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A PROFIT-BASED UNIT COMMITMENT USING DIFFERENT HYBRID PARTICLE SWARM OPTIMIZATION FOR COMPETITIVE MARKET

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ABSTRACT

This paper proposes two approaches for optimal scheduling of unit commitment (UC) considering reserve generating for competitive market. The particle swarm optimization (PSO) technique is used to find out the solution of both optimal UC and power generation problems, simultaneously. The two proposed approaches depend on various sigmoid functions to obtain the binary values PSO. The first approach takes the fuzzification of generation costs as a sigmoid function; while the second approach takes the fuzzification of power generation as sigmoid function. A proposed objective function is presented dependent on the exponential form which leads to fast convergence of PSO solution. This objective aims to minimize the generation costs as well as maximize their own profit while all load demand and generation reserve are satisfied. Hence, the generations companies (GENCO) schedule their generators with objective maximize their own profit with regard for system social benefit. This means that, this objective helps GENCO to make a decision, how much power and reserve should be sold in markets and how to schedule generators in order to receive the maximum the profit. Different comparisons are carried out using various standard test systems to show the capability of the two proposed sigmoid approaches and the proposed objective function compared with other techniques.

يقدم هذا البحث أسلوبان مقترحان للجدولة المثلي لوحدات التوليد مع الأخذ في الاعتبار القدرة الاحتياطية لوحدات التوليد في السوق التنافسية حيث تم استخدام طريقة مثلي للأسراب (SWARM) لإيجاد الحل الأمثـل لمشـكلة جدولة إشراك وحدات التوليد ومشكلة التوزيع الاقتصادي لتلك الوحدات. أعتمد الأسلوبان المقترحان علي معادلتين جديدتين لإيجاد القيمة الثنائية (Sigmoid) . الأسلوب الأول أعتمد على الشكل الغيمي لدالة التكاليف، بينما اعتمد الأسلوب الثاني على الشكل الغيمي لقيم قدرات التوليد للنظام.

كما تم اقتراح دالة هدف تعتمد على الشكل الأسى الذي أدي إلي تقارب سريع في الحل باستخدام الطريقة المثلـي للأسراب وكذلك تقليل تكاليف التوليد مع زيادة الربحية لشركات التوليد وتحقيق الطلب والفائض للقدرة الاحتياطية للمولدات، حيث أن شركات التوليد تقوم بجدولة إشراك وحدات التوليد للحصول على أعلي ربحية لها مع تحقيـق قيود النظام الخاصة بجدولة إشراك تلك الوحدات.

تم في هذا البحث العديد من المقارنات مختلفة باستخدام نظم كهربية قياسية متعددة لتوضيح قدرة وكفاءة الأسلوبين المقترحين وكذلك دالة الهدف المقترحة مقارنة بطرق أخري.

Keywords: Hybrid particle swarm optimization (HPSO), bidding strategies, competitive auction markets, unit commitment, optimization methods, power generation dispatch.

1. INTRODUCTION

Electricity traders make bids and offers that are matched subject to the approval of an independent contract administrator (ICA) who ensures that the system is operating safely within limits. Traditional power system operation, planning, and control need changes. In the past, utilities had to produce power to satisfy their customers with the minimum production cost. That means utilities run UC with the condition that all demand and reserve must be met. After the structure changed; however, they are more competitive under deregulation. The objective of UC is not to minimize costs as before, but to make the maximum profit for company. Generation companies (GENCO) can now consider the amount of power is sold on the market as well as generator scheduling plan that create the maximum profit without regard that demand and reserve have been completely met or not.

A survey of literature on UC methods reveals that various numerical optimization techniques have been employed to address the UC problems. Specifically, there are priority list methods [1], integer programming [2], dynamic programming [3], mixed-integer programming [4], branch-and-bound methods [5], and Lagrangian relaxation methods [6]. There is another class of numerical techniques applied to the UC problem Meta-heuristic approaches include expert systems (ES) [7], fuzzy logic (FL) [8], artificial neural networks (ANNs) [9], genetic algorithm (GA) [10], evolutionary programming (EP) [11], simulated annealing (SA) [12], and tabu search (TS) [13]. These methods can accommodate more complicated constraints and are claimed to have better solution quality.

Among these methods, the priority list method is simple and fast, but the quality of final solution is not guaranteed (but the quality of solution is low). Dynamic programming method which is based on priority list method is flexible. This method has many advantages such as its ability to maintain solution feasibility. Nevertheless, this method has dimensional problem with a large power system because the problem size increases rapidly with the number of generating units to be committed, which results in an unacceptable solution time. Branch-and-bound adopts a linear function to represent the fuel consumption and time-dependent start cost and obtains the required lower and upper bounds. The disadvantage of the branch-and-bound method is the exponential growth in the execution time with the size of the UC problem. The integer and mixed-integer methods adopt linear programming technique to solve and check for an integer solution. These methods have only been applied to small UC problems and have required major assumptions that limit the solution space. The Lagrangian relaxation method provides a fast solution, but it may suffer from numerical convergence and solution quality problems.

