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Joint Coordination of Wind Farms and Pumped Storage Plants in Generation Scheduling Using Modified Particle Swarm Optimization with Bacteria Foraging Concept

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Abstract

Increasing penetration of renewable energy resources, especially wind power in power system operation, has some technical and economic effects because of the variable and uncertain nature of these resources. Therefore, it is very important for system operators to consider these behaviors necessary to solve the problem in this regard, especially generation scheduling problem. One of the most important strategies to increase the benefit of power system operation is to manage and control of wind power generation using pumped storage plants. A pumped storage plant can be used to provide added value to a wind farm to manage power output uncertainties. This paper presents a new approach for solving the weekly generation scheduling including wind farms and pumped storage plants. The hybrid PSO mechanism is suggested to solve this scheduling problem based on implementation of bacterial foraging concepts. The proposed PSO is applied to two test systems (which are included two wind farms and one pumped storage 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: Generation scheduling, Bacteria foraging, particle swarm optimization, wind power generation.

1. INTRODUCTION

In recent years, the conventional energy resources have caused the increase of concerns in front of decision makers to install new generation capacity. One of the most concerns is air pollution and greenhouse gas problem which are established new market for sustainable energy sources such as wind,

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solar and so on. The most challenging issue to cope with using renewable energies with other resources in power system operation is the stochastic behavior. The main characteristic of this behavior is twofold; uncertainty and variability. Therefore, these factors make some difficulties for system operators to manage and control the power system situation to meet load during different time periods.

A very important task in the operation of power system concerns the optimal generation scheduling (GS) considering technical and economical constraints over a time horizon. The GS problem consists of determining the optimal operation strategy for the next scheduling period, subject to a variety of constraints. One of the most important strategies for increasing profits of system operator is to integrate the wind power resources with limited energy resources such as pumped storage plants. A pumped storage plant can be used to provide added value to a wind farm which takes part in the market in comparison with separate participation of them. The possibility of storing energy in pumped storage 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 from wind power and provide the reserve and flexibility needed in systems with large amounts of wind power. Several studies have been tried to develop a decision approach to set different objective functions such as profit maximization [1], carbon emission reduction [2] curtailment reduction [3]. Pumped storage would also benefit the system by balancing wind power in a market [4] or in an isolated power system [5].

This paper extends GS problem by introducing additional constraints to represent the wind farms generation with pumped storage plants into the problem formulation. The main contributions of this work are as follows:

1. A new generation scheduling formulation is presented which integrates both wind power generation and pumped storage plants,
2. A hybrid particle swarm optimization is presented based on the concept of bacterial foraging,
3. The results of different bacterial foraging concepts implemented in PSO are presented and compared.

In next section, problem formulation of GS and the related constraints are discussed. The wind turbine and pumped storage models are presented in this Section. 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 fifteen conventional units) are used to present the optimization method capabilities in section 4. The results of conventional and passive congregation PSO are compared to the results of proposed hybrid PSO with some modifications based on bacterial foraging concepts. Conclusion of this paper is presented in Section 5.

2. PROBLEM FORMULATION

The main concept of this paper is based on coordination of conventional units, wind farms and pumped storage plants. Therefore, this cooperation can be defined by different objective functions between different owners especially GenCos. In general, this problem can be called the generation scheduling (GS) which is formulated in this paper based on coordination of these three types of generating units to obtain the maximum profit. Thus, it is assumed that these players can estimate their participation in the power market based on own forecasted load to maximize their own profit.

At first, the model of both wind turbine and pumped storage unit will be presented and based on these models the GS formulation will be introduced in two main parts: the objective function and all different constraints during time horizon (168 hours of a week).

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 against 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 from:

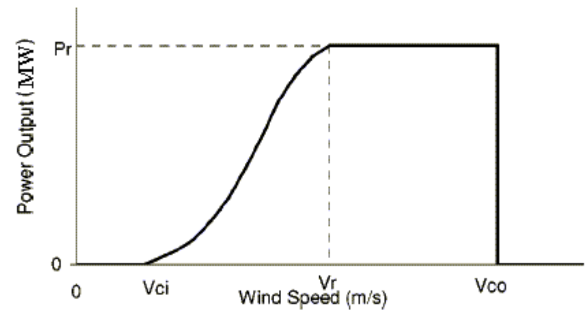

Fig. 1. Power curve of a wind turbine.

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

where the constants A, B, and C are presented as follows [6]:

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

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

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

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, with cut-in rated, cut-out wind speeds of 3.5, 12.5, and 25 m/s, respectively.

2.2. Pumped-Storage Model

The pumped-storage plant (PS) is composed of an upper and lower reservoir. Typically, a reversible pump-turbine makes the storing of energy in off-peak hours possible that it can be sold during peak hours which provides the operation to be economically profitable. Thus, the pump-turbine will work as a turbine when water is released from the upper reservoir to the lower one, 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 pumped-storage plant are considered in terms of energy in the model. 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. Similarly, the volume capacity of both reservoirs will be expressed as maximum and minimum energy levels that can be stored in the reservoirs [7]. The energy stored in each lower and upper reservoirs of pumped storage plant has an upper and a lower capacity limitation which are:

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

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

In this paper, contribution of pumped storage plant in reserve power market is not considered.

