Signal Processing and Renewable Energy
September 2018, (pp.1-13)
ISSN: 2588-7327
eISSN: 2588-7335

Integrating Wind Farms and Pumped Storage Plants in Power System Unit Commitment Using Modified Particle Swarm Optimization

Hasan Siahkali[1*]

[1] Department of Electrical Engineering, Islamic Azad University, South Tehran Branch, Tehran, Iran.
Received: 2-May-2018, Revised: 7-July-2018, Accepted: 21-July-2018.

Abstract
Wind energy as a main part of renewable energy has important role in many electricity industries, because of increasing concerns about environmental impacts of conventional power plants fuels. Wind power integration in the electricity system operation has some technical and economic effects because of the intermittent and variety nature of wind power production. Therefore, it is important for every utility or system operator to consider these technical or economical aspects especially as unit commitment problem. One of the most important strategies for increasing profits of each utility is integrating the wind power resources with limited energy resources such as pumped storage (PS) plants. Pumped storage can provide some of the flexibility that power system operators need to balance load and generation in an uncertain environment, and thus enhance a power system's ability to incorporate wind power. This paper presents a new approach for solving the weekly unit commitment including wind farms and PS plants. For this purpose, the modified PSO mechanism is recommended. The proposed PSO is applied to two test systems (which are included two wind farms and one PS plant) and the results of this modified PSO are compared with the conventional PSO. Evaluation of the results of these test systems' solutions show that better optimal schedules are obtained.

Keywords: Unit commitment, particle Swarm optimization, pumped storage plant, wind power availability.

1. INTRODUCTION

Among the non-conventional energy resources, renewable energy has been recognized as the most promising means of new electric power generation in future. At present, small-scale and large-scale applications of wind and/or solar energy are in operation and are steadily gaining new markets. The growing public awareness, regarding the existing environment hazardous impacts potential associated with conventional electric power generation plants, resulted in an increased emphasis on the large-scale utilization of these renewable resources.

The intermittency nature of wind generation increases the fluctuation and the uncertainty on the net load. When wind generation makes up a large proportion of the committed generation capacity, minimum load problems can arise when thermal generating units cannot operate at a much reduced output or cannot be stopped. Wind generation may then have to be curtailed [4]. Large-scale wind power integration also requires additional operating reserve [5]. Pumped

*Corresponding Author's Email: H_siahkali@azad.ac.ir

hydro storage units can be used to store the excess energy from wind power and provide the reserve and flexibility needed in systems with large amounts of wind power.

An important task in the operation of power system is the optimal unit commitment (UC) that consider the technical and economic constraints over a time horizon. The UC problem consists of determining the optimal operation strategy for the next scheduling period, subject to a variety of constraints. This optimization is done under considering the different constraints. For example, the total output power at each time period must meet the demand anticipated over a given time horizon (usually a duration of one day to one week). The UC is a combinatorial optimization problem with both binary and continuous variables. The number of combinations of binary variables grows exponentially as being a large-scale problem. Therefore, UC is one of the most difficult problems in power systems studies.

The scope of UC problem will vary strongly from one utility to another utility due to the type of mixture of the generating units and particular operating constraints. The economic consequences of operational scheduling are very important. Since fuel cost is a major cost component in electricity generation, reducing the fuel cost by 0.5% can result in savings of millions of dollars per year for large utilities.

The exact solution of the unit commitment problem can be obtained by complete enumeration of all feasible combinations of generating units, which is possible in a realistic power system [1]. Since large economic benefits could be achieved from unit scheduling improvement, a considerable attention has been devoted to develop the related solution methods. Various mathematical programming and heuristic based approaches have been used to solve the UC problem [2]-[8].

One of the most important strategies for increasing profits of each utility is integrating the wind power resources with limited energy resources such as PS plants. A PS plant can be used to provide added value to a wind farm that takes place in the market in comparison with separate participation of them. The possibility of storing energy in PS plants can significantly reduce the risk of self-scheduling for wind power producers in the market. Pumped storage units can be used to store the excess energy of the wind power and provide the systems reserve and flexibility with large amounts of wind power. Several studies tried to develop a decision approach to set different objective functions such as profit maximization [9], carbon emission reduction [10] and curtailment reduction [11]. PS would also benefit the system by balancing wind power in a market [12] or in an isolated power system [13].

This paper extends UC problem by introducing additional constraints to represent the wind farms generation with PS plants into the problem formulation. The main contributions of this work are listed in following.

1. Presenting a new unit commitment formulation which integrates both wind power generation and PS plants.
2. Presenting a modified particle swarm optimization based on the concept of bacterial foraging.

In Section 2, the problem formulation of UC and the related constraints are discussed. The wind turbine and pumped storage models are also presented in Section 2. In Section 3, the hybrid particle swarm optimization has been developed by some aspects of bacterial foraging concepts. The test systems (which have six and twenty six conventional units) are used to present the optimization method capabilities in Section 4. Also, the results of conventional and passive congregation PSO are compared. Finally, conclusion of this paper is presented in Section 5.

2. PROBLEM FORMULATION

In this section, wind farm and pumped storage (PS) plant models are presented and then UC formulation is introduced with the objective function and all main constraints based on a week time horizon with one hour period.

