Refined Binary Particle Swarm Optimization and Application in Power System

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Abstract: - This paper presents new solution methods and results based on a refined binary particle swarm optimization (RBPSO) for solving the generation/pumping scheduling problem within the power system operation with pumped-storage units. The proposed RBPSO approach combines a basic particle swarm optimization (PSO) with binary encoding/decoding techniques. Complete solution algorithms and encoding/decoding techniques are proposed in the paper. The optimal schedules of both pumped-storage and thermal units are concurrently obtained within the evolutionary process of evaluation functions. Significantly, no hydro-thermal iteration is needed. The proposed approach is applied with success to an actual utility system, which consists of four pumped-storage units and 34 thermal units. The results indicate the attractive properties of the RBPSO approach in practical application, namely, a highly optimal solution cost and more robust convergence behavior.

Key-Words: - Refined binary particle swarm optimization, Power system, Pumped-storage.

1 Introduction

This work presents a novel methodology based on a refined binary particle swarm optimization (RBPSO) approach for solving the pumped-storage (P/S) scheduling problem within the power system operation. The generation/pumping scheduling of P/S units has been reckoned as a difficult part of the power system operation. It aims to minimize the total fuel costs of a power system while satisfying various local and coupling constraints. The exact optimal solution to the P/S scheduling problem can be obtained by exhaustive enumeration of all P/S and thermal unit combinations at each time period. However, the burden of computation makes it unacceptable for realistic applications. Conventional methods for solving the P/S scheduling problem are based on decomposition approaches that involve a hydro and a thermal subproblem [1-7]. These two subproblems are usually coordinated by LaGrange multipliers, then, the optimal generation schedules of both P/S and thermal units are obtained via repetitive hydro-thermal iterations. A well-recognized difficulty is that the solutions to these two subproblems may oscillate between maximum and minimum generations with slight changes of the multipliers [4,7]. As a result, the solution cost usually gets stuck at a local optimum rather than at the global optimum. However, the optimality of solution is very important to electric utility. Even a small reduction in percentage production cost may lead to large saving of money. Obviously, a complete and efficient algorithm for solving the P/S scheduling problem is still in demand.

A global optimization technique known as genetic algorithm (GA) has emerged as a candidate for many optimization applications due to its flexibility and efficiency. In our previous efforts, GA has been successfully applied in various areas such as economic dispatch [8-10], hydroelectric scheduling [11], and pumped-storage scheduling [12]. Although the GA had been applied successfully to solve complex optimization problems, recent researches have shown some deficiencies in GA performance. This degradation in efficiency is apparently in applications where the parameters being optimized are highly correlated [13]. Moreover, the premature convergence of GA degrades its performance and reduces its search capability [13].

Recently, Eberhart and Kennedy proposed a particle swarm optimization (PSO) based on the analogy of swarm of bird and school of fish [14]. The PSO mimics the behavior of individuals in a swarm to maximize the survival of the species. In the PSO, each individual makes his direction using the experience of his own and whole group. The individual particle moves stochastically toward the position that affected by the present velocity, previous best performance, and the best previous performance of the group [15]. The main advantages of PSO algorithm are simple concept, easy implementation, robustness to control parameters, and computational efficiency when compared with mathematical algorithm and other heuristic optimization techniques.

In this paper, a refined binary PSO (RBPSO) approach is developed for solving the P/S scheduling problem for the coming 24 hours. Kennedy and Eberhart [16] first introduced the concept of binary PSO and demonstrated that a binary PSO was successfully applied to solve a discrete binary problem. In this work, since all Taipower's P/S units are designed for constant power pumping, novel binary encoding/decoding techniques are judiciously devised to model the discrete characteristic in pumping mode as well as the continuous characteristic in generation mode. One of the advantages of the new approach is the use of stochastic operators rather than deterministic rules to obtain the global optimum in order to escape from local optimums where other methods might land. A representative test example based on the actual Taipower system is presented and analyzed to illustrate the capability of the proposed approach in practical applications.