2.3. Generation Scheduling Model

The main objective of a GS problem is to maximize 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 hourly intervals. The objective function of GS problem is defined as follows:

$$Max \quad JJ = F_2 - F_1 \tag{4}$$

$$\begin{aligned} F_1 = & \sum_{t=1}^{T}\sum_{g=1}^{N_G}\left\{P_{GD}(g,t)\cdot U(g,t)\right\}\cdot EP(t) \\ & + \sum_{t=1}^{T}\sum_{g=1}^{N_G}\left\{P_{GR}(g,t)\cdot U(g,t)\right\}\cdot RP(t) \\ & - \sum_{t=1}^{T}\sum_{g=1}^{N_G} F\left(P_{GD}(g,t)\right)\cdot U(g,t) \\ & - \sum_{t=1}^{T}\sum_{g=1}^{N_G} SU(g)\cdot U(g,t)\cdot(1-U(g,t-1)) \\ & - \sum_{t=1}^{T}\sum_{g=1}^{N_G}\{(P_{GD}(g,t)+P_{GR}(g,t)) \\ & \cdot OMVCT(g)\}\cdot U(g,t) \end{aligned} \tag{5}$$

$$\begin{aligned} F(P_{GD}(g,t)) = & a_g + b_g \cdot P_{GD}(g,t) \\ & + c_g \cdot P_{GD}(g,t)^2 \end{aligned} \tag{6}$$

$$\begin{aligned} F_2 = & \sum_{t=1}^{T}\sum_{w=1}^{N_W}\left\{P_W(w,t)\cdot V(w,t)\right\}\cdot EP(t) \\ & + \sum_{t=1}^{T}\sum_{s=1}^{N_S}\left\{PS_g(s,t)\cdot M(s,t)\right\}\cdot EP(t) \\ & - RESW\cdot\sum_{w=1}^{N_W}\left\{P_W(w,t)\cdot V(w,t)\right\}\cdot RP(t) \\ & - \sum_{t=1}^{T}\sum_{s=1}^{N_S}\left\{PS_p(s,t)\cdot(1-M(s,t))\right\}\cdot EP(t) \\ & - \sum_{t=1}^{T}\sum_{w=1}^{N_W}\left\{P_W(w,t)\cdot OMVCW(w)\right\}\cdot V(w,t) \end{aligned} \tag{7}$$

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 pumped storage generation. To comply system demand, it is required to have the following equation satisfied:

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

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 one 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 by assessing the recorded data on wind speed at wind turbine site [8]. In this study, the RESW is assumed 10%.

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

The generating unit constraints should be also satisfied. Therefore, the wind power availability is written as follows:

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

And the maximum and minimum generation of the conventional units are:

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

Consider a pumped storage 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 pumped storage plant should be calculated and satisfied as follows:

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

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

3. IMPLEMENTATION OF PSO WITH BACTERIAL FORAGING CONCEPTS

Particle Swarm Optimization (PSO) was firstly proposed by Kennedy and Eberhart [10] in 1995. This technique was inspired by the choreography of a bird flock and can be seen as a distributed behavior algorithm that performs multidimensional search. According to PSO, either the best local or the best global particle to help it which 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 ($pbest$) 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 best position of the group.

Suppose that the search space is D-dimensional; then, the i^th particle of the swarm can be represented by a D-dimensional vector, $X_i = (x_{i1}, x_{i2}, ..., x_{iD})$. The velocity (position change) of this particle can be represented by another D-dimensional vector $V_i = (v_{i1}, v_{i2}, ..., v_{iD})$. The best previously visited position of the i^th particle is denoted as $pbest_i = (p_{i1}, p_{i2}, ..., p_{iD})$. Defining $pbest$ as the best particle in the swarm, then the swarm is updated according to the following equation (Conventional PSO):

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

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

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

The model using (15) is called inertia weights approach (IWA) [11]. Using the above equation, the diversification of characteristic is gradually decreased and a certain velocity, which gradually moves the current searching point, closes to $pbest$, and $gbest$ can be calculated. Moreover, in order to guarantee the convergence of the PSO algorithm, the constriction factor is defined as [12]. In this constriction factor approach (CFA), the basic system equations of the PSO can be used.

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

The current position (searching point in the solution space) can be modified by the following equation:

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

3.2. Overview of the Congregation PSO

According to the local-neighborhood variant of the PSO algorithm (LPSO) [13], each particle moves toward its best previous position and toward the best particle in its restricted neighborhood. As 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 has been introduced in [14]. However, it has been 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 [15] have proposed mathematical models to show how these forces organize the swarms. These can be classified in 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 [15]. 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], [9].

Congregation, on the other hand, is a swarming by social forces, which is the source of attraction of a particle to others, and it is classified in 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. For example, ants that have high genetic relation use antennal contacts to transfer information about location of resources [15], [9]. 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) [9] that is enhanced with the constriction factor approach [14], [16], is employed. The swarms of the enhanced GPAC are manipulated by the velocity update,

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

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) [17].

3.3. Concept of Bacterial Foraging Method

Bacterial foraging optimization algorithm proposed by Kevin Passino [18] is a new optimization method based on nature inspired algorithm. Application of group foraging strategy of a swarm of E. coli bacteria in multi-optimal function optimization is the key idea of this new algorithm. Natural selection tends to eliminate animals with poor foraging strategies and favors the propagation of genes of those animals that have successful foraging strategies since they are more likely to enjoy reproductive success. After many generations, poor foraging strategies are either eliminated or shaped into good ones. The control system of these bacteria that dictates how foraging should proceed can be subdivided into four sections namely Chemotaxis, Swarming, Reproduction and Elimination and Dispersal [18], [19].

