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A Profit-Based Unit Commitment using Different Hybrid Particle Swarm Optimization for Competitive Market

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Abstract – *Two proposed approaches are presented for optimal scheduling of unit commitment (UC) in competitive market. The particle swarm optimization (PSO) technique is used to find out the solution of both optimal UC scheduling and power generation dispatching problems, simultaneously. These approaches depend on two sigmoid functions to obtain the binary values for the PSO technique. The first approach considers the fuzzification of power generation costs as a sigmoid function, while the second approach considers the fuzzification of power generation as a sigmoid function. An exponential function is proposed to minimize power generation costs as well as maximize their own profit, while all load demand and the power generation constraints are satisfied. Therefore, the generations companies (GENCO) can schedule their output power according to a maximum own profit. This means that, the GENCO must take a decision, how much power and reserve generations should be sold in the markets to obtain a maximum own profit. Different applications are carried out using various standard test systems to show the capability of the proposed approaches the competitive market.*

Keywords – Bidding strategies, competitive auction markets, hybrid particle swarm optimization (HPSO), optimization methods, power generation dispatch, unit commitment.

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.

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 are another classes of numerical techniques applied to the UC problem, which are: 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.

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Dynamic programming method [3] 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. One main drawback of SA is that, it takes a large computational time to find the near-global minimum solution. GAs is a general-purpose stochastic and parallel search methods based on the mechanics of natural selection and natural genetics.

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. 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 the generation units. The ED decision involves the allocation of the system demand and spinning reserve capacity among the operating units during each specific hour of the operation.

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

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 [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 [17]. 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 [18]:

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

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

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 factor (*w*) in Equation 1 provides a balance between global and local explorations. 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-BASED UC PROBLEM FORMULATION

A profit-based UC (PBUC) problem under competitive environment is presented as an optimization procedure. The objective function of PBUC is to maximize the profit subject to all prevailing constraints [10]:

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

In a restructured system, GENCO sell the power generation in energy market and sell reserve in the reserve (ancillary) market. When the power reserve is used, GENCO receives the spot price for the reserve that is generated. In this case, reserve price is much lower than the spot price. Revenue and costs in Equation 5 can be calculated from [19]:

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

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

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 are the unit cost coefficients. Subject to:

1. Demand constraint:

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

2. Reserve constraint:

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

3. Power generation and reserve limits:

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

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

4. Minimum up and downtime 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.

Based HPSO Method

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:

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

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.

First Proposed HPSO Approach

This approach is dependent on a suggested fuzzy membership function, as shown in Figure 1 that can be expressed as:

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

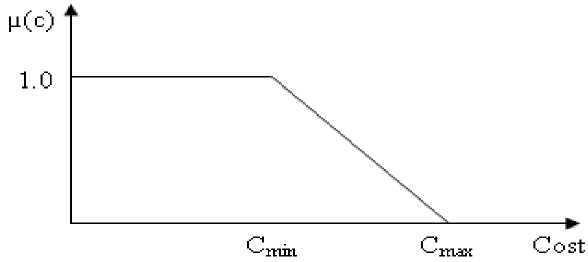

Fig. 1. Membership function of the first proposed HPSO approach.

Second Proposed HPSO Approach

This approach is dependent on a suggested fuzzy membership function, as shown in Figure 2 that can be expressed as:

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

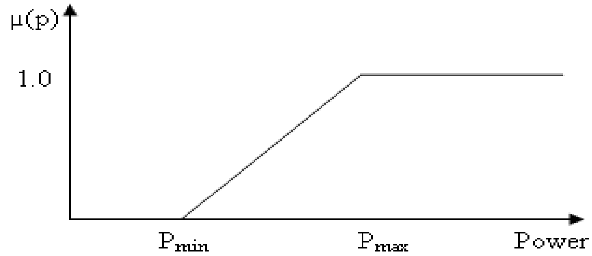

Fig. 2. Membership function of the second proposed HPSO approach.