2 Problem Formulation

2.1 List of symbols

P_{si}^t : power generation of thermal unit i in hour t

P_{hj}^t : power generating or pumping of P/S plant j in hour t, positive: generating; negative: pumping

$F_i^t(P_{si}^t)$: production cost for P_{si}^t

T : number of scheduling hours

N_h : number of P/S plants

N_s : number of thermal units

P_L^t : system load demand in hour t

P_{loss}^t : system transmission network losses in hour t

V_j^t : water volume of the upper reservoir of plant j at the ending of hour t

$V_{j,l}^t$: water volume of the lower reservoir of plant j at the ending of hour t

I_j^t : natural inflow into reservoir j in hour t

Q_j^t : water discharge of P/S plant j in hour t

$Q_{j,p}^t$: water pumping of P/S plant j in hour t

S_j^t : water spillage of P/S plant j in hour t

UR_{si} : up ramp rate limit of thermal unit i

DR_{si} : down ramp rate limit of thermal unit i

$R_{si}^t(P_{si}^t)$: spinning reserve contribution for P_{si}^t

$R_{hj}^t(P_{hj}^t)$: spinning reserve contribution of for P_{hj}^t

R_{req}^t : system spinning reserve requirement in hour t

2.2 Modeling of pumped-storage plant

A P/S hydro plant, which consists of an upper and a lower reservoir, is designed to save fuel costs by generating during peak load with water in the upper reservoir, which would be pumped up during light load hours, as shown in Fig. 1.

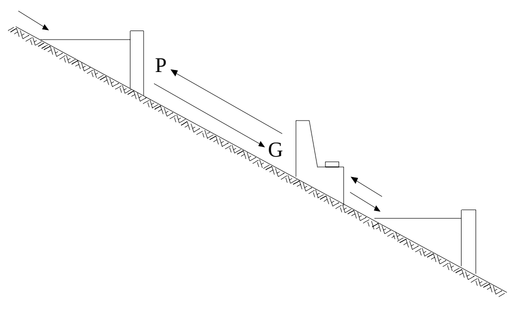

Fig. 1. Pumped-storage hydro plant.

The equivalent plant model can be obtained using an off-line mathematical procedure which maximizes the total plant generation output under different water discharge rates [2]. The generation output of an equivalent hydro plant is a function of the water discharge through the turbine and the net head (or the content of reservoir). The general form is expressed by:

$$P_{hj}^{t} = f(Q_j^t, V_j^{t-1}) \tag{1}$$

The quadratic discharge-generation function to be used in this paper as a good approximation of the hydro plant generation characteristics, considering the net head effect, is given below:

$$P_{hj}^{t} = \alpha_j^{t-1} Q_j^{t^2} + \beta_j^{t-1} Q_j^t + \gamma_j^{t-1} \tag{2}$$

where coefficients α_j^{t-1}, β_j^{t-1}, and γ_j^{t-1} depend on the content of the upper reservoir at the ending of hour *t-1*. In this work, the read-in data include five groups of α, β, γ coefficients that relate to different storage volumes, from minimum to maximum, for the upper reservoir. Then, the corresponding coefficients for any reservoir volume are calculated by using a linear interpolation [3] between the two closest volumes, as shown in the first quadrant of Fig. 2.

In pumping mode, since all P/S units of Taipower are designed for constant power pumping, the characteristic function of a P/S plant is a discrete distribution as shown in the third quadrant of Fig. 2.

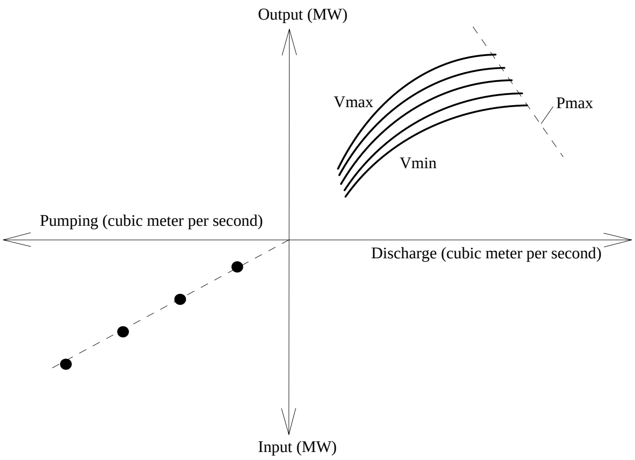

Fig. 2. Input-output characteristic for a P/S plant.