Each bacterium can move in the different ways. It can swim in the same direction or it may tumble and alternate between these two modes of operation for the entire lifetime. In each decreasing step, each bacterium position is updated based on (19):

$$\theta_b(j+1,k,l)=\theta_b(j,k,l)+C(b)\cdot\psi(j) \quad (19)$$

where b is the index of the bacterium, and $\theta_b(j,k,l)$ is the position of the b^{th} bacterium in the j^{th} step of chemotaxis, the k^{th} stage of reproduction, and the lth stage of elimination-dispersal. The cost function of the bth bacterium is determined based on its position and is represented by $J(b,j,k,l)$. $J_{\min}$ is represented by the minimum fitness value. In the swim stage, the cost function of bacterium at position $\theta_b(j+1,k,l)$ becomes better than the cost value at position $\theta_b(j,k,l)$, another step will be taken in the same direction. This sequence will continue up to upper limit of swim steps (N_{ST}). To consider of the repellant and attractant effects of each bacterium, the cost function (20) is added to the actual cost function. Then, the cost function can be updated by (21).

$$J_{CC}(\theta,P(j,k,l))=\sum_{b=1}^{N_B}J_{CC}^{b}(\theta,P(j,k,l)) \quad (20)$$

$$J(b,j,k,l)=J(b,j,k,l)+J_{CC}(\theta,P) \quad (21)$$

- Reproduction process

The original set of bacteria, after getting evolved through several chemo tactic stages, reaches the reproduction stage. Here, best set of bacteria gets divided into two groups. The least healthy bacteria eventually die and replace with the other healthier bacteria, which split into two bacteria and then placed in the same location. This keeps the population of bacteria fixed. It reduces unpromising diversity in the searching space to accelerate the process. A reproduction step is executed after specified chemotactic steps.

- Elimination-dispersal process

Gradual or sudden changes in the local environment where a bacterium population lives may occur due to various reasons. Events can occur such that all the bacteria in a region are killed or a group is dispersed into a new part of the environment. While this may destroy the progress achieved through the chemotactic process thus far, it may happen that the bacterium may find itself closer to new source of nutrients. It increases global searching ability. One elimination-dispersal step is undertaken after specified reproduction steps are completed.

3.4. Modified GPAC PSO with Bacteria Foraging Concept

The PSO is a heuristic optimization method which is developed and based on social practices of individuals within a group for food finding. This approach is a population-based algorithm like the genetic algorithm. All particles move in steps throughout a region and the objective function at each particle evaluate at each step. During this search procedure, the members of the entire population are maintained constant. Therefore, the traditional PSO has some disadvantage from the premature