SA is a powerful, general-purpose stochastic optimization technique, which can theoretically converge asymptotically to a global optimum solution with probability 1. One main drawback, however, of SA is that it takes a large CPU time to find the near-global minimum. GAs is a general-purpose stochastic and parallel search methods based on the mechanics of natural selection and natural genetics. It is a search method and has the potential of obtaining a near-global minimum.

The PSO approach is motivated from the social behavior of bird flocking and fish schooling. Kennedy and Eberhart introduced PSO in 1995 in terms of social and cognitive behavior. The PSO has been widely used as a problem-solving method in engineering and computer science. Some examples of PSO application in the area of electric power systems, PSO seems to be gaining popularity. The PSO has been used to solve the optimal power flow problem [14], the reactive power and voltage control problem [15], and the distribution state estimation problem [16].

In solving the unit commitment problem, generally two basic decisions are involved, namely the ‘unit commitment’ (UC) decision and the ‘economic dispatch’ (ED) decision. The UC decision involves the determination of the generating units to be running during each hour of the operation and planning horizon, considering system capacity requirements, including the reserve, and the constraints on the start up and shut down of units. The ED decision involves the allocation of the system demand and spinning reserve capacity among the operating units during each specific hour of operation.

This paper proposes two approaches based on hybrid particle swarm optimization (HPSO) approaches in solving the UC problem. The main different of the two approaches are in binary decision. A proposed objective function is presented dependent on the exponential form which leads to fast convergence of PSO solution.

This paper is organized as follows. Part 2 describes the particle swarm optimization technique. Part 3 briefly describes the profit-based UC problem in the competitive environment. Part 4 discusses implications of the updated UC on bidding strategies. Part 5 describes the proposed approaches. Part 6 describes the proposed procedure. Part 7 presents the results of some illustrative examples. Finally, Part 8 provides some conclusions and identifies areas of future work.

2. PARTICLE SWARM OPTIMIZATION

Particle swarm optimization is a computing technique introduced by Kennedy and Eberhart in 1995, which was inspired by the social behavior of bird flocking or fish schooling (Reynolds, 1987). They theorize that the process of cultural adaptation can be summarized in terms of three principles: evaluate, compare and imitate. An organism, a bird in PSO, evaluates its neighbors, compares itself to others in the population and then imitates only those neighbors who are superior [17]. PSO is inspired by particles moving around in the search space. The individuals in a PSO thus have their own positions and velocities. These individuals are denoted as particles. Traditionally, PSO has no crossover between individuals, has no mutation, and particles are never substituted by other individuals during the run [18]. The update of the particles is accomplished to calculate a new velocity for each particle (potential solution) based on its previous velocity (v_{id}), the particle's location at which the best fitness so far has been achieved ($pbest_{id}$), and the population global location ($gbest_d$) at which the best fitness so far has been achieved. Then, each particle’s position in the solution hyperspace is updated. The modified velocity and position of each particle can be calculated using the current velocity and distance from $pbest_{id}$ to $gbest_d$ as shown in the following equations, [17]:

$$v_{id}^{(tn+1)} = w.v_{id}^{(tn)} + c_1.rand_1(.).(pbest_{id} - x_{id}^{(tn)}) + c_2.rand_2(.).(gbest_d - x_{id}^{(tn)}) \quad (1)$$

$$x_{id}^{(tn+1)} = x_{id}^{(tn)} + v_{id}^{(tn+1)} \quad (2)$$

Velocity of particle i at iteration t ; in d-dimensional space is limited by: $v_{d,\min} < v_{id}^{(tn)} < v_{d,\max}$, Appropriate selection of inertia weight in (1) provides a balance between global and local explorations. As originally developed, often decreases linearly during a run. In general, the inertia weight factor (w) is set to the following equation:

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{iter_{\max}} iter \quad (3)$$

The velocity of particle i in d-dimensional space is limited by some maximum value, $v_{d,\max}$. This limit enhances the local exploration of the problem space and it realistically simulates the incremental changes of human learning. To ensure uniform velocity through all dimensions, the maximum velocity in the d-dimension is presented as:

$$v_{d,\max} = \frac{x_{di,\max} - x_{di,\min}}{Nt} \quad (4)$$

3. PROFIT-BASD UC PROBLEM FORMULATION

A profit-based UC (PBUC) problem under competitive environment is presented as an optimization procedure which can be formulated mathematically by the following equations:

The objective function of PBUC is to maximize the profit (i.e. revenue minus cost) subject to all prevailing constraints [10]:

$$Max \;\; PF = RV - TC \quad (5)$$

In a restructured system, GENCO sells power in energy market and sells reserve in the reserve (ancillary) market. The amount of power and reserve sold depend on the way reserve payments are made. In this paper the payment for reserve allocated is presented [19]. Using this method, GENCO receives the reserve price per unit for every time period that the reserve is allocated and not used. When the reserve is used, GENCO receives the spot price for the reserve that is generated. In this method, reserve price is much lower than the spot price. Revenue and costs in (5) can be calculated from:

$$RV = \sum_i^N \sum_t^T SP_t.P_{it} + \sum_i^N \sum_t^T ((1-r)RP_t + r.SP_t)R_{it}.U_{it} \quad (6)$$

$$TC = \sum_i^N \sum_t^T [(1-r).F(P_{it}) + r.F(P_{it} + \mathrm{R}_{\mathrm{it}})].\mathrm{U}_{\mathrm{it}} + SUC_{it}.(1-\mathrm{U}_{\mathrm{it}}).\mathrm{U}_{\mathrm{it}} + SDC_{it}.(1-\mathrm{U}_{\mathrm{it}}).\mathrm{U}_{\mathrm{i,(t-1)}} \quad (7)$$

The generator fuel-cost function can be expressed as:

$$F(P_{it}) = a_i + b_i..P_{it} + c_i.P_{it}^2 \quad (8)$$

where, a_i, b_i and c_i present the unit cost coefficient.