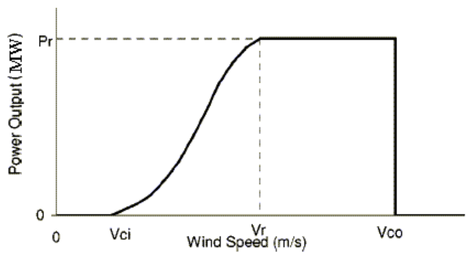

Fig. 1. Power curve of a wind turbine.

2.1. Wind Farm Model

The generated power varies with the wind speed at the wind farm (WF) site. The power output of a wind turbine can be determined from its power curve, which is a plot of output power versus wind speed. A turbine is designed to start generating at the cut-in wind speed (V_{ci}) and is shut down for safety reasons at the cut-out wind speed (V_{co}). Rated power P_r is generated, when the wind speed is between the rated wind speed (V_r) and the cut-out wind speed. There is a nonlinear relationship between the power output and the wind speed when the wind speed lies within the cut-in and the rated wind speed as shown in Figure 1.

Therefore, the wind power generated corresponding to a given wind speed can be obtained as,

$$Wav(w,t) = P_r * \begin{cases} A + B*WS(w,t) + C*WS(w,t)^2 & V_{ci} \le WS(w,t) < V_r \\ 1 & V_r \le WS(w,t) \le V_{co} \\ 0 & Otherwise \end{cases} \quad (1)$$

where the constants A, B, and C [14] are presented as,

$$A = \frac{1}{(V_{ci} - V_r)^2} \left\{ V_{ci}(V_{ci} + V_r) - 4V_{ci}V_r \left[\frac{V_{ci} + V_r}{2V_r} \right]^3 \right\}$$

$$B = \frac{1}{(V_{ci} - V_r)^2} \left\{ 4(V_{ci} + V_r) \left[\frac{V_{ci} + V_r}{2V_r} \right]^3 - (3V_{ci} + V_r) \right\}$$

$$C = \frac{1}{(V_{ci} - V_r)^2} \left\{ 2 - 4 \left[\frac{V_{ci} + V_r}{2V_r} \right]^3 \right\}$$

The application of the common wind power generation model is illustrated in this paper by applying it to a wind turbine rated power at 2 MW, and with cut-in, rated, and cut-out wind speeds of 3.5, 12.5, and 25 m/s, respectively.

2.2. Pumped-Storage Model

The PS plant is composed of upper and lower reservoirs. Typically, a reversible pump-turbine makes storing of energy in off-peak hours possible that it can be sold during peak hours. That means, the operation is economically profitable. Thus, the pump-turbine will work as a turbine when water is released from the upper reservoir to the lower one, i.e. injecting its production to the network. Likewise, when pumping is taking place, the energy is consumed to store water in the upper reservoir, which will be available later on for generation mode.

The variables associated to the PS plant in the model are considered in terms of energy. Thus, in each period, the state of the upper and lower reservoirs will be determined by the energy stored in them at the end of the period. Likewise, the volume capacity of both reservoirs are expressed as maximum and minimum energy levels that can be stored in the reservoirs [27]. The energy stored in each lower and upper reservoirs of PS plant has an upper and a lower capacity limits as,

$$Eu_{\min} \le Eu(t) \le Eu_{\max} \quad (2)$$

$$El_{\min} \le El(t) \le El_{\max} \quad (3)$$

It should be mentioned that in this paper, the contribution of PS plant in reserve power market is not considered.

2.3. Unit Commitment Model

The main objective of a UC problem is maximizing the total profit of its generating units in the scheduled horizon. While the operation is constrained by a number of system and generating units' constraints, total revenue is obtained from both energy and reserve market based on energy and reserve power forecasted prices. The time horizon of this problem is one week, with one hour as interval. The objective function of UC problem is defined as,

$$Max \quad J = TR - TC \quad (4)$$

$$TR=\sum_{t=1}^{T}\sum_{g=1}^{N_G}\{P_{GD}(g,t)\cdot U(g,t)\}\cdot EP(t)+\sum_{t=1}^{T}\sum_{w=1}^{N_W}\{P_W(w,t)\cdot V(w,t)\}\cdot EP(t)$$
$$+\sum_{t=1}^{T}\left\{\sum_{g=1}^{N_G}\{P_{GR}(g,t)\cdot U(g,t)\}-RESW\cdot\sum_{w=1}^{N_W}\{P_W(w,t)\cdot V(w,t)\}\right\}\cdot RP(t) \quad (5)$$
$$+\sum_{t=1}^{T}\sum_{s=1}^{N_S}\{PS_g(s,t)\cdot M(s,t)\}\cdot EP(t)$$

$$TC=\sum_{t=1}^{T}\sum_{g=1}^{N_G}F(P_{GD}(g,t))\cdot U(g,t)+\sum_{t=1}^{T}\sum_{g=1}^{N_G}SU(g)\cdot U(g,t)\cdot(1-U(g,t-1))$$
$$+\sum_{t=1}^{T}\sum_{g=1}^{N_G}\{(P_{GD}(g,t)+P_{GR}(g,t))\cdot OMVCT(g)\}\cdot U(g,t)$$
$$+\sum_{t=1}^{T}\sum_{s=1}^{N_S}\{PS_p(s,t)\cdot(1-M(s,t))\}\cdot EP(t) \quad (6)$$
$$+\sum_{t=1}^{T}\sum_{w=1}^{N_W}\{P_W(w,t)\cdot OMVCW(w)\}\cdot V(w,t)$$

$$F(P_{GD}(g,t))=a_g+b_g\cdot P_{GD}(g,t)+c_g\cdot P_{GD}(g,t)^2 \quad (7)$$

This objective function is subjected to many constraints; including: the forecasted demand, the reserve power requirement, the generating units' constraints, and the wind power and PS generation. In order to satisfy the system demand, it is required that,

$$\sum_{g=1}^{N_G}P_{GD}(g,t)\cdot U(g,t)+\sum_{w=1}^{N_W}P_W(w,t)\cdot V(w,t)+\sum_{s=1}^{N_S}PS_g(s,t)\cdot M(s,t)$$
$$=P_d(t)+\sum_{s=1}^{N_S}PS_p(s,t)\cdot(1-M(s,t)) \quad (8)$$
$$t=1,2,...,T$$