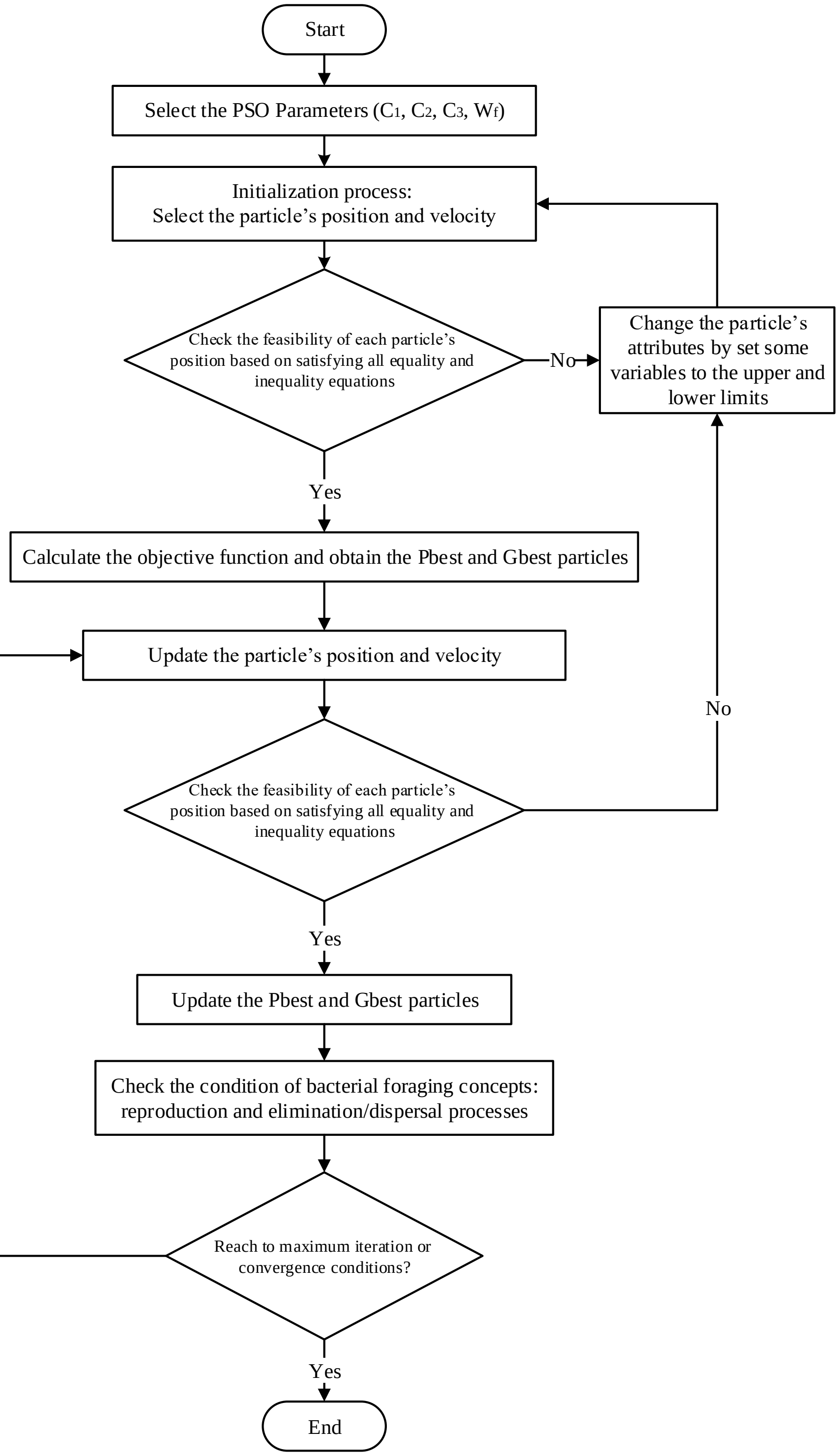

Fig. 2. Flowchart of hybrid PSO.

convergence when it tries to find the global optimization. This is caused to present some modifications to add filtering operation (such as crossover and/or mutation) or diversification methods to improve PSO performance.

In this paper, the concept of reproduction and elimination/dispersal processes are implemented in particle swarm optimization method. As mentioned in previous part, both reproduction and stagnation/elimination approaches are completed at fixed number of searching steps. Like reproduction in bacterial Foraging (BF), we use this concept in our proposed hybrid PSO. Based on the reproduction concept, a constant percentage of all particles with the worst value of fitness function have been replaced by the existing particles with the best value of fitness function (PSO+BFO type 1). In this paper, reproduction stage is executed after each %35 of maximum iteration of PSO algorithm.

Same as above approach, to avoid premature convergence into a local optimum, the elimination/dispersal concept is used in our proposed hybrid PSO. This concept can be implemented by elimination of a fixed percentage of all particles with the same value or lowest value of fitness function and replaced by same number of new particles (PSO+BFO type 2). This stage is performed after each %25 of maximum iteration of PSO algorithm. The process of the modified PSO algorithm can be summarized as follows (Fig. 2).

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 GS 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 as the vector of

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

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 all of 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 should be determined in advance based on which parameters' values have been obtained the best outputs' results. 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) Modified PSO Based on bacterial foraging: As mentioned before, based on fixed number of iterations, both concepts of reproduction and stagnation/elimination

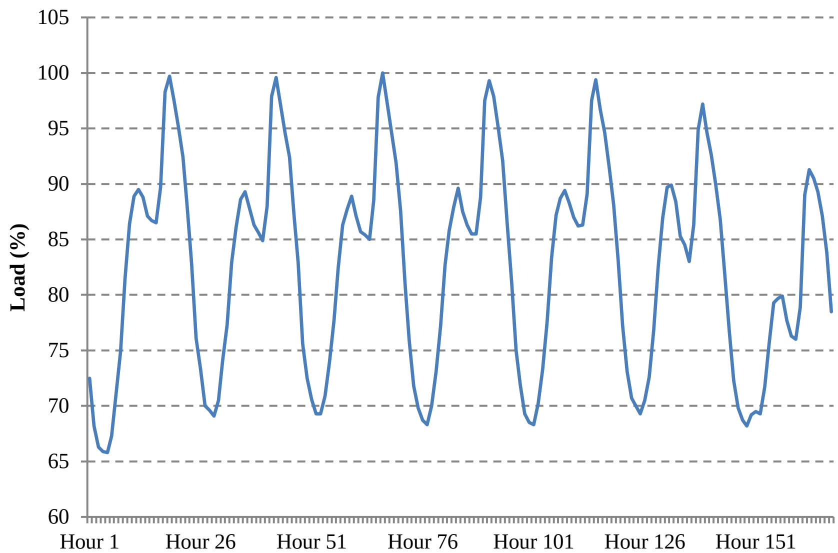

Fig. 3. Forecasted hourly load.

approaches are applied on particles. Update of Pbest and Gbest: The Pbest of each particle at any iteration and Gbest are updated with respect to cost function. Based on reproduction approach, a fixed number of particles are replaced by the particles that have better value of fitness function. Then, this procedure goes back to step 2 to update the positions, but based on stagnation/elimination approach, a fixed number of particles that have worst value of fitness function must be selected to replace by new particles. Thus, this procedure has to come back to step 1.

Step 5) Stopping Criteria: This process is terminated if the iteration approaches to the predefined maximum iteration.

At the end, both concept of reproduction and elimination/dispersal is applied together into PSO method at different time of execution of PSO algorithm (at fixed number of maximum iteration). The abbreviation of this approach is PSO+ BFO type 1&2.

4. RESULTS OF TEST SYSTEMS

To examine the merits of the proposed method, two test systems are simulated in this section. In both test systems, two wind farms and one pumped storage plant are included. Each wind farms have 20 wind turbine units with 2 MW power output. The forecasted load shaped in percentage at each time interval of the study period is shown in Figure 3.