5. PROPOSED FEATURE OF FITNESS FUNCTION

Recently, several methods use the cost function F(x) to evaluate a feasible solution, for the optimization problems as [10], [18]:

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

nd the constraint violation measure $\Phi_u(x)$ for the $r+m$ constraints were defined in [18].

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:

$$\Phi(x) = \Phi_f(x) + \Phi_u(x) \tag{21}$$

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:

$$\Phi_u(x) = \sum_{i=1}^{r+m} \exp(g_i^+(x)) \tag{22}$$

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, $1 \le i \le r+m$. Where, r is the number of inequality constraints, and m is the number of equality constraints.

Power Demand, Reserve and Power Generation Constraints

The objective of the UC problem is formulated as a combination of total production cost (as the main objective) with power balance (as equality constraints) and spinning reserve as well as generation limits (as inequality constraints), whereby TC in (7) and $\Phi_u(x)$ are equivalent to the blend of power balance and spinning reserve constraints, respectively. 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 of (9) is occurred in, while 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 equal to 0.

The choice of c_1 and c_2 are depending on the accuracy and the speed of the convergence requirements which may be 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 security-constraint unit commitment (SCUC) and 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 constraints. This term is formulated for SCUC and PBUC as:

$$\Phi_g(x) = \Phi_{g\max}(x) + \Phi_{g\min}(x) \quad (26)$$

where, the maximum power generation limit is defined as:

$$\Phi_{g\max}(x) = \max\left\{0, \sum_{i=1}^{N} (P_i - P_{i,\max}).U_{it})\right\} \quad (27)$$

and the minimum power generation limit is defined as:

$$\Phi_{g\min}(x) = \max\left\{0, \sum_{i=1}^{N} (P_{i,\min} - P_i).U_{it})\right\} \quad (28)$$

By substituting Equation 7 into Equation 23, the fitness function for evaluating every particle in the population of PSO for an hour can be defined as:

$$\Phi(x) = \sum_{i}^{N} \{[(1-r).F(P_{it}) + r.F(P_{it} + \mathrm{R}_{\mathrm{it}})].\mathrm{U}_{\mathrm{it}} + SUC_{it}.(1-\mathrm{U}_{\mathrm{it}})]\mathrm{U}_{\mathrm{it}}\} + w.\exp(c_1.\Phi_d(x)) + w_2.\exp(c_2.\Phi_R(x)) + w_3.\exp(c_3.\Phi_g(x))) \quad (29)$$

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

$$\Phi(x) = \sum_{t}^{T} \left\{ \begin{array}{l} \sum_{i}^{N} \{[(1-r).F(P_{it}) + r.F(P_{it} + \mathrm{R}_{\mathrm{it}})] \\ .\mathrm{U}_{\mathrm{it}} + SUC_{it}.(1-\mathrm{U}_{\mathrm{it}})]\mathrm{U}_{\mathrm{it}}\} + w_1 \\ .\exp(c_1.\Phi_d(x)) + w_2.\exp(c_2.\Phi_R(x)) \\ + w_3.\exp(c_3.\Phi_g(x)) \end{array} \right\} \quad (30)$$

The fitness functions for evaluating every particle in the population of PSO for certain hours for PBUC can be expressed as:

$$\Phi(x) = \sum_{t}^{T} \left\{ \begin{array}{l} \sum_{i}^{N} \{[(1-r).F(P_{it}) + r.F(P_{it} + \mathrm{R}_{\mathrm{it}})].\mathrm{U}_{\mathrm{it}} + \\ SUC_{it}.(1-\mathrm{U}_{\mathrm{it}})]\mathrm{U}_{\mathrm{it}}\} - \sum_{i}^{N} \{SP_t.P_{it} + ((1-r) \\ .RP_t + r.SP_t)R_{it}.U_{it}\} + w_1.\exp(c_1.\Phi_d(x)) + \\ w_2.\exp(c_2.\Phi_R(x)) + w_3.\exp(c_3.\Phi_g(x)) \end{array} \right\} \quad (31)$$

Satisfying the Minimum Up and Down Time Constraints

The min-up (MU) and min-down (MD) time constraints are checked at every iteration. The resulting advantages for this type of representation are:

1. Reduced problem formulation complexity.
2. The population pool consists of a set of feasible solutions, thus increasing the accuracy of the obtained solutions.
3. With the set of feasible solutions, the power system operator can trade off between the solution within this set according to the performance index TC.
4. An urgent property of the suggested approach is the fast convergence compared to that obtained from [18].