Subject to:

1) Demand Constraint:

$$\sum_{i=1}^N P_{it}U_{it} \le D_t^{'} \qquad t=1,\dots,T \quad (9)$$

2) Reserve Constraint:

$$\sum_{i=1}^N R_{it}U_{it} \le SR_t^{'} \qquad t=1,\dots,T \quad (10)$$

However, the power demand and reserve constraints are different from traditional UC problem because GENCO can now select to produce demand and reserve less than the forecasted level if it creates more profit.

3) Power generation and reserve limits:

$$P_{i\min} \le P_{(i,t)} \le P_{i\max} \qquad i=1,\dots,N \quad (11)$$

$$0 \le R_{(i,t)} \le P_{i\max} - P_{i\min} \qquad i=1,\dots,N \quad (12)$$

4) Minimum Up and Down time Constraints:

$$[\mathrm{X}_{(i,t-1)}^{on} - \mathrm{T}_i^{on}][\mathrm{U}_{(i,t-1)} - \mathrm{U}_{it}] \ge 0 \quad (13)$$

$$[\mathrm{X}_{(i,t-1)}^{off} - \mathrm{T}_i^{off}][\mathrm{U}_{it} - \mathrm{U}_{(i,t-1)}] \ge 0 \quad (14)$$

Start-up cost is calculated from

$$SUC_{it} = \begin{cases} \mathrm{HSC}_i, & \mathrm{X}_{(i,t-1)}^{off} \le \mathrm{T}_i^{off} + CH_i \\ CSC_i, & \mathrm{X}_{(i,t-1)}^{off} > \mathrm{T}_i^{off} + CH_i \end{cases} \quad (15)$$

4. OPTIMAL UC SCHEMES

Two hybrid particle swarm optimization (HPSO) approaches in solving the UC problem are proposed. The main different of the two approaches are in binary decision.

4.1. Based HPSO Method [40]

The original version of PSO operates on real values. The term “hybrid particle swarm optimization” was first mentioned in [20], whereby the term hybrid meant the combination of PSO and GA. However, in this approach, hybrid is meant to highlight the concept of blending real valued PSO (solving economic load dispatch (ELD)) with binary valued PSO (solving UC) running independently and simultaneously. The binary PSO (BPSO) is made possible with a simple modification to the particle swarm algorithm. This BPSO solves binary problems similar to those traditionally optimized by GAs. Kennedy and Eberhart [21] showed that the binary particle swarm was able to successfully optimize the De Jong [22] suite of test functions. Further, Kennedy and Spears [23] compared the binary particle swarm algorithm to GAs comprising crossover only, mutation only, and both crossover and mutation, in Spears' multimodal random problem generator. It was seen that the particle swarm found global optima faster than any of the three kinds of GAs in all conditions except for problems featuring low dimensionality. In binary particle swarm, X_i and $Pbest$ can take values of 0 or 1 only. The V_i velocity will determine a probability threshold. If V_i is higher, the individual is more likely to choose 1, and lower values favor the 0 choice. Such a threshold needs to stay in the range [0.0, 1.0]. One straightforward function for accomplishing this is common in neural networks. The function is called the sigmoid function and is defined as follows:

$$\mu(V_i) = \frac{1}{1+\exp(V_i)} \tag{16}$$

The function squashes its input into the requisite range and has properties that make it agreeable to be used as a probability threshold. Random number (drawn from a uniform distribution between 0.0 and 1.0) is then generated, whereby X_i is set to 1 if the random number is less than the value from the sigmoid function as illustrated in the following equation:

$$\text{If } Rand() < \mu(V_i), \text{ then } U_i = 1, \text{ else } U_i = 0 \tag{17}$$

In the UC problem, U_i represents the on or off state of generator i. In order to ensure that there is always some chance of a bit flipping (on and off of generators); a constant V_{max} can be set at the start of a trial to limit the range of V_i. A large V_{max} value results in a low frequency of changing state of generator, whereas a small value increases the frequency of on/off of a generator. In practice, V_{max} is often set at ±4.0, so that there is always at least a good chance that a bit will change state. The $\mu(V_i)$ does not approach too close to 0.0 or 1.0. In this binary model, V_{max} functions similarly to the mutation rate in GAs.