The variation of available wind power generations of these two wind farms during the study time are shown in Figure 4. The forecasted market prices for energy and reserve power are shown in Figure 5. In this study, the RESW is assumed to be 10% of the total available wind power of two wind farms.

The pumped storage plant has the efficiency of 80% and the maximum capacity of generating and pumping modes are 90 and 80 MW respectively. The maximum and

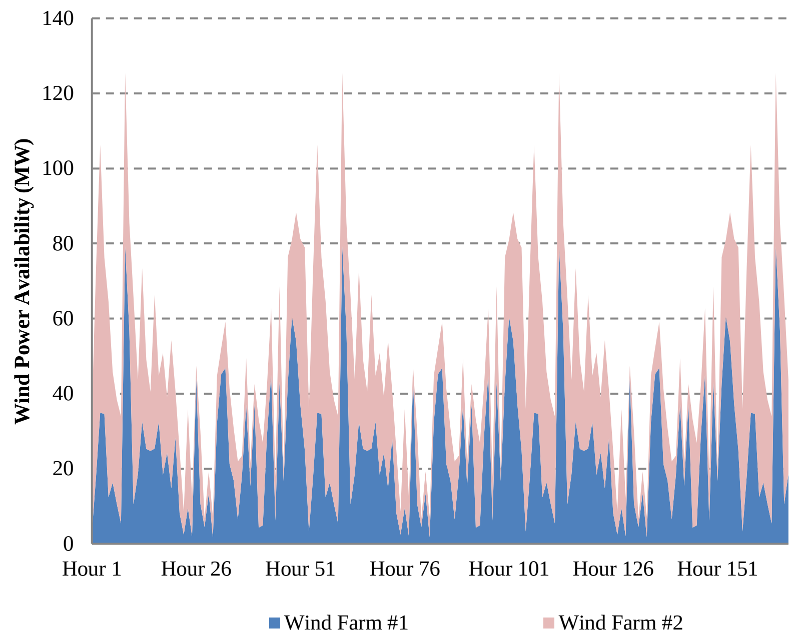

Fig. 4. Available power generation of wind farms.

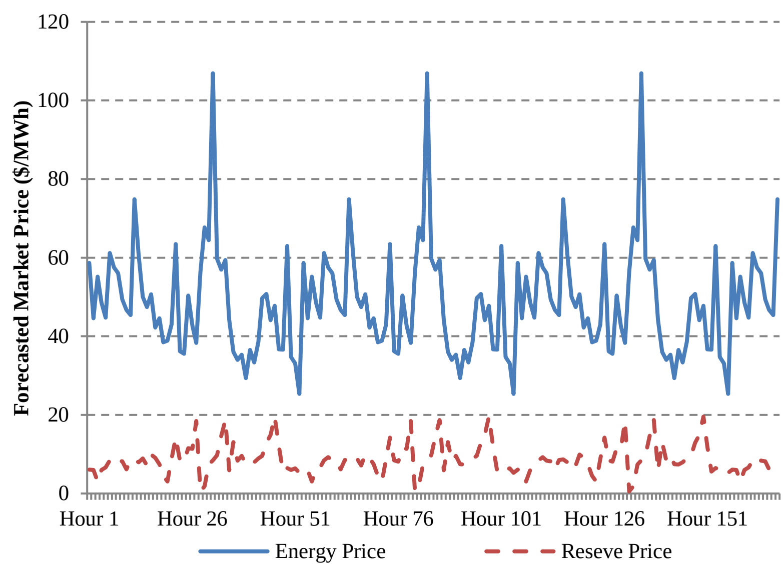

Fig. 5. Forecasted prices of energy and reserve power.

minimum capacity of energy storage in upper dam is assumed 1250 and 450 MWh and for lower dam are 800 and 0 MWh consecutively. The running cost of pumped storage plants are ignored in both generating and pumping modes.

4.1. Test System #1

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

Careful selection of the parameters settings is important to produce competent results in this simulation. There are several parameters to be determined for the implementation of the proposed PSO. In this paper, some parameters have been determined through the experiments. The values of $w_{\max}$, $w_{\min}$ and $\max iter$ are assumed as 0.5, 0.3 and 200 in a row. The other parameters such as c_1, c_2 and c_3 are selected after many runs on the test system #1. The values of c_1 and c_2 are varied from 0.1 to 1.0 in; 10 steps (each one is 0.1). It is assumed that $c_3 = 0.0$ when we employ the conventional PSO (CPSO).

Table 2 shows the best result of these variations. 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

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 Conventional PSO 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$)
Conventional PSO 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