Figure 3 shows the flowchart of the two proposed approaches for the optimal scheduling of UC.

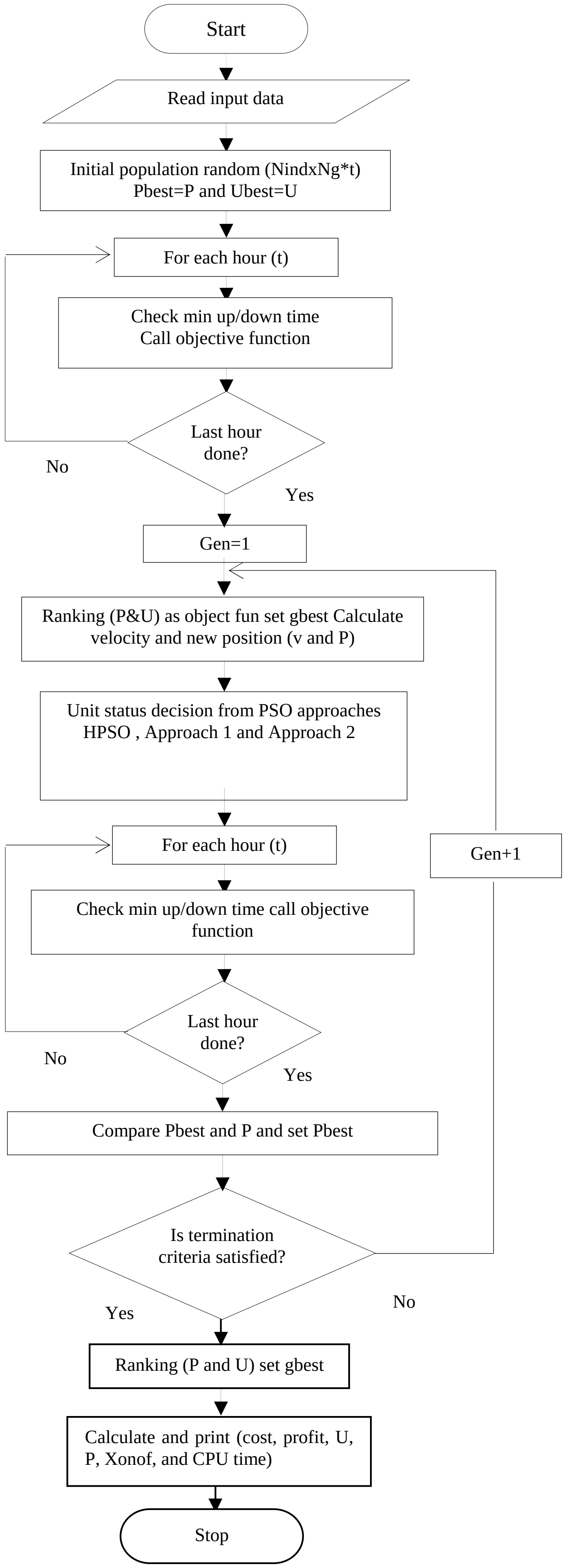

Fig. 3. Flowchart of the two proposed approaches.

6. SIMULATION RESULTS

In this section, two case studies are used 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 effect of r and the reserve price on the profit of GENCO are simulated using the first test system. The second test system is used to show the capability of the proposed approaches. All simulation results are compared with the results obtained using the traditional UC and LR-EP methods [19]. The PSO technique seems to be sensitive to the tuning of some weights or parameters, according to the experiences of many references [19].