The reserve requirement should be satisfied. The operating reserve requirement has two parts; one is in form of a percent of total system load (e.g. 5%) and the other is a surplus reserve which is chosen to compensate the errors in prediction of actually produced wind power. Thus, the reserve for wind power errors (RESW) can be obtained assessing the recorded data on wind speed at wind turbine site [28]. In this study, the RESW is assumed 10%.

$$\sum_{g=1}^{N_G}P_{GR}(g,t)\cdot U(g,t)-RESW*\sum_{w=1}^{N_W}P_W(w,t)\cdot V(w,t)\ge P_R(t) \quad (9)$$
$$t=1,2,...,T$$

The generating unit Constraints also should be satisfied. Therefore the wind power availability should be satisfied as follows:

$$P_W(w,t)\le W_{av}(w,t) \quad (10)$$
$$t=1,2,...,T$$

And the maximum and minimum generation of the conventional units should be satisfied as follows:

$$P_{Gg,\min}\le P_{GD}(g,t)+P_{GR}(g,t)\le P_{Gg,\max} \quad (11)$$

Consider a PS unit having an efficiency of pumping (η) with an initial energy stored in the lower and upper reservoirs. Also, assume that within a time period of study horizon, the stored energy in both reservoirs is the same as initial states. The maximum and minimum energy storing in upper and lower reservoirs of PS plant is to be calculated and satisfied as,

$$Eu_{\min}(s)\le Eu(s,t)=Eu(s,t-1)-PS_g(s,t)\times M(s,t)$$
$$+\eta(s)\times[PS_p(s,t)\times(1-M(s,t))]\le Eu_{\max}(s) \quad (12)$$

$$El_{\min}(s)\le El(s,t)=El(s,t-1)+PS_g(s,t)\times M(s,t)$$
$$-\eta(s)\times[PS_p(s,t)\times(1-M(s,t))]\le El_{\max}(s) \quad (13)$$

3. IMPLEMENTATION OF MODIFIED PSO

Particle Swarm Optimization (PSO) was proposed by Kennedy and Eberhart [16] in 1995. This technique was inspired by the choreography of a bird flock and can be seen as a distributed behavior algorithm that performs 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.

3.1. Overview of the Conventional PSO

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

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

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

Suppose that the search space is D-dimension, then the ith 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 ith 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 (Conventional PSO):

$$v_{id}^{k+1} = cfk \cdot [wf \cdot v_{id}^k + c_1 r_1^k (pbest_{id}^k - x_{id}^k) + c_2 r_2^k (gbest_d^k - x_{id}^k)] \quad (14)$$

n this velocity updating process ($cfk = 1$), the values of parameters such as wf, c_1 and c_2 are determined in advance. In general, the weighting factor (wf) of equation (14) is set as,

$$wf = wf_{\max} - \frac{wf_{\max} - wf_{\min}}{\max iter} \times iter \quad (15)$$

The model using (15) is called inertia weights approach (IWA) [17]. 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. Moreover, in order to guarantee the convergence of the PSO algorithm, the constriction factor was defined in [18]. In this constriction factor approach (CFA), the basic system equations of the PSO can be used.

$$cfk = \frac{2}{\left|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}\right|}, \quad \varphi = c_1 + c_2, \quad \varphi \geq 4 \quad (16)$$

The current position (searching point in the solution space) can be modified by,

$$x_{id}^{k+1} = x_{id}^k + v_{id}^{k+1} \quad (17)$$

3.2 Modified Congregation PSO (GPAC)

According to the local-neighborhood variant of the PSO algorithm (LPSO) [19], each particle moves toward its best previous position and toward the best particle in its restricted neighborhood. The local-neighborhood leader of a particle, its nearest particle (in terms of distance in the decision space) with the better evaluation is considered. Since the constriction factor approach generates higher quality solutions in the basic PSO, the LPSO with the constriction factor was proposed in [20]. However, it was shown recently that more biological forces than those adopted in the state-of-the-art PSO are essential for preserving the swarm's integrity. Specifically, Parrish and Hammer [21] proposed mathematical models to show how these forces organize the swarms. These can be classified into two categories: the aggregation and the congregation forces.

Aggregation refers to the swarming of particles by nonsocial, external physical forces. There are two types of aggregation: passive aggregation and active aggregation. Passive aggregation is a swarming by physical forces, such as the water currents in the open sea group the plankton [21]. Active aggregation is a swarming by attractive resources such as the place with the most food. The second term in the conventional PSO algorithm (14) (the global best position) represents the active aggregation [15], [21].