4.2. First Proposed HPSO Approach

This approach is dependent on the suggested formulation of sigmoid function which related to define the membership function shown in Fig. 1. This approach depends on the fuzzy membership function represent in following equation:

$$\mu(c) = \frac{C_{\max} - C}{C_{\max} - C_{\min}} \tag{18}$$

4.3. Second Proposed HPSO Approach

This approach is dependent on the suggested formulation of sigmoid function, shown in Fig. 2, and depends on the membership function represent in following equation:

$$\mu(P) = \frac{P - P_{\min}}{P_{\max} - P_{\min}} \tag{19}$$

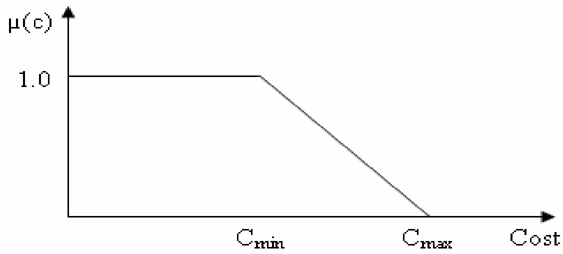

Fig. 1 Membership function of the first proposed HPSO approach

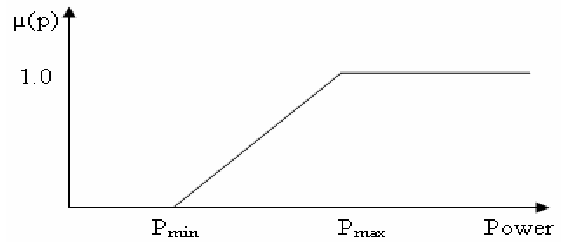

Fig. 2 Membership function of the second proposed HPSO approach

5. PROPOSED FEATURE OF FITNESS FUNCTION

Recently, several methods for handling infeasible solutions for continuous numerical optimization problems have emerged [10,17]. Some of them are based on penalty functions. They differ, however, in how the penalty function is designed and applied to infeasible solutions. They commonly use the cost function F(x) to evaluate a feasible solution, i.e.

$$\Phi_f(x) = F(x) \tag{20}$$

And the constraint violation measure $\Phi_u(x)$ for the $r+m$ constraints were defined in [17].

Then the total evaluation of an individual, which can be interpreted as the error (for a minimization problem) of an individual x, is obtained as:

$$\Phi(x) = \Phi_f(x) + \Phi_u(x) \quad (21)$$

In this paper, a new approach of the constraint violation measure $\Phi_u(x)$ is proposed, which results in reducing formulation and computation requirement for the $r+m$ constraints, as:

$$\Phi u(x) = \sum_{i=1}^{r+m} \exp(g_i^+(x)) \quad (22)$$

Where, $g_i^+(x) = \max\{0, g_i(x)\}$. In other words, $g_i^+(x)$ is the magnitude of the violation of the i_{th} equality and inequality constraint, where $1 \le i \le r+m$. Where, r is the number of inequality constraints, and m is the number of equality constraints.

5.1. Satisfying Power Demand, Reserve and Generation Limit Constraints

The objective of the UC problem can be formulated as a combination of total production cost (as the main objective) with power balance (as equality constraints) and spinning reserve and generation limits (as inequality constraints), whereby TC in (7) and $\Phi_u(x)$ is equivalent to the blend of power balance and spinning reserve constraints. Consequently, the formulation of the proposed fitness function can be expressed as:

$$\Phi(x) = \Phi_f(x) + w_1.\exp(c_1.\Phi_d(x)) + w_2 .\exp(c_2.\Phi_R(x)) + w_3.\exp(c_3.\Phi_g(x)) \quad (23)$$

Where, w_1 is set to 1 if a violation to constraint (9) occurs and w_2 = 0 and w_3=0 whenever (9) is not violated. Likewise, w_2 is also set to 1 whenever a violation of (10) is detected, otherwise it remains 0.

The choice of c_1 and c_2 are dependant on the accuracy and speed of convergence requirement. From the experiment, the values of c_1 and c_2 are equal to 2.

The first term in the penalty factor is the power balance constraint. This term is formulated for profit-based unit commitment (PBUC) as:

$$\Phi_d(x) = \max\left\{0, (\sum_{i=1}^{N} P_{it} U_{it} - D_t^{'})\right\} \quad (24)$$

The second term in the penalty factor is the reserve constraint, where R_t is 10% of power demand $D_t^{'}$. This term is formulated for SCUC for PBUC as:

$$\Phi_R(x) = \max\left\{0, (\sum_{i=1}^{N} P_{i,\max} U_{it} - (D_t^{'} + R_t^{'}))\right\} \quad (25)$$

The third term in the penalty factor is the generation limits constraint. This term is formulated for SCUC and PBUC as:

$$\Phi_g(x) = \Phi_{g\max}(x) + \Phi_{g\min}(x) \quad (28)$$

Where, the maximum power generation limit is defined as:

$$\Phi_{g\max}(x) = \max\left\{0, \sum_{i=1}^{N} (P_i - P_{i,\max}).U_{it}\right\} \quad (29)$$

And the minimum power generation limit is defined as:

$$\Phi_{g\min}(x) = \max\left\{0, \sum_{i=1}^{N} (P_{i,\min} - P_i).U_{it}\right\} \quad (30)$$

By substituting (7) into (23), the fitness function for evaluating every particle in the population of PSO for an hour is defined as:

$$\Phi(x) = \sum_{i}^{N} \{[[(1-r).F(P_{it}) + r.F(P_{it} + \mathrm{R}_{it})].\mathrm{U}_{it} + SUC_{it}.(1-\mathrm{U}_{it})]\mathrm{U}_{it}\} + w.\exp(c_1.\Phi_d(x)) + w_2.\exp(c_2.\Phi_R(x)) + w_3.\exp(c_3.\Phi_g(x))) \quad (31)$$