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

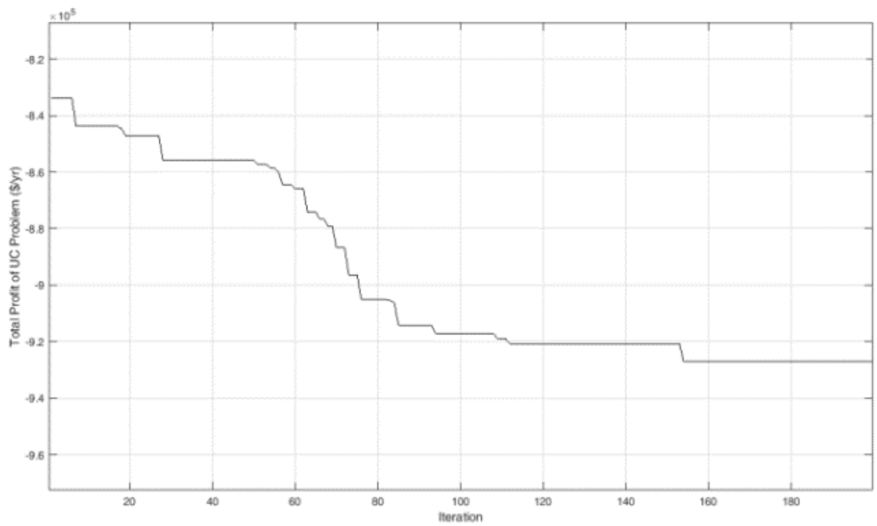

Fig. 6. Convergence index for best results of GPAC PSO (Test Case #1).

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 6 shows the convergence of GPAC PSO when the best value is selected for c_3 ($c_3 = 1.3$). The negative value of total profit is shown in this figure.

The results of GS problem of test system #1 which is executed by GPAC PSO with selected coefficients of Table 3 are presented in Figures 7. The power generation of conventional units, wind farms and pumped storage plant is shown in this figure.

Now, the proposed PSO with bacterial foraging concepts is implemented in three different aspects as mentioned in previous section. Figure 8 shows the convergence of the different PSO methods such as

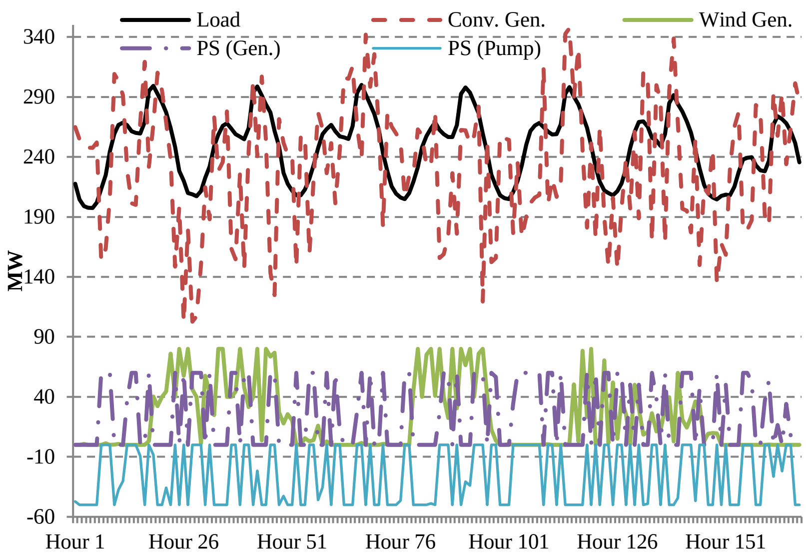

Fig. 7. Individual output generation of all unit's categories and total demand (PSO during setting coefficients process-best output of Table 3).

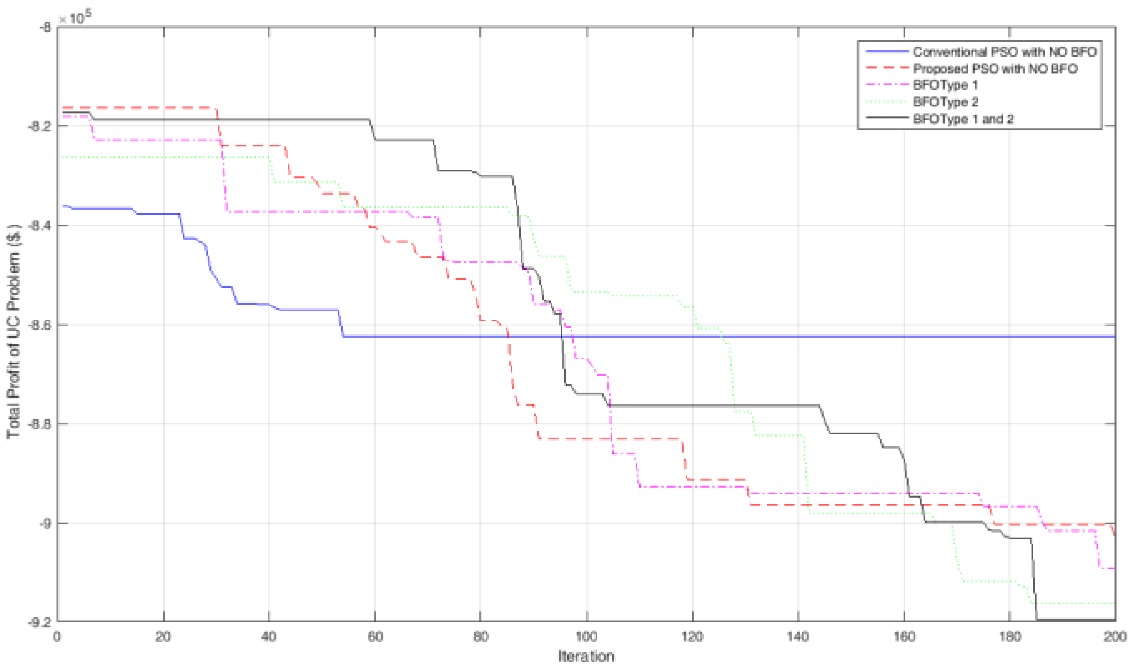

Fig. 8. Convergence index for particle swarm method and modified PSO with BF implementation in Test System #1.

conventional PSO and GPAC PSO with our proposed PSO with bacterial foraging concepts (BFO type 1, type 2 and type 1&2). The GPAC PSO is used to apply all three different types of bacterial foraging concepts.