2.3 Objective function and constraints

The scheduling of P/S units deals with the problem of obtaining the optimal generations both for P/S and thermal units. It aims to minimize the production costs of thermal units while satisfying various constraints. With discretization of the total scheduling time into a set of shorter time intervals (say, one hour as one time interval), the scheduling of P/S units can be mathematically formulated as a constrained nonlinear optimization problem as follows:

Problem: $$\text{Minimize} \sum_{t=1}^{T}\sum_{i=1}^{N_s} F_i^t(P_{si}^t) \tag{3}$$

Subject to the following constraints:

o <u>*System power balance*</u>

$$\sum_{i=1}^{N_s} P_{si}^t + \sum_{j=1}^{N_h} P_{hj}^t - P_L^t - P_{loss}^t = 0 \tag{4}$$

o <u>*Water dynamic balance*</u>

$$V_j^t = V_j^{t-1} + I_j^t - Q_j^t + Q_{j,p}^t - S_j^t \tag{5}$$

$$V_{j,l}^t = V_{j,l}^{t-1} + Q_j^t - Q_{j,p}^t + S_j^t \tag{6}$$

o <u>*Thermal generation and ramp rate limits*</u>

$$Max(\underline{P_{si}}, P_{si}^{t-1} - DR_{si}) \le P_{si}^t \le Min(\overline{P_{si}}, P_{si}^{t-1} + UR_{si}) \tag{7}$$

o <u>*Water discharge limits*</u>

$$\underline{Q_j} \le Q_j^t \le \overline{Q_j} \tag{8}$$

o <u>*Water pumping limits*</u>

$$\underline{Q_{j,p}} \le Q_{j,p}^t \le \overline{Q_{j,p}} \tag{9}$$

o <u>*Reservoir limits*</u>

$$\underline{V_j} \le V_j^t \le \overline{V_j} \tag{10}$$

$$\underline{V_{j,l}} \le V_{j,l}^{t} \le \overline{V_{j,l}} \tag{11}$$

o <u>System spinning reserve requirement</u>

$$\sum_{i=1}^{N_s} R_{si}^{t}(P_{si}^{t}) + \sum_{j=1}^{N_h} R_{hj}^{t}(P_{hj}^{t}) \ge R_{req}^{t} \tag{12}$$

3 RBPSO Methodology

3.1 Brief review of PSO

A global optimization technique called PSO is one of the modern heuristic algorithms, which first introduced by Kennedy and Eberhart [14]. Recently, the use of PSO to solve real world problems has aroused researchers' interest due to its flexibility and efficiency. Limitations regarding the form of the objective function employed and the continuity of variables used for the classical greedy search technique can be completely eliminated. It was developed through simulation of a simplified social system, and has been found to be robust in solving continuous nonlinear optimization problems. The PSO technique can generate a high-quality solution within shorter calculation time and stable convergence characteristic than other stochastic methods. Gaing has presented a PSO for solving the economic dispatch problem considering the generator constraints [17]. Many researches are still in progress for proving the potential of the PSO in solving complex power system operation problems [18].

3.2 Representation of binary string

For ease of exposition, consider a P/S plant consisting of four units. The binary string that translates the encoded parameter-water discharges of each plant into their binary representation is shown in Fig. 3.

Using a plant's water discharge, instead of the plant's generation output, the encoded parameter is more beneficial for dealing with the difficult water balance constraints. Each binary string contains 24 genes to represent the solution for the hourly discharge/pumping schedules of the P/S plant in a 24-hour period. Each gene is assigned by the same number of five bits. The first bit is used to identify whether the plant is in generating or in pumping mode. The other four bits are used to represent a normalized water discharge q_j^t in generating mode, or to represent the number of pumping units in pumping mode. The resolution is equal to $1/2^4$ of the discharge difference from minimum to maximum in generating mode.

Hour	1		2		.....	24	
	1	0 0 0 1	0	0 0 1 1	.....	1	0 0 1 0

Fig. 3. Binary string for a 4-unit P/S plant.

3.3 Decoding of binary string

Evaluation of an individual within the PSO is accomplished by decoding the encoded binary string and computing the string's evaluation function using the decoded parameter. The detailed decoding procedure is summarized in the following steps:

Step 1. Decode the first bit to identify whether the plant is in generating, pumping, or idle mode:

Hour t

b_1	b_2	b_3	b_4	b_5

b_1="0" → "pumping mode"

b_1="1" → "generating mode"

b_2=b_3=b_4=b_5="0" → "idle mode"

Step 2. If in pumping mode, go to step 3; if in generating mode, go to step 6; if in idle mode, P_{hj}^{t}=0, then go to step 10.

Step 3. Decode the other four bits of the gene to calculate the number of pumping units and the total volumes of water pumping:

Hour t

0	b_2	b_3	b_4	b_5

$$N_p = \sum_{i=2}^{5}(b_i) \qquad b_i \in \{0,1\} \tag{13}$$

$$Q^t_{j,p} = Q_{j,sp} \times N_p \tag{14}$$

where $Q_{j,sp}$ is the constant water pumping per unit.