While the fitness function for evaluating every particle in the population of PSO for some hours can be expressed as:

$$\Phi(x) = \sum_{t}^{T} \left\{ \begin{array}{l} \sum_{i}^{N} \{[(1-r).F(P_{it}) + r.F(P_{it} + \mathrm{R}_{it})] \\ .\mathrm{U}_{it} + SUC_{it}.(1-\mathrm{U}_{it})]\mathrm{U}_{it}\} + w_1 \\ .\exp(c_1.\Phi_d(x)) + w_2.\exp(c_2.\Phi_R(x)) \\ + w_3.\exp(c_3.\Phi_g(x)) \end{array} \right\} \quad (32)$$

The fitness functions for evaluating every particle in the population of PSO for some hours for PBUC is defined as:

$$\Phi(x) = \sum_{t}^{T} \left\{ \begin{array}{l} \sum_{i}^{N} \{[[(1-r).F(P_{it}) + r.F(P_{it} + \mathrm{R}_{it})].\mathrm{U}_{it} + \\ SUC_{it}.(1-\mathrm{U}_{it})]\mathrm{U}_{it}\} - \sum_{i}^{N} \{SP_t.P_{it} + ((1-r) \\ .RP_t + r.SP_t)R_{it}.U_{it}\} + w_1.\exp(c_1.\Phi_d(x)) + \\ w_2.\exp(c_2.\Phi_R(x)) + w_3.\exp(c_3.\Phi_g(x)) \end{array} \right\} \quad (33)$$

5.2. Satisfying the Minimum Up and Down Time Constraints

The technique used to satisfy the min-up (MU) and min-down (MD) time in this paper is extremely simple. As the solution is based upon the best particle (gbest) in the history of the entire population, constraints are taken care of by forcing the binary value in to change its state whenever either MU or MD constraint is violated. However, this may change the current fitness, which is evaluated using (21). It implies that the current might no longer be the best among all the other particles. To correct this error, the gbest will be revaluated using the same equation.

The resulting advantages for this type of representation are:

1. Reduced complexity of problem formulation. The TC consists of objectives and constraint transformed objectives. The PSO has the task of only minimizing the objective functions; it is very good at neglecting the related constraints.
2. The population pool consists of feasible solutions, thus providing a best and a set of nearly best solutions. With the set of feasible solutions, the individual with the minimum value of performance index (TC) corresponds to the best feasible solution so far and other less priority (ordered) individuals correspond to the next best feasible solutions. This provides the uses with the choice of selection an solution with regard to other objectives.
3. The solution obtained by this proposed feature of objective function is best of the solution from [17], because it is leads to fast convergence of PSO solution.

6. SIMULATION RESULTS

In this section, two cases are studied to illustrate the effectiveness of the proposed approaches in terms of its solution quality. Simulations are carried out using two test systems adapted from [10] and [19]. The first system consists of three generating units, 12-hour scheduling periods. The second system consists of ten generating units, 24-hour scheduling periods. The data of these systems are given in [19].

The effect of r and price on the profit of GENCO are simulated using the three-unit system. The ten-unit system is used to show the capability of the proposed approaches for application on a larger power system. All simulation results are compared with the results obtained using the traditional UC and LR-EP methods [19]. The PSO method seems to be sensitive to the tuning of some weights or parameters, according to the experiences of many references [19]. The simulating parameters of the proposed approaches are given bellows:

- Population size = 100;
- Initial inertia weight (wmax) = 0.9;
- Final inertia weight (wmin) = 0.4;
- Acceleration constant c1 = 2 and c2 = 2;

Where, Fig. 3 shows the flow chart of the proposed procedure for the two proposed approaches.