The best results are obtained in BFO type 1&2 which is developed based on both concepts of reproduction and elimination/dispersal approaches. Figure 9

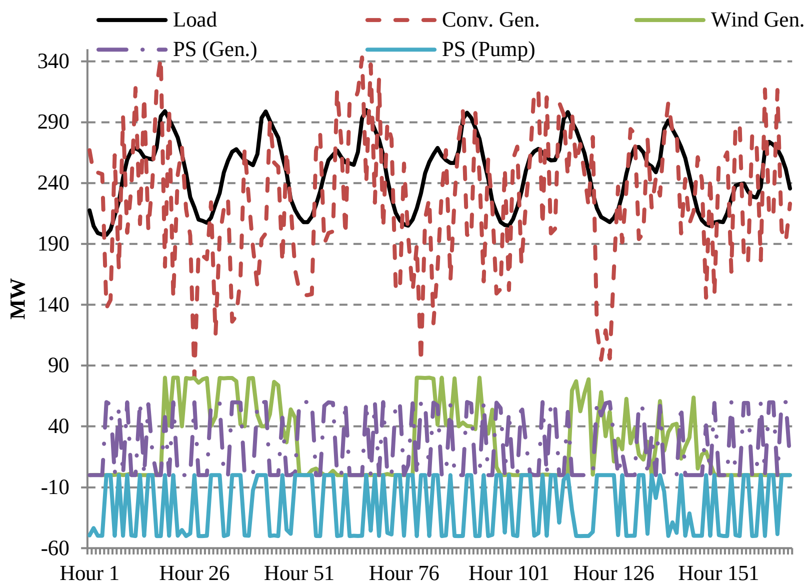

Fig. 9. Individual output generation of all units' categories and total demand (PPSO with bf type 1& 2-best output of Table 4).

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
PPSO with BF Type 1	10	0.3	0.9	1.9	823.477	862.963	909.145	21.1182
PPSO with BF Type 2	10	0.3	0.9	1.9	818.874	858.833	916.173	23.5166
PPSO with BF Type 1 & 2	10	0.3	0.9	1.9	816.526	859.899	919.539	24.7124

shows individual output of different types of power generation in the best value of objective function (proposed PSO with BFO type 1&2).

The maximum, average and minimum of objective function of GS is presented by application of PSO coefficients which is set in previous part. Table 4 shows the best result of this GS problem employing 100 iterations and 100 trails in different PSO methods.

Table 4 shows that the maximum value of total profit has been obtained in the proposed PSO with BFO type 1&2 with respect to other PSO methods. Nevertheless, based on the average values, the proposed PSO with BFO type 1 has the higher total profit than other PSO methods. Maximum total profit of test system in this weekly scheduling is 919.539 thousand dollars per week.

4.2. Test System #2 (15C+2W+2PS)

The other test system has 15 conventional units; two wind farms and one pumped storage plants that the data for these wind farms and pumped storage plants are given in previous section. The input data of all conventional units of this test system is categorized in Table 5 [20, 21], and also, the total peak load is 2630 MW. The data for other units is as same as the data in test system #1.

After execution of PSO parameter selection procedure, the value of these three coefficients set to $c_1 = 0.8$, $c_2 = 0.3$ and $c_3 = 1.3$. Now, the proposed PSO with bacterial foraging concepts is implemented in three different aspects as mentioned in previous section. Figure 10 shows the convergence of the different PSO methods such as conventional PSO and GPAC PSO with our proposed PSO with bacterial foraging concepts (BFO type 1, type 2 and type 1&2). The GPAC PSO is used to apply all three different types of bacterial foraging concepts. The best results are obtained in BFO type 1&2 which is developed based on both concepts of reproduction and elimination/dispersal approaches. Figure 11 shows individual output of different types of power generation in the best value of objective function (proposed PSO with BFO type 1&2).

The maximum, average and minimum of objective function of GS are presented by application of PSO coefficients which is set in previous part. Table 6 shows the best result of this GS problem employing 100 iterations and 100 trails in different PSO

Table 5. ***Generator characteristics and cost function coefficients.***

Unit	$P_{G,\min}$ (MW)	$P_{G,\max}$ (MW)	a ($/hr)	b ($/MWh)	c ($/MW^{2}h)	Variable O&M Cost ($/MWh)
1	150	455	671	10.1	0.000299	0.3
2	150	455	574	10.2	0.000181	0.3
3	20	130	374	8.8	0.001126	0.8
4	20	130	374	8.8	0.001126	0.8
5	150	470	461	10.4	0.000205	0.3
6	135	460	630	10.1	0.000301	0.3
7	135	465	548	9.8	0.000364	0.3
8	60	300	227	11.2	0.000338	0.4
9	25	162	173	11.2	0.000807	0.8
10	25	160	175	10.7	0.001203	0.9
11	20	80	186	10.2	0.003586	0.8
12	20	80	230	9.9	0.005513	0.9
13	25	85	225	13.1	0.000371	0.9
14	15	55	309	12.1	0.001929	0.9
15	15	55	323	12.4	0.004447	0.9