Step 4. Calculate the upper boundary of the water pumping:

$$\overline{Q^t_{j,p}} = Min[\overline{Q_{j,p}},\ (V^{t-1}_{j,l} - \underline{V_{j,l}})] \tag{15}$$

If the total volumes of water pumping exceed the upper boundary, then decrease the number of pumping units until satisfied.

Step 5. Calculate the MW power for pumping:

$$P^t_{hj} = -\left(P_{j,sp} \times N_p\right) \tag{16}$$

where $P_{j,sp}$ is the constant power for pumping per unit. Then go to step 10.

Step 6. Decode the other four bits of the gene to obtain the normalized discharge q^t_j in decimal values:

Hour t

1	b_2	b_3	b_4	b_5
	×	×	×	×
	2^{-1}	2^{-2}	2^{-3}	2^{-4}

$$q^t_j = \sum_{i=2}^{5} \left(b_i \times 2^{-(i-1)}\right) \qquad b_i \in \{0,1\} \tag{17}$$

Step 7. Calculate the upper boundary of the discharge:

$$\overline{Q^t_j} = Min\left[\overline{Q_j},\ \left(\overline{V_{j,l}} - V^{t-1}_{j,l}\right)\right] \tag{18}$$

Step 8. Translate the normalized value q^t_j to the actual value Q^t_j :

$$Q^t_j = \underline{Q_j} + q^t_j\left(\overline{Q^t_j} - \underline{Q_j}\right) \tag{19}$$

Step 9. Calculate the generation output P^t_{hj} using (2).

Step 10. Calculate the remaining thermal load:

$$P^t_{rm} = P^t_L - P^t_{hj} \tag{20}$$

where P^t_{rm} is the remaining thermal load in hour *t*.

Step 11. Continue the computation of the above 10 steps from hour 1 to hour 24.

Step 12. Do thermal unit commitment (UC) for the remaining thermal load profile, and return the corresponding thermal cost to the main program.

Step 13. Translate the corresponding thermal cost to the evaluation function.

Step 14. Repeat the above 13 steps from the first binary string to the last binary string.

In this work, a GA based package [19] is used for solving the thermal unit commitment task, taking into account fuel cost, start-up cost, ramp rate limits, and minimal up/down time.

3.4 Evaluation Function

The evaluation function adopted is the thermal production cost plus the penalty cost. In order to emphasize the "best" binary strings and speed up the convergence of the evolutionary process, evaluation function is normalized into the range between 0 and 1. The evaluation function of the i-th binary string in the population is defined as:

$$FIT(i) = \frac{1}{1 + k\left(\frac{\text{cost(i)}}{\text{cost(min)}} - 1\right)} \tag{21}$$

where cost(i) is the corresponding thermal cost plus the excessive discharge penalty cost of the i-th binary string, and cost(min) is the cost of the highest ranking binary string, namely, the presently best binary string, and k is a scaling constant (k=300 in this study). Taking the penalty cost into account, excessive discharge can be avoided in the final solution.

3.5 Searching optimal solution

Searching procedures by RBPSO based on the above concept can be described as follows: a flock of individuals optimizes a certain objective function. Each individual knows its best value *Pbest* so far and its position. Moreover, each individual knows the best value in the group *Gbest* among *Pbest*, namely the best value so far of the group. The modified velocity of each individual can be calculated using the current velocity and the distance from *Pbest* and *Gbest* as shown below:

$$v_i^{k+1} = \omega v_i^k + c_1 Rand(\,) \times (Pbest_i^k - s_i^k) + c_2 Rand(\,) \times (Gbest^k - s_i^k) \qquad (22)$$

$$s_i^{k+1} = \begin{cases} s_i^k + v_i^{k+1} & if \;\; s_{i,\min} \le s_i^k + v_i^{k+1} \le s_{i,\max} \\ s_{i,\min} & if \;\; s_i^k + v_i^{k+1} < s_{i,\min} \\ s_{i,\max} & if \;\; s_i^k + v_i^{k+1} > s_{i,\max} \end{cases} \qquad (23)$$

where,

v_i^k : current velocity of individual i at iteration k

v_i^{k+1}: modified velocity of individual i at iteration k+1

$Rand(\,)$: random number between 0 and 1

s_i^k : current position of individual i at iteration k

$Pbest_i^k$: *Pbest* of individual i until iteration k

$Gbest^k$: *Gbest* of the group until iteration k

ω : weight function for velocity of individual

c_i : weight coefficients for each term

$s_{i,\max}$, $s_{i,\min}$: the maximum/minimum boundary of allowable searching space