However, the congregation is a swarming by social forces, which is the source of attraction of a particle to others and it is classified into two types: social and passive. Social congregation usually happens when the swarm's fidelity is high, such as genetic relation. Social congregation necessitates active information transfer, e.g., ants that have high genetic relation use antennal contacts to transfer information about location of resources [15], [21]. Finally, passive congregation is an attraction of a particle to other swarm members, where there is no display of social behavior since particles need to monitor both environment and their immediate surroundings such as the position and the speed of neighbors. Such information transfer can be employed in the passive congregation. In this paper, the global variant-based passive congregation PSO (GPAC PSO) [15] with the constriction factor approach [20], [22] is enhanced and employed. The swarms of the enhanced GPAC are manipulated by the velocity update,

$$v_{id}^{k+1} = cfk \cdot [wf \cdot v_{id}^{k} + c_1 r_1^k (pbest_{id}^k - x_{id}^k) + c_2 r_2^k (lbest_{md}^k - x_{id}^k) + c_3 r_3^k (pcong_{rd}^k - x_{id}^k)] \quad (18)$$

where $pbest_{id}^k$ is the best previous position of the i[th] particle; $lbest_{md}^k$ is either the global best position ever attained among all particles (similar to conventional PSO or CPSO) or the local best position of particle-i (namely, the position of its nearest particle-m with better evaluation similar to LPSO) and $pcong_{rd}^k$ is the position of passive congregator (position of a randomly chosen particle-r) [23].

3.3. Algorithm of GPAC PSO

In this Section, a new approach to develop a PSO based algorithm for solving the UC problems is proposed. The proposed method deals with the equality and inequality constraints of the UC problems when modifying each particle's search point in the PSO algorithm. The process of the modified PSO algorithm are:

Step 1) Initialization and Structure of Particles: In the initialization process, a set of particles is created at a random order. In this paper, the structure of a particle for UC problem is composed of a set of elements (i.e., generation, reserve, wind power and pumped storage outputs of all units in each time interval). Therefore, particle i's position at iteration 0 in period of t can be represented in vector form as,

$$X_i^0 = (P_{GDi,1,t}^0, P_{GDi,2,t}^0, ..., P_{GDi,N_G,t}^0, P_{GRi,1,t}^0, P_{GRi,2,t}^0, ..., P_{GRi,N_G,t}^0, P_{Wi,1,t}^0, P_{Wi,2,t}^0, ..., P_{Wi,N_W,t}^0, PS_{Pi,1,t}^0, PS_{Pi,2,t}^0, ..., PS_{Pi,N_S,t}^0, PS_{gi,1,t}^0, PS_{gi,2,t}^0, ..., PS_{gi,N_S,t}^0)$$

Thus, the dimension of each particle in this study is $D = (2N_G + N_W + N_S) \cdot T$. Note that it is very important to create a group of individuals satisfying the constraints (8) to (13). This procedure must be repeated for the all time periods.

Step 2) Position Updating Considering Constraints: After creating the initial position of each particle, the velocity of each particle is also created at random. To modify the position of each particle, it is necessary to calculate the velocity of each particle, which is obtained from (14) or (18). In this position updating process, the values of parameters such as wf, c_1, c_2 and c_3 are determined in advance. The resulting position of a particle is not always guaranteed to satisfy the equality/inequality constraints due to over/under velocity. If any element of a particle violates its inequality constraint due to over/under speed then the position of the particle is fixed to its maximum/ minimum operating point.

Step 3) Update of Pbest and Gbest: The Pbest of each particle at any iteration and Gbest are updated with respect to cost function.

Step 4) Stopping Criteria: This process is terminated if the iteration approaches to the predefined maximum iteration.

4. RESULTS OF TEST SYSTEMS

To examine the merits of the proposed method, two test systems are simulated in this Section. For both test systems, two wind farms and one PS plant are included. The input data of two wind farms (wind1 and wind2) are given in Table 1. Each wind farm has 20 wind turbine units with 2 MW power output. The forecasted load shape in percentage at each time interval of the study period is shown in Figure 2.

The variation of available wind power generations of these two wind farms during the study time are shown in Figure 3. The forecasted market prices for energy and reserve power are shown in Figure 4. In this study, the RESW is assumed to be 10% of the total available wind power of two wind farms.

The PS plant has the efficiency of 80% and the maximum capacity of generating and pumping modes are 90 and 80 MW, respectively. The maximum and minimum capacity of energy storage in upper dam is assumed 1250 and 450 MWh and for lower dam are 800 and 0 MWh. The running cost of PS plants is ignored in both generating and pumping modes.

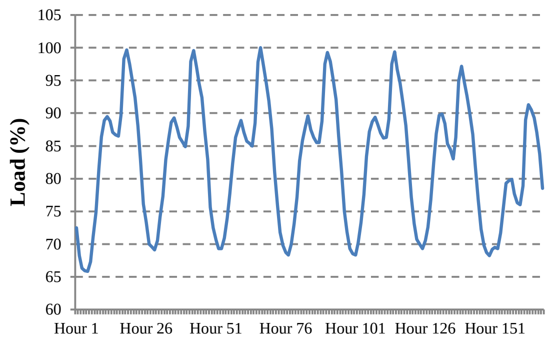

Fig. 2. Forecasted hourly load.