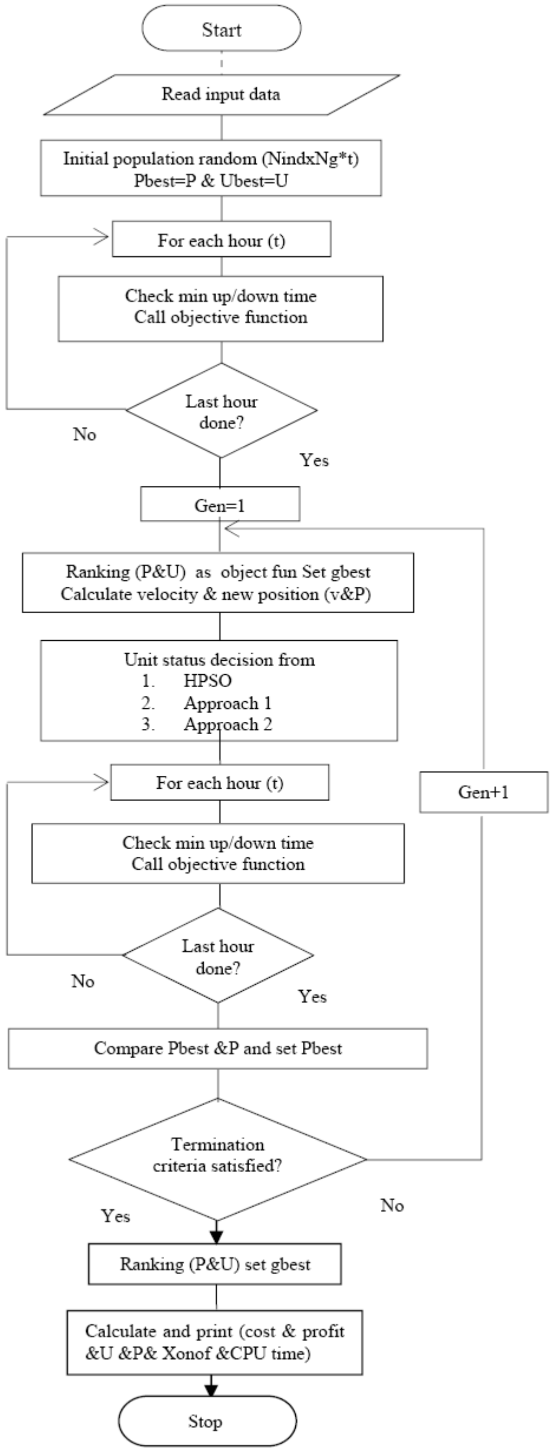

Fig. 3 Flow chart of the two proposed approaches

Three-Unit Test System: Table 1 shows the power generation and reserve scheduling for reserve payment using the first approach at r equals to 0.005 and reserve price equals to 4% of spot price. In this table at profit-based UC, the unit 1 is off at all scheduling periods to sell power generation and reserve to obtain higher profit than running all units.

Fig. 4 shows the different values of the revenue, cost and profit at various operating hours. In this figure, the profit of GENCO, which is the different between the revenue and generation costs, has a highest value at hr 7 because the load demand is taken from only two unit (as show in Table 1) that have low start-up costs, which leads to increase the revenue of GENCO, while the generation costs are remained fixed and the spot price is increased.

Table 2 shows a comparison between the different approaches for the total production cost, profit of GENCO and the computational time (CPU) for r = 0.005 and reserve price= 0.04 of spot price. The first proposed approach has best values for the generation costs, profit and computational time compared to the second proposed approach and HPSO approach.

Fig. 5 shows the effect of probability r that power reserve is called and generated on the profit of GENCO, using the traditional profit and the profit-based methods. The reserve payment price is fixed at 4% of spot price and r is changed from 0.005 to 0.05.

Fig. 6 shows the effect of reserve price on the profit of GENCO, using the traditional profit and the profit-based methods, when the probability r is fixed at 0.05.

From Figures 5 and 6, the profit of GENCO is increased using the profit-based method compared with the traditional profit method because the power demand and power reserve in profit-based method is dependent on equation (9) and (10). However, the traditional profit means that the profit of GENCO is computed dependent on the economical dispatch of UC.

Fig. 7 shows the fitness shapes of the proposed approaches compared with the based HPSO method. In this figure, the fitness of the first proposed approach has the fastest convergence compared with other approaches.

Table 1. Power and reserve generation for 3-unit test system (r = 0.005, reserve price= 4% of spot price) using the first proposed approach

	Traditional Unit Commitment					Profit-based Unit Commitment					
Hour	**Unit 1**	**Unit 2**	**Unit 3**	**Cost ($)**	**Profit ($)**	**Unit 1**	**Unit 2**	**Unit 3**	**Reserve (MW)**	**Cost ($)**	**Profit ($)**
1	0	100/0	70/20	1671	131.9	0	0	170/20	20	1265.3	537.7
2	0	100/0	150/25	2240	359.6	0	0	200/0	0	1500	570
3	0	200/40	200/0	3502	114.3	0	0	200/0	0	1500	300
4	0	320/55	200/0	4619	318.6	0	0	200/0	0	1500	390
5	100/70	400/0	200/0	7374	-342.3	0	330/70	200/0	70	5115.8	215.7
6	450/95	400/0	200/0	10811	1049.5	0	400/0	200/0	0	5400	1350
7	500/100	400/0	200/0	11406	1074.5	0	400/0	200/0	0	5400	1380
8	200/80	400/0	200/0	7984	573.8	0	400/0	200/0	0	5400	990
9	100/15	350/50	200/0	6432	325.5	0	387.2/12.2	200/0	12.2	5273.1	810
10	100/0	100/0	130/35	3614	99.4	0	130/35	200/0	35	2883.8	829.8
11	100/0	100/40	200/0	4149	170.4	0	200/40	200/0	40	3501.8	817.4
12	100	250/55	200	5482	3744	0	350/50	200/0	50	4908.4	945
Total				69283	42498					43248	9136

Table 2. Comparison between the different approaches for the total production cost, profit of GENCO and CPU for 3-unit test system

	PBUC			SCUC		
Approach	**Cost ($)**	**Profit ($)**	**CPU (sec)**	**Cost ($)**	**Profit ($)**	**CPU (sec)**
HPSO	44460	9119.9	4.39	69283	42498	4.64
Approach 1	43648	9136	2.123	69283	42498	3.1
Approach 2	43648	9136	3.828	69283	42498	3.85
LR-EP [36]	43648	9136			3975	
traditional		3975			3975	