The constants c_1 and c_2 represent the weighting of the stochastic acceleration terms that pull each individual toward the *Pbest* and *Gbest* positions. Low values allow individual to roam far from the target regions before being tugged back. On the other hand, high values result in abrupt movement toward target regions. Hence, the acceleration constants c_1 and c_2 were often set to be 2.0 according to simulation experiences. Suitable selection of inertia weight ω in (22) provides a balance between global and local explorations, thus requiring less iteration on average to find a sufficiently optimal solution. As originally developed ω often decreases linearly from about 0.9 to 0.4 during a run. In general, the inertia weight ω is set according to the following equation:

$$\omega = \omega_{\max} - \frac{\omega_{\max} - \omega_{\min}}{Iter_{\max}} \times Iter \qquad (24)$$

where

$\omega_{\max}$: initial weight

$\omega_{\min}$: final weight

$Iter_{\max}$: maximum number of iterations

$Iter$: current number of iterations

The search mechanism of the PSO using the modified velocity and position of individual based on (22) and (23) is illustrated in Fig. 4. The solution methodology for solving the P/S scheduling problem using the proposed approach is outlined in the general flow chart, as shown in Fig. 5.

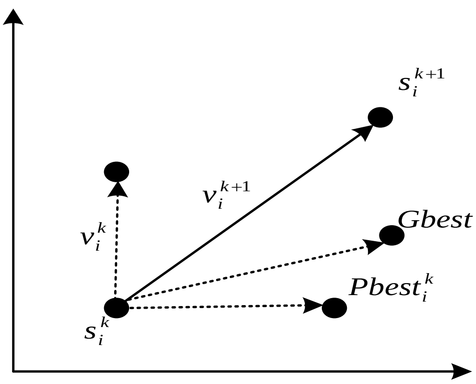

Fig. 4. Searching scheme of the RBPSO

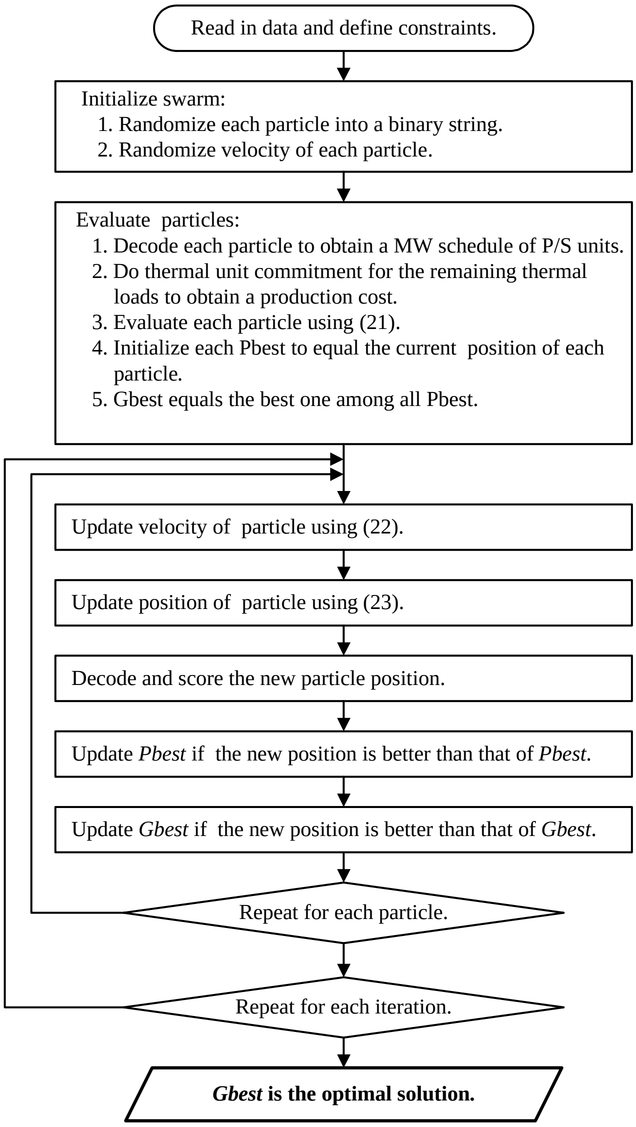

Fig. 5. General flow chart of the proposed RBPSO approach.