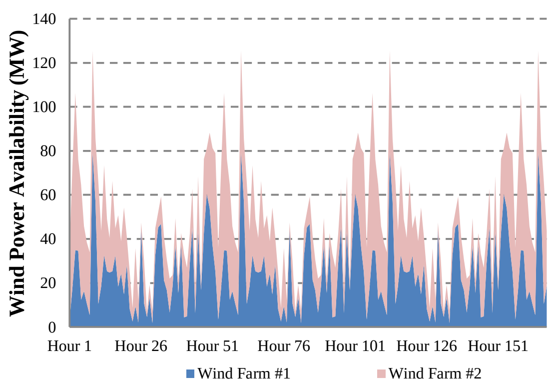

Fig. 3. Available wind power generation of wind farms.

The PS plant has the efficiency of 80% and the maximum capacity of generating and pumping modes are 90 and 80 MW, respectively. The maximum and minimum capacity of energy storage in upper dam is assumed 1250 and 450 MWh and for lower dam are 800 and 0 MWh. The running cost of PS plants are ignored in both generating and pumping modes.

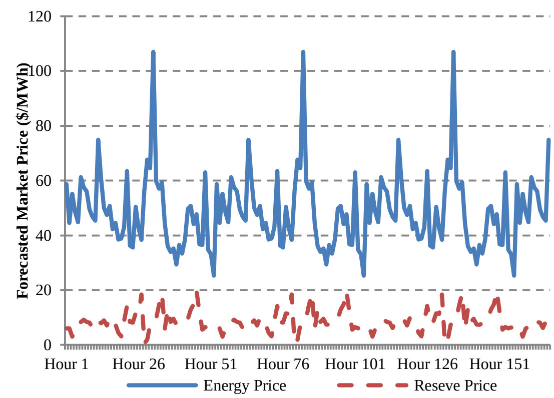

Fig. 4. Forecasted energy and reserve power market prices.

4.1. Test the First System

This test system has six conventional generating units, two wind farms and one PS plant (briefly: 6C+2W+1PS). The input data of 6 conventional units of this test case is written in Table 1. The weekly peak load is predicted to be 300 MW for this study.

Careful value selection of the parameters is important in order to have appropriate results in this simulation. Several parameters are to be determined for implementation of the proposed PSO. In this paper, some parameters have been obtained through the experiments. The values of $w_{\max}$, $w_{\min}$ and $\max iter$ are assumed as 0.5, 0.3 and 200, respectively. The other parameters such as c_1, c_2 and c_3 are selected after many runs on the first test system. The values of c_1 and c_2 are varied from 0.1 to 1.0 in; 10 steps

Table 1. ***Generator characteristics and cost function coefficients.***

Parameters	Unit 1	Unit 2	Unit 3	Unit 4	Unit 5	Unit 6	Wind 1	Wind 2
$P_{G,\max}$ (MW)	50	60	100	120	100	60	80	80
$P_{G,\min}$ (MW)	10	10	10	10	10	10	0	0
Variable O&M Cost ($/MWh)	0.9	0.9	0.8	0.8	0.8	0.9	3	2
a ($/hr)	500	650	700	450	500	600	-	-
b ($/MWh)	25	26.5	18	16	15	27.5	-	-
c ($/MW^{2}h)	0.01	0.012	0.004	0.006	0.004	0.01	-	-

Table 2. ***Best results in CPSO for different values of constants (*** $0.1 \le c_1, c_2 \le 1.0$ ***and*** $c_3 = 0.0$***).***

Approach	Population	c_1	c_2	Total Profit (K$)
CPSO with IWA	10	0.1	0.8	892.056
	10	0.2	0.9	870.658
	10	0.3	0.7	874.541
	10	0.4	1.0	878.025
	10	0.5	0.8	899.260
	10	0.6	0.9	885.996
	10	0.7	0.7	879.682
	10	0.8	1.0	891.693
	10	0.9	0.8	901.032
	10	1.0	0.9	867.792

(each one is 0.1). It is assumed that $c_3 = 0.0$, when employing the conventional PSO (CPSO)

The best results of these variations are written in Table 2. For example, the maximum total profit is obtained at $c_1 = 0.9$ and $c_2 = 0.8$ in conventional PSO for 10 particles (grey area in Table 2). Now, with these values of c_1 and c_2, the variation of c_3 in GPAC PSO model is selected from 1.0 to 2.0 in step 0.1. Table 3 shows the value of c_3 for the best result of objective function (grey area in Table 3). Figure 5 shows the convergence of GPAC PSO when the best value is selected for c_3 ($c_3 = 1.3$ when c_1 and c_2 are 0.4 and 1.0). The minus value of total profit is also shown in Figure 5.

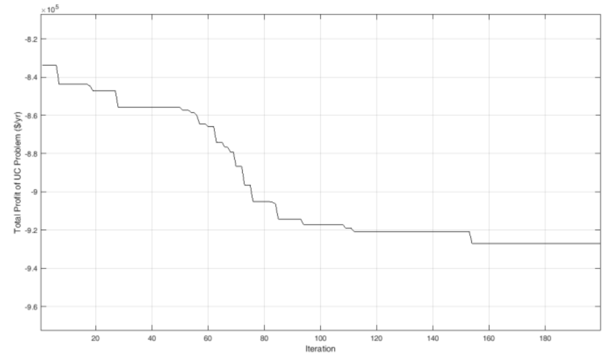

Fig. 5. Convergence index for best results of GPAC PSO (the first test case).