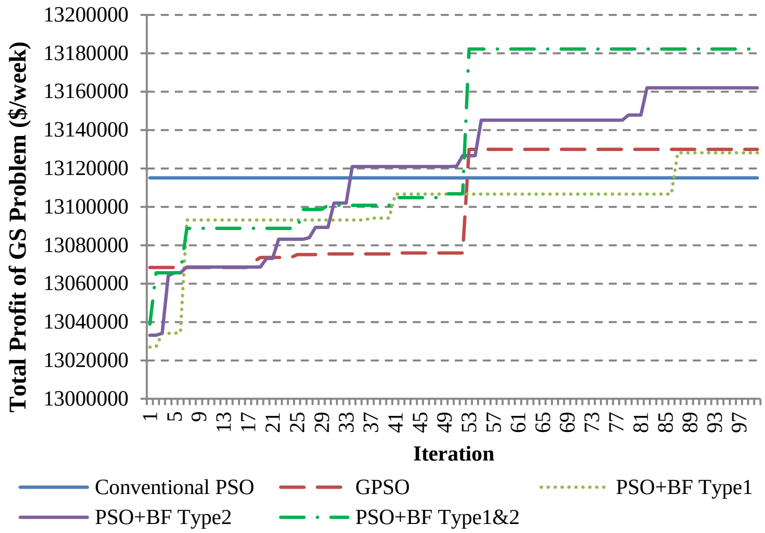

Fig. 10. Convergence index for particle swarm method and modified PSO with BF implementation in Test System #2.

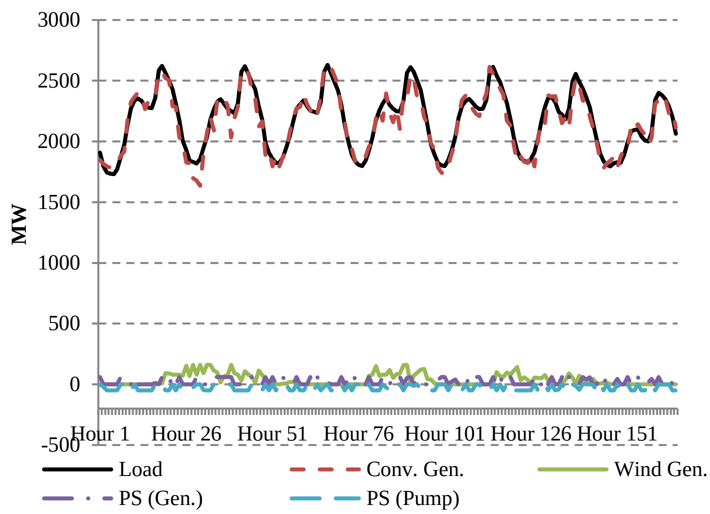

Fig. 11. Individual output generation of all units' categories and total demand in Test System #2 (PSO with BFO type 1&2).

methods. Table 6 shows that the maximum value of total profit has been obtained in the proposed PSO with respect to conventional PSO method.

5. CONCLUSION

This paper presents a new approach to solve the GS problem based on the hybrid PSO algorithm. A new formulation for GS problem is developed to manage the uncertainties of wind power generation with pumped storage plant. Hybrid PSO is obtained by implementation of bacterial foraging concept. The reproduction process and stagnation/elimination step are two main concepts of bacterial foraging optimization that are applied to conventional PSO to

Table 6. ***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.
Conventional PSO	10	0.8	0.3	0.0	13.0462	13.0686	13.1151	0.014309
GPAC PSO	10	0.8	0.3	1.9	13.0784	13.1051	13.130	0.011460
PPSO with BF Type 1	10	0.8	0.3	1.9	13.0727	13.1042	13.1282	0.010777
PPSO with BF Type 2	10	0.8	0.3	1.9	13.0942	13.1261	13.1620	0.013908
PPSO with BF Type 1 & 2	10	0.8	0.3	1.9	13.0909	13.1254	13.1822	0.014456

establish hybrid PSO. This new GS model is applied to a test system and solved using conventional and hybrid PSO methods. The results have been shown that the best utility profit has been obtained by modified particle swarm optimization with bacterial foraging concepts.

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

$J(b, j, k, l)$ Cost function of the b^{th} bacterium in the jth step of chemotaxis, the kth stage of reproduction, and the lth stage of elimination-dispersal

k The iteration numbers

$\max iter$ 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_B Number of bacteria

N_G Number of thermal generator units

N_S Number of pumped storage plants

N_{ST} Number of the swim steps

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

$P(j,k,l)$ The position of each member in the population of the b bacterium at each stage

$P_d(t)$ 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

$P_{GDi,g,t}^{k}$ Load contribution of thermal unit g at time t for particle i at iteration k, in MW

$P_{GRi,g,t}^{k}$ Reserve contribution of thermal unit g at time t for particle i at iteration k, in MW

$P_{Wi,w,t}^{k}$ Generation of wind unit w at time t for particle i at iteration k, in MW

$PS_{Pi,s,t}^{k}$ Pumping mode of pumped storage s at time period t for particle i at iteration k, in MW

$PS_{gi,s,t}^{k}$ Generation mode of pumped storage s at time period t for particle i at iteration k, 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)

JJ Total profits

$U(g,t)$ 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

$\psi(j)$ The direction angle of the j^{th} step

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

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