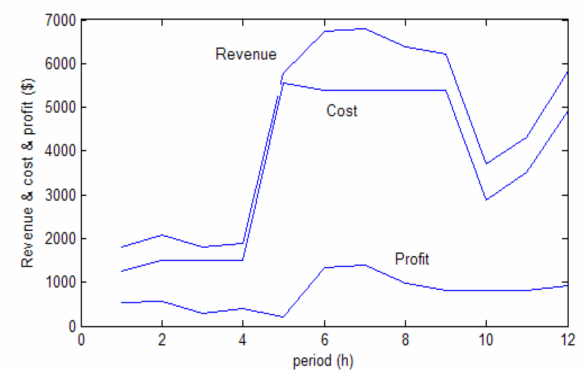

Fig. 4 Revenue, generation costs and profit of GENCO for 3-unit system

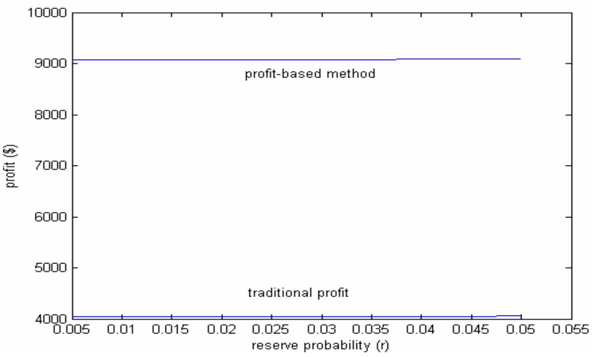

Fig. 5 Effect of r on profit of GENCO

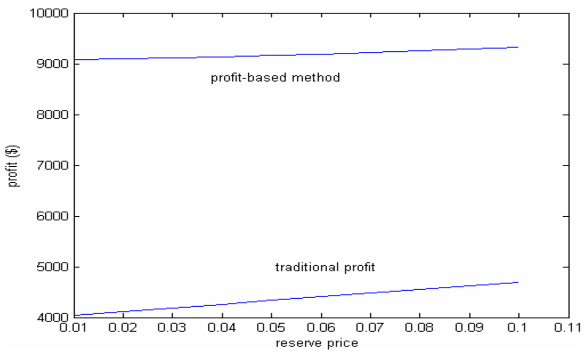

Fig. 6 Effect of reserve price on profit of GENCO

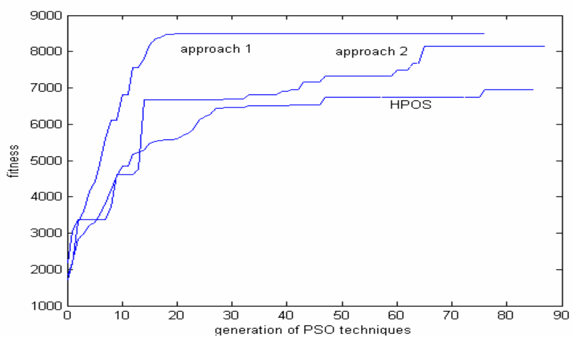

Fig. 7 The fitness function of three method with the generation of PSO techniques

Ten-Unit Test System: Tables 3 and 4 include the same results of Tables 1and 2 but for 10-unit test system.

Fig. 8 presents the same results of Fig. 4 but for 10-unit test system.

Fig. 9 shows the computational time (CUP) against the number of power generation units for the different approaches. The different approaches are applied of 2-unit [10], 3-unit [19], 4-unit [17] and 10-unit [19]. From this figure, the first proposed approach has a minimum computational time compared with other approaches.

Table 3. Power and reserve generation for 10-unit test system (r = 0.005, reserve price= 1% of spot price) using the first proposed approach

	Power (MW) / Reserve (MW)						
	1	2	3	4	5	6	7-10
1	455/0	245/70	0/0	0/0	0/0	0/0	0/0
2	455/0	295/75	0/0	0/0	0/0	0/0	0/0
3	455/0	395/60	0/0	0/0	0/0	0/0	0/0
4	455/0	455/0	0/0	0/0	0/0	0/0	0/0
5	455/0	455/0	0/0	0/0	0/0	0/0	0/0
6	455/0	455/0	0/0	130/0	0/0	0/0	0/0
7	455/0	455/0	0/0	130/0	0/0	0/0	0/0
8	455/0	455/0	0/0	130/0	0/0	0/0	0/0
9	455/0	455/0	130/0	130/0	0/0	0/0	0/0
10	455/0	455/0	130/0	130/0	162/0	68/0	0/0
11	455/0	455/0	130/0	130/0	162/0	80/0	0/0
12	455/0	455/0	130/0	130/0	162/0	80/0	0/0
13	455/0	455/0	130/0	130/0	162/0	0/0	0/0
14	455/0	455/0	130/0	130/0	130/32	0/0	0/0
15	455/0	455/0	0/0	130/0	160/2	0/0	0/0
16	455/0	455/0	0/0	130/0	0/0	0/0	0/0
17	455/0	455/0	0/0	130/0	0/0	0/0	0/0
18	455/0	455/0	0/0	130/0	0/0	0/0	0/0
19	455/0	455/0	0/0	130/0	0/0	0/0	0/0
20	455/0	455/0	0/0	130/0	0/0	0/0	0/0
21	455/0	455/0	0/0	130/0	0/0	0/0	0/0
22	455/0	455/0	0/0	130/0	0/0	0/0	0/0
23	455/0	455/10	0/0	0/0	0/0	0/0	0/0
24	455/0	345/80	0/0	0/0	0/0	0/0	0/0