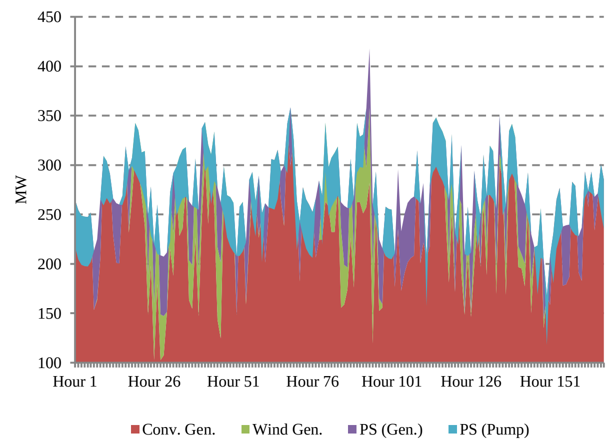

Fig. 6. Individual output generation of all unit's categories and total demand (PSO during setting coefficients process-best output of Table 3).

Table 3. ***Best results in GPAC approaches of PSO for different values of constants (*** $1.0 \le c_3 \le 2.0$***).***

Approach	Population	c_1	c_2	c_3	Total Profit (K$)
Proposed PSO with IWA	10	0.1	0.8	1.4	902.367
	10	0.2	0.9	1.2	891.409
	10	0.3	0.7	1.8	902.141
	10	0.4	1.0	1.3	926.909
	10	0.5	0.8	1.3	894.826
	10	0.6	0.9	1.7	915.157
	10	0.7	0.7	1.8	884.873
	10	0.8	1.0	1.0	895.284
	10	0.9	0.8	1.8	895.507
	10	1.0	0.9	1.4	919.127

Table 4. ***Best results in different approaches of PSO for 100 iterations and 100 runs.***

Approach	Pop.	c_1	c_2	c_3	Total Profit (K$)			
					Min.	Ave.	Max.	Std. Dev.
Conventional PSO	10	0.3	0.9	-	812.851	828.099	862.491	7.6364
GPAC PSO	10	0.3	0.9	1.9	818.683	854.764	903.521	21.4819

The results of UC problem of the first test system which is executed by GPAC PSO with selected coefficients of Table 3 including the power generation of conventional units, wind farms and PS plant, are presented in Figure 6.

The maximum, average and minimum of objective function of UC is presented by application of PSO coefficients which is set in previous part. Table 4 writes the best result of this UC problem employing 100 iterations and 100 trails in different PSO methods. Also, Table 4 shows that the maximum value of total profit has been obtained in the proposed PSO with respect to CPSO method.

4.2. Test the Second System (26C+2W+2PS)

The other test system has 26 conventional units (modified IEEE 24-bus system), two wind farms and one PS plants that the data for these wind farms and PS plants are given in previous Section. The input data of all conventional units of this test system is given in [24] and [25], and also, the total peak load is 2700 MW. Other cost data for this test system was given in [26].

Table 5 shows the best result of these variations. For example, the maximum total profit is obtained at $c_1 = 0.5$ and $c_2 = 0.1$ in conventional PSO for 10 particles (grey area in Table 5). Now, with these values of c_1 and c_2, the variation of c_3 in GPAC PSO model is selected from 1.0 to 2.0 in step 0.1. Table 6 shows the value of c_3 for the best result of objective function (see the grey part). Figure 7 shows the convergence of GPAC PSO when the best value is selected for $c_3 = 1.3$. The minus value of total profit is shown in Figure 7.

Table 5. ***Best results in CPSO for different values of constants (*** $0.1 \le c_1, c_2 \le 1.0$ ***and*** $c_3 = 0.0$***).***

Approach	Population	c_1	c_2	Total Profit (M$)
CPSO with IWA	10	0.1	0.2	12.3690
	10	0.2	0.1	12.3863
	10	0.3	0.1	12.3579
	10	0.4	0.5	12.3378
	10	0.5	0.1	12.3886
	10	0.6	0.1	12.3694
	10	0.7	0.1	12.3585
	10	0.8	0.3	12.3845
	10	0.9	0.1	12.3800
	10	1.0	0.2	12.3751

Table 6. ***Best results in GPAC approaches of PSO for different values of constants (*** $1.0 \le c_3 \le 2.0$***).***

Approach	Population	c_1	c_2	c_3	Total Profit (M$)
Proposed PSO with IWA	10	0.1	0.2	1.2	12.4351
	10	0.2	0.1	1.0	12.4390
	10	0.3	0.1	1.3	12.4256
	10	0.4	0.5	1.9	12.4053
	10	0.5	0.1	1.3	12.4613
	10	0.6	0.1	1.3	12.4528
	10	0.7	0.1	1.3	12.4353
	10	0.8	0.3	1.3	12.4569
	10	0.9	0.1	1.5	12.4357
	10	1.0	0.2	1.6	12.4589

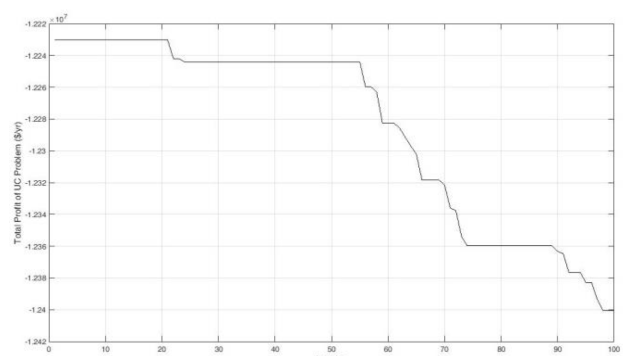

Fig. 7. Convergence index for GPAC PSO for the second test system.