The parameters of the proposed approaches are given as:

- Population size = 100;
- Initial inertia weight (wmax) = 0.9;
- Final inertia weight (wmin) = 0.4;
- Acceleration constant c_1 = 2 and c_2 = 2;

Figure 3 shows the flow chart of the proposed procedure for the two proposed approaches.

First Test System: Table 1 shows the power generation and reserve scheduling using the first approach at r equals to 0.005 and reserve price equals to 4% of the spot price. At profit-based UC, the unit 1 is off at all scheduling periods to sell power and reserve generation to obtain the highest profit.

Figure 4 shows the different values of the revenue, cost and profit at the various operating hours. In this figure, the profit of GENCO, which is the different between the revenue and generation costs, has the highest value at hour 7 because the load demand is taken from only two units (see Table 1) that have low start-up costs, while the generation costs are remained fixed and the spot price is increased.

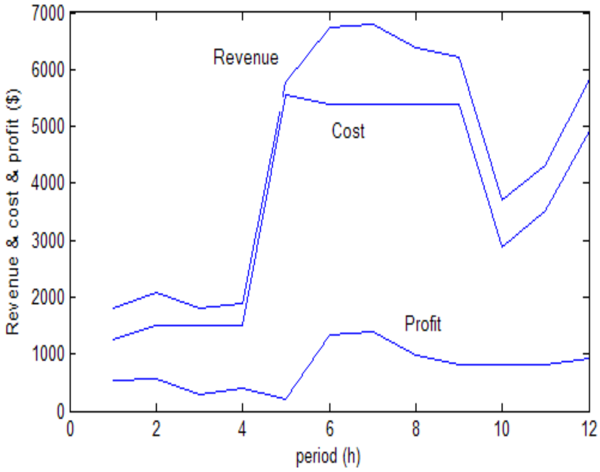

Fig. 4. Revenue, generation costs and profit of GENCO for 3-unit system.

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	374.4	0	350/50	200/0	50	4908.4	945
Total				69283	4249.6					43248	9136

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

Approach	PBUC			SCUC		
	Cost ($)	Profit ($)	CPU (sec)	Cost ($)	Profit ($)	CPU (sec)
HPSO	44460	9119.9	4.39	69283	4249.6	4.64
Approach 1	43648	9136	2.123	69283	4249.6	3.1
Approach 2	43648	9136	3.828	69283	4249.6	3.85
LR-EP [36]	43648	9136			3975	
Traditional		3975			3975	

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

Figure 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 power reserve payment price is fixed at 4% of spot price while r is changed from 0.005 to 0.05.

Figure 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 proposed profit-based method compared with the traditional profit method because the power demand and power reserve.

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

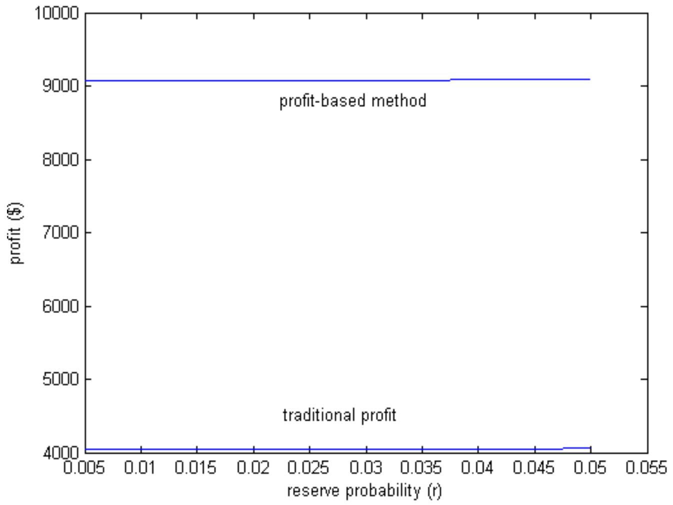

Fig. 5. Effect of r on profit of GENCO.

