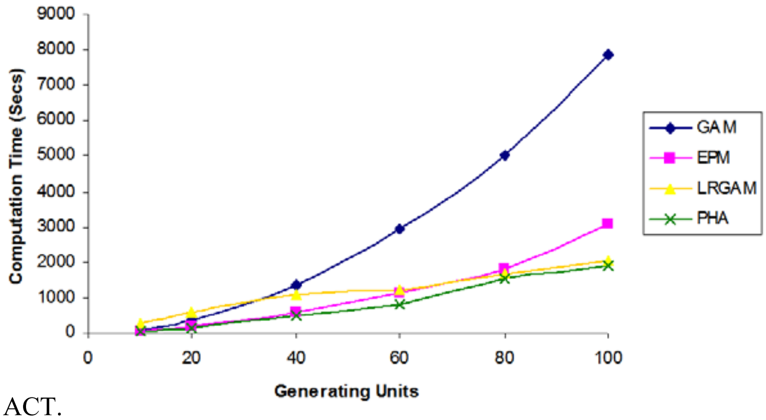

Fig. 2: Comparison of ACT.

problems. The maximum number of generations for convergence check is taken as 600, 1200, 2500, 3000, 5000 and 6000 for 10,20,40,60,80 and 100 unit system respectively. The results of the PHA is compared with LRM (Kazarlis, 1996), EALRM (Weerakorn Ongsakul, 2004), genetic algorithm based method (GAM) (Kazarlis, 1996), evolutionary programming based method (EPM) (Juste, 1999) and combined LR and GA based method (LRGAM) (Cheng, 2000) in order to validate the results in Table 1. The analysis of this table obviously indicates that the PHA offers global optimal solution that corresponds to lower production cost than that of other methods. The PHA is therefore ideally suitable for practical implementations.

The average computation time (ACT) of the PHA is graphically compared with evolutionary algorithms of GAM, EPM and LRGA in Fig. 2. The computation times given in articles (Kazarlis, 1996) and (Juste, 1999) for GAM, EPM and LRGA were measured before a decade and hence are suitably scaled down using a factor of 0.5 with a view to compare with the computation times of PHA executed using the present day fast computers. From this figure, it is very clear that the PHA is reasonably faster than the other two methods.

7. Conclusions:

A hybrid algorithm based on PSO and enhanced LR technique has been proposed for unit commitment in this paper. This method exploits the advantages of both the PSO and enhanced LR and provides global optimal solution. The results on various test systems clearly indicate the effectiveness of the proposed algorithm. This method is ideally suitable for practical implementations.

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Appendix:

Table 1: Unit data for the 10 unit system

	Unit 1	Unit 2	Unit 3	Unit 4	Unit 5	Unit 6	Unit 7	Unit 8	Unit 9	Unit 10
P^{max}	455	455	130	130	162	80	85	55	55	55
P^{min}	150	150	20	20	25	20	25	10	10	10
a	1000	970	700	680	450	370	480	660	665	670
b	16.19	17.26	16.6	16.5	19.7	22.26	27.74	25.92	27.27	27.79
c	0.00048	0.00031	0.002	0.00211	0.00398	0.000712	0.00079	0.00413	0.00222	0.00173
T^{up}	8	8	5	5	6	3	3	1	1	1
T^{down}	8	8	5	5	6	3	3	1	1	1
HST	4500	5000	550	560	900	170	260	30	30	30
CST	9000	10000	1100	1120	1800	340	520	60	60	60
T^{cold}	5	5	4	4	4	2	2	0	0	0
Initial status	8	8	-5	-5	-6	-3	-3	-1	-1	-1
FLAPC	18.57	19.533	22.245	22.005	23.122	27.455	34.059	38.147	40.582	40.067

Table 2: Load demand data

Hour	1	2	3	4	5	6	7	8	9	10	11	12
Load (MW)	700	750	850	950	1000	1100	1150	1200	1300	1400	1450	1500
Hour	13	14	15	16	17	18	19	20	21	22	23	24
Load (MW)	1400	1300	1200	1050	1000	1100	1200	1400	1300	1100	900	800

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