Table 7. ***Best results in different approaches of PSO for 100 iterations and 100 runs.***

Approach	Pop.	c_1	c_2	c_3	Total Profit (M$) Min.	Ave.	Max.	Std. Dev.
CPSO	10	0.5	0.1	0.0	12.2660	12.3623	12.4039	0.020589
GPAC PSO	10	0.5	0.1	1.3	12.3714	12.4268	12.4908	0.0182485

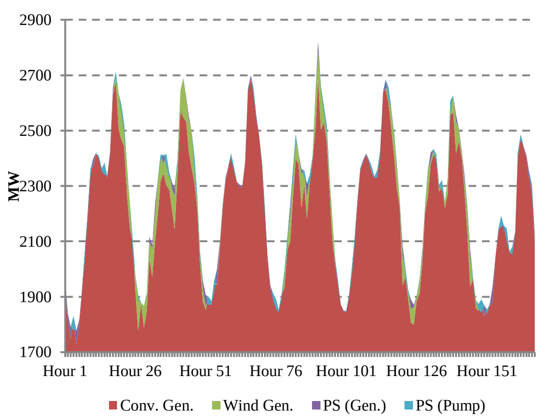

Fig. 8. Individual output generation of all units' categories and total demand for the second test system.

The results of UC problem of the first test system which is executed by GPAC PSO with selected coefficients of Table 3 are presented in Figure 8.

The maximum, average and minimum of objective function of UC is presented by application of PSO coefficients which is set in previous part. Table 7 shows the best result of this UC problem employing 100 iterations and 100 trails in different PSO methods.
Table 7 shows that the maximum value of total profit has been obtained in the proposed PSO with respect to CPSO method.

5. CONCLUSION

This paper presents a new approach to solve the UC problem based on the hybrid PSO algorithm. A new formulation for UC problem is developed to manage the uncertainties of wind power generation with PS plant. Modified PSO is obtained by implementation of social forces. This new UC model is applied to two test systems and solved using conventional and modified PSO methods. The results show that the best utility profit obtained by modified particle swarm optimization.

NOMENCLATURE

a_g, b_g, c_g	The coefficients of generating unit g
c_1, c_2, c_3	Weighting factors called acceleration constants
$C(b)$	The step size of the tumble for the b[th] bacterium, which determines the height of each random step
cfk	Constriction factor in CFA
D	Dimension of the particle
$El(s,t)$	Lower reservoir energy level of pumped storage s at time period t, in MWh
$El_{\max}(s)$	Lower reservoir energy capacity limit of pumped storage s, in MWh
$EP(t)$	Forecasted energy price at time period t, in \$/MWh
$Eu(s,t)$	Upper reservoir energy level of pumped storage s at time period t, in MWh
$Eu_{\max}(s)$	Upper reservoir energy capacity limit of pumped storage s, in MWh
$gbest_d^k$	Dimension d of the best particle in the swarm group until iteration k
g	Index for thermal generator unit
$iter$	Current iteration number
k	The iteration number
$\max iter$	Maximum number of iterations
$M(s,t)$	Commitment state of pumped storage s at time period t (generation mode = 1, pumping mode = 0)
N	The size of the swarm
N_G	Number of thermal generator units
N_S	Number of pumped storage plants
N_W	Number of wind farms
$OMVCT(g)$	Operation and maintenance variable cost of thermal unit g, in \$/MWh
$OMVCW(w)$	Operation and maintenance variable cost of wind unit w, 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 thermal unit g, in MW
$P_{Gg,\max}$	Upper limit of thermal unit g, in MW
$P_{GD}(g,t)$	Load contribution of thermal unit g at time t, in MW
$P_R(t)$	System reserve requirement at time t, in MW

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

$P_W(w,t)$ Generation of wind unit w at time t, in MW

$P_{W,\max}$ Maximum generation of wind unit w, in MW

$PS_{g,\max}(s)$ Maximum limit of generation mode of pumped storage s, in MW

$PS_g(s,t)$ Generation mode of pumped storage s at time period t, in MW

$PS_p(s,t)$ Pumping mode of pumped storage s at time period t, in MW

$PS_{p,\max}(s)$ Maximum limit of pumping mode of pumped storage s, in MW

r_1^k, r_2^k, r_3^k Random numbers, uniformly distributed in [0,1] at iteration k

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

$RESW$ Uncertainty of wind power, in percent

$RP(t)$ Forecasted reserve price at time period t, in \$/MWh

s Index for pumped storage plant

t Index for time

T Number of periods under study (168 Hours)

TC Total operating costs

TR Total revenues

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

$V(w,t)$ Commitment state of wind unit w at time t (on = 1, off = 0)

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

w Index for wind unit

$W_{av}(w,t)$ Maximum available wind power of wind unit w at time t, in MW

wf Weighting function

$wf_{\max}$ Final value of weighting coefficient

$wf_{\min}$ Initial value of weighting coefficient

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

$\eta(s)$ Efficiency of pumping mode of pumped storage s

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. on Power Syst., Vol. 6, No. 3, pp. 1203–1209, 1991.

[3] K. A. Juste, et al., An evolutionary programming solution to the unit commitment problem, IEEE Trans. on Power Syst., Vol. 14, No. 4, pp. 1452–1459, 1999.