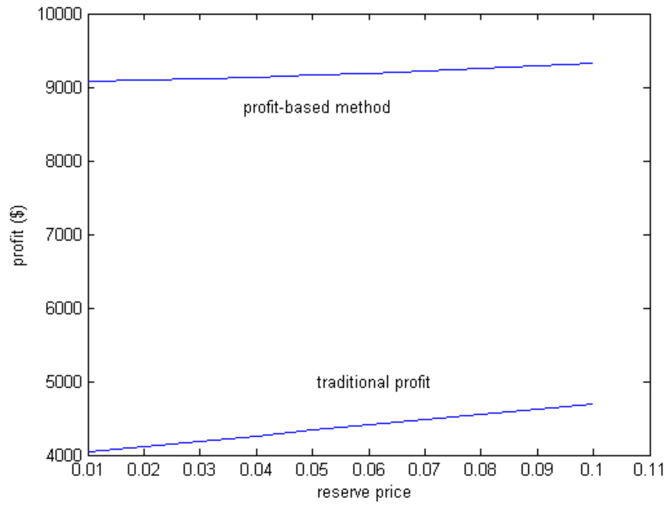

Fig. 6. Effect of reserve price on profit of GENCO.

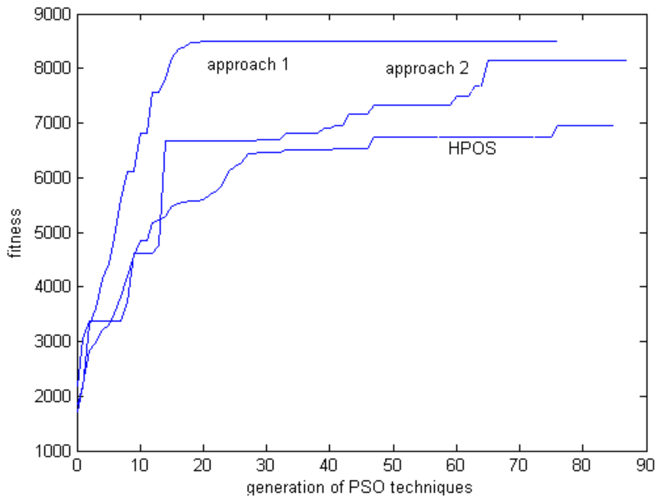

Fig. 7. Fitness function of three method with the generation of PSO techniques.

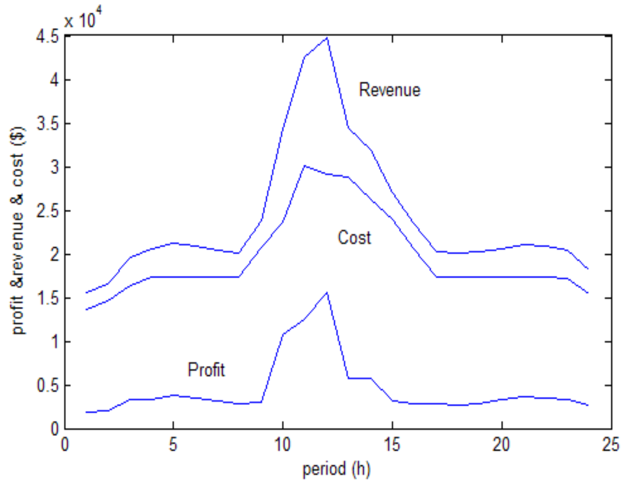

Fig. 8. Revenue, generation cost and profit of GENCO for 10-unit system.