Total profit: 109485.19 $

Table 4. Comparison between the different approaches for profit of GENCO and CPU for 10-unit test system using the different approaches

	PBUC	
Method	Profit ($)	CPU (sec)
HPSO	100844	60
Approach 1	109485.19	31
Approach 2	107440	35
LR-EP [36]	107838.57	-

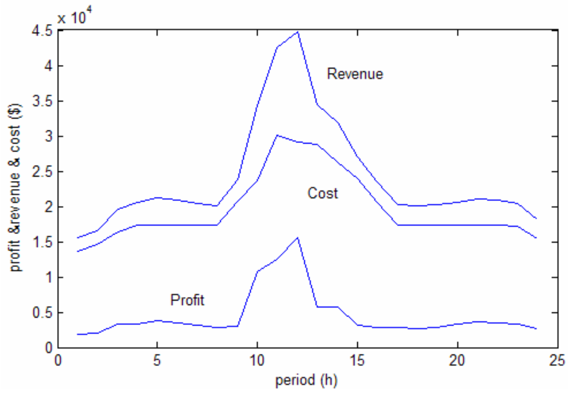

Fig.8 Daily revenue, generation cost and profit of GENCO for 10-unit system

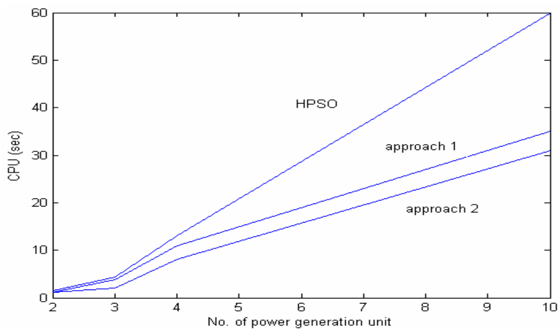

Fig.9 CPU against the no. of power generation units for different approaches

7. CONCOLUSIONS

This paper presents two efficiently and accurately approaches for optimal scheduling of unit commitment (UC) considering the power generation and reserve generating for competitive market. The two proposed approaches depend on various sigmoid functions to obtain the binary values for PSO technique. These approaches have the fastest convergence fitness function compared with HPSO and LR-EP techniques. These approaches can be used for helping GENCO to decide how much power and reserve should be sold in energy and ancillary markets in order to receive a maximum profit. Based on forecasted data, profit-based UC has been solved by considering power and reserve generation simultaneously. A proposed fitness objective function has been successfully applied proposed fitness function dependent on the exponential form which leads to fast convergence of PSO solution. The results obtained from simulation have been confirmed that the first approach is the fastest convergence lowest generation cost, and highest profit of GENCO compared to the other second approaches.

8. NOMENCLATURE

$F(P_{it})$ Production cost of unit in time period ($)
PF Profit of GENCO ($)
RV Revenue of GENCO ($)
SUC_{it} Start-up cost for unit i time period ($)
TC Total cost of GENCO ($)
CH_i The cold start hour (h)
CSC_i The unit's cold start-up cost ($)
HSC_i The unit's hot start-up cost ($)
HPSO Hybrid particle swarm optimization.
D_t' Forecasted demand at hour t (MW)
N Number of generator units
Nt a chosen number of intervals
$P_{i\min}$ Minimum generation limit of generator i (MW)
P_{it} Power generation of generator i at hour t (MW)
$P_{i\max}$ Maximum generation limit of generator i (MW)
R_{it} Reserve generation of generator i at hour t (MW)
SDC_{it} Shut-down cost for unit i time period ($)
SP_t Forecasted spot price at hour t ($)
SR_t' Forecasted reserve at hour t (MW)
T Number of hours (hr)
$\mathrm{T}_i^{\mathrm{off}}$ Minimum off time of unit *i* (hr)
$\mathrm{T}_i^{\mathrm{on}}$ Minimum on time of unit *i* (hr)
U_{it} On/off status of generator i at hour t
$\mathrm{X}_{(\mathrm{i,t-1})}^{\mathrm{on}}$ Time duration for which unit *i* has been on at hour *t* (hr)
$\mathrm{X}_{(\mathrm{i,t-1})}^{\mathrm{off}}$ Time duration for which unit *i* has been off at hour *t* (hr)
RP_t Forecasted reserve price at hour
r Probability that the reserve is called and generated
$v_{id}^{(tn)}$ Velocity of particle i at iteration t
$x_{id}^{(tn)}$ Current position of particle i at iteration t
W Inertia weight factor
tn Number of iterations
n Number of particles in a group
m Number of members in a particle
c_1 *and* c_2 Acceleration constant of PSO
$rand_1(\cdot)$ and $rand_2(\cdot)$ Random numbers between 0 and 1
$iter_{\max}$ and $iter$ The maximum and the current number of iterations
SCUC Security-constraint unit commitment
PBUC Profit-based unit commitment

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