[4] I. G. Damousis, A. G. Bakirtzis, and P. S. Dokopoulos, A solution to the unit-commitment problem using integer-coded genetic algorithm, IEEE Trans. on Power Syst., Vol. 19, No. 2, pp. 1165–1172, 2004.

[5] C. P. Cheng, C. W. Liu and C. C. Liu, Unit commitment by Lagrangian relaxation and genetic algorithms, IEEE Trans. on Power Syst., Vol. 15, No. 2, pp. 707–714, 2000.

[6] E. Zareii, M. Mohammadian and A. A. Gharaveisi, Scheduling Security Constraint Unit Commitment for Power System Including Stochastic Wind Power Generation, Journal of Iranian Association of Electrical and Electronics Engineers, Vol. 14, No. 4, pp. 95–102, 2017.

[7] A. Y. Saber, et al, Unit commitment computation - A novel fuzzy adaptive particle swarm optimization approach, IEEE Power Systems Conf., pp. 1820–1828, 2006.

[8] P. Sriyanyong and Y.H.Song, Unit commitment using particle swarm optimization combined with Lagrange Relaxation, IEEE PES General Meeting, 2005.

[9] G. Qin, G. Liu, Z. Jing and Y. Zhang, A preliminary research on the optimal daily

operation mode of pumped-storage power plants under electricity market environment, IEEE/PES Transm. and Dist. Conf. & Exhib., Asia and Pacific, China, 2005.
[10] A. Tuohy and M. O'Malley, Impact of pumped storage on power systems with increasing wind penetration, IEEE Power and Energy Society General Meeting, Canada, 2009.
[11] N. Shi, S. Zhu, X. Su, R. Yang and X. Zhu, Unit commitment and multi-objective optimal dispatch model for wind-hydro-thermal power system with pumped storage, IEEE Inter. Power Elect. And Motion Control Conf., 2016.
[12] J. Garcia-Gonzalez, R. M. R. de laMuela, L.M. Santos and A.M. Gonzalez, Stochastic joint optimization of wind generation and pumped storage units in an electricity market, IEEE Trans. Power Syst., Vol. 23, No. 2, pp. 460–468, 2008.
[13] P. D. Brown, J. A. P. Lopes and M. A. Matos, Optimization of pumped storage capacity in an isolated power system with large renewable penetration, IEEE Trans. on Power Syst., Vol. 23, No. 2, pp. 523-531, 2008.
[14] P. Giorsetto and K. F. Utsurogi, Development of a new procedure for reliability modeling of wind turbine generators, IEEE Trans. Power App. Syst., Vol. 102, No. 1, pp. 134–143, 1983.
[15] S. He, Q. H. Wu, J. Y. Wen, J. R. Saunders, and P. C. Patton, A particle swarm optimizer with passive congregation, Biosyst., Vol. 78, pp. 135–147, 2004.
[16] J. Kennedy and R. Eberhard, Particle swarm optimization, IEEE Intern. Conf. on Neural Networks, Australia, pp. 1942–1948, 1995.
[17] Y. Shi and R. Eberhart, Parameter selection in particle swarm optimization, in evolutionary programming VII: proc. EP98, Springer, pp. 591–600, 1998.
[18] R. Eberhart and Y. Shi, Comparing inertia weights and constriction factors in particle swarm optimization, in Proc. Congr. Evolutionary Computation, pp. 84–88, 2000.
[19] R. C. Eberhard and J. Kennedy, Swarm Intelligence, San Mateo, CA: Morgan Kaufmann, 2002.
[20] M. Clerc and J. Kennedy, The particle swarm: Explosion, stability and convergence in a multi-dimensional complex space, IEEE Trans. on Evol. Comput., Vol. 2, No. 3, pp. 91–96, 1998.
[21] J. K. Parrish and W. M. Hammer, Animal Groups in Three Dimensions, Cambridge, U.K.: Cambridge Univ. Press, 1997.
[22] S. Naka, T. Genji, T. Yura, and Y. Fukuyama, A hybrid particle swarm optimization for distribution state estimation, IEEE Trans. on Power Syst., Vol. 18, No. 1, pp. 60–68, 2003.
[23] J. G. Vlachogiannis and K. Y. Lee, A Comparative study on particle swarm optimization for optimal steady state performance of power systems, IEEE Trans. on Power Syst., Vol. 21, No. 4, pp. 1718–1728, 2006.
[24] IEEE Reliability Test System Task Force, The IEEE reliability test system – 1996, IEEE Trans. Power Syst., Vol. 14, No. 3, pp. 1010-1020, 1999.
[25] S. J. Wang, S. M. shahidehpour, D. S. Kirschen, S. Mokhtari and G. D. Irisarri, Short term generation scheduling with transmission and environmental constraints using an augmented lagrangian relaxation, IEEE Trans. Power Syst., Vol. 10, No. 3, pp. 1294-1301, 1995.
[26] H. Siahkali and M. Vakilian, Electricity generation scheduling with large-scale wind farms using particle swarm optimization, Elect. Power Syst. Res., Vol. 79, pp. 826-836, 2009.
[27] N. Lu and J. H. Chow and A. A. Desrochers, Pumped-storage hydro-turbine bidding strategies in competitive

electricity market, IEEE Trans. on Power Syst., Vol. 19, No. 2, pp. 885-895, 2004.

[28] C. L. Chen, Optimal wind–thermal generating unit commitment, IEEE Trans. Energy Conver., Vol. 23, No. 1, pp. 273-280, 2008.