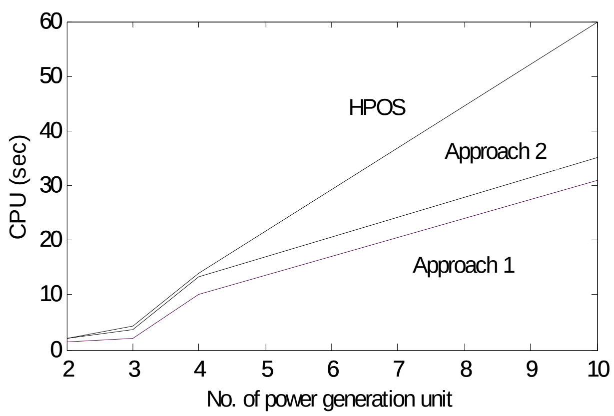

Fig. 9. CPU against the number of power generation units for different approaches.

Figure 7 shows the fitness shapes of the proposed approaches compared to the based HPSO method. In this figure, the fitness of the first proposed approach has the fastest.

Second Test System: Tables 3 and 4 include the same results of Tables 1and 2. Figure 8 presents the same results of Figure 4 but for the second test system. Figure 9 shows the computational time (CUP) against the number of power generation units for the different approaches. The different approaches are applied to 2-unit [10], 3-unit [19], 4-unit [18] and 10-unit [19]. From this figure, the first proposed approach has a minimum computational time compared to other approaches.

Table 3. Comparison between the different approaches for profit of GENCO and CPU for 10-unit test system using different approaches.

	PBUC	
Method	Profit ($)	CPU (sec)
HPSO	101489.4	60
Approach 1	109661	31
Approach 2	107443.9	35
LR-EP [36]	107838.57	-

Table 4. 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:	109661 $						

7. CONCLUSION

Two efficient and accurate approaches for optimal scheduling of unit commitment (UC) in competitive market have been presented in this paper. The optimal solution of of UC power generations scheduling problems has been obtained, simultaneously. These approaches depend on two fuzzy sigmoid functions to accelerate the solution convergence compared with the HPSO and LR-EP techniques. obtain the binary values for PSO technique. These approaches have been used for maximizing the profit of GENCO by considering the power and reserve generation, simultaneously. A proposed exponential objective function has been successfully applied which leads to fast convergence of the PSO technique. The results the first approach have the lowest generation costs, highest profit of GENCO and lowest CPU compared with the other approaches.

NOMENCLATURE

$F(P_{it})$	Production cost of unit *i* in time period *t* ($).
PF	Profit of GENCO ($).
RV	Revenue of GENCO ($).
SUC_{it}	Start-up cost for unit *i* in time period *t* ($).
TC	Total cost of GENCO ($).
CH_{i}	The cold start hour (hr) at unit *i*.
CSC_i	The unit's cold start-up cost at unit *i* ($).
HSC_i	The unit's hot start-up cost at unit *i* ($).
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 limit of generator i (MW).
P_{it}	Power generation of unit i at hour t (MW).

$P_{i\max}$	Maximum limit of generator *i* (MW).
R_{it}	Reserve generation of unit *i* at hour *t* (MW).
SDC_{it}	Shut-down cost of unit *i* at time period *t* ($).
SP_t	Forecasted spot price at hour *t* ($).
$SR_t^{'}$	Forecasted reserve at hour *t* (MW).
T	Number of hours.
$\mathrm{T_i^{off}}$	Minimum off-time of unit *i* (hr).
$\mathrm{T_i^{on}}$	Minimum-on time of unit *i* (hr).
$\mathrm{U_{it}}$	On/off status of generator i at hour t.
$\mathrm{X_{(i,t-1)}^{on}}$	Time duration for which unit *i* has been on-time at hour *t* (hr).
$\mathrm{X_{(i,t-1)}^{off}}$	Time duration for which unit *i* has been off-time at hour *t* (hr).
RP_t	Forecasted reserve price at hour *t*.
r	Probability that the reserve is called and generated.
$v_{id}^{(tn)}$	Velocity of particle *i* at iteration *tn*.
$x_{id}^{(tn)}$	Current position of particle *i* at iteration *tn*.
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 $iter$	Maximum and the current number of iterations.
SCUC	Security-constraint unit commitment.
PBUC	Profit-based unit commitment.

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