4 Test Results

4.1 Test Results of RBPSO Method

The proposed RBPSO approach was implemented in a software and tested on a portion of the Taipower generation system, which consists of 34 thermal units and the Ming-Hu P/S plant with four units. In addition to the common constraints listed in Section 2, the Taipower system has three additional characteristics that increase the difficulty of the problem:

1. The Taipower system is an isolated system, thus, it must remain self-sufficient at all times. The 300MW system spinning reserve requirement must be satisfied each hour.

2. The large load fluctuations, especially at the noon lunch-break hours, are difficult to handle by thermal units due to their ramp rate limits.

3. The lower reservoir of the Ming-Hu P/S plant has only a small storage volume.

Detailed characteristic data of the Ming-Hu P/S plant are given in Table 1. The thermal system consists of 34 thermal units involving six large coal-fired units, eight small coal-fired units, seven oil-fired units, ten gas turbine units, and three combined cycle units. For data on the characteristics of the 34-unit thermal system please refer to [19].

Table 1. Characteristics of the Ming-Hu P/S plant.

Installed Capacity	Maximal Discharge (m^3/s)	Maximal Pumping (m^3/s)	Lower Reservoir		Efficiency
			Maximal Storage (k×m^3)	Minimal Storage (k×m^3)	
250MW×4	380	249	9,756	1,478	0.74

The proposed RBPSO approach is tested on a summer weekday whose load profile, as shown in Fig. 6, is obtained by subtracting the expected generation output of other hydro plants and nuclear units from the actual system load profile. The optimal schedules of both P/S units and thermal units are obtained within 5 minutes, well satisfied the Taipower's requirement. Test results are schematically shown in Fig. 7, Fig. 8, and Fig. 9. Fig. 7 shows the total generating/pumping profile created by the proposed approach. Fig. 8 shows the variation of water storage in the small lower reservoir. Fig. 9 shows the remaining thermal load profile.
From the above study, several interesting and important observations can be summarized as follows:

1. The generating/pumping profiles basically follow the load fluctuation that is consistent with our economic expectation. The Ming-Hu P/S plant generates 3,881 MWh power during peak load hours and pumps up 5,250 MWh power during light load hours, resulting in a cost saving of 5.89 million NT dollars in one day.

2. The P/S units are the major source of system spinning reserve due to their fast response characteristics. The reason the P/S units do not generate to their maximum during peak load hours is because of the system spinning reserve requirement.

3. Variation of water storage in the small lower reservoir is always kept within the maximum and minimum boundaries. The final volume returns to the same as the initial volume.

4. The load factor is improved from 0.82 up to 0.88 thanks to the contribution of the four P/S units.

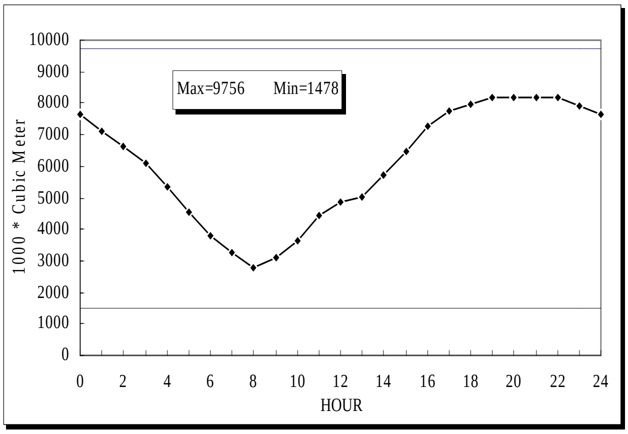

Fig. 8. Variation of water storage in lower reservoir.

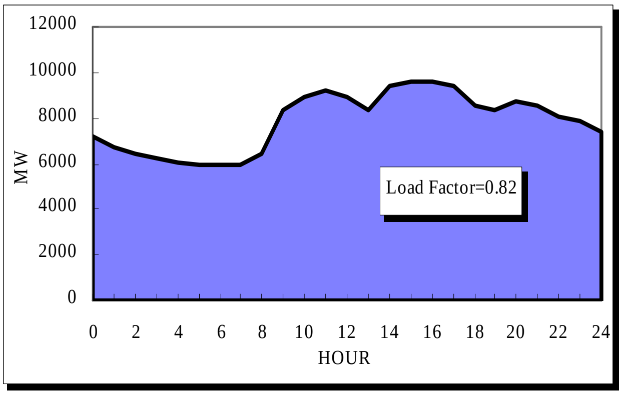

Fig. 6. A summer weekday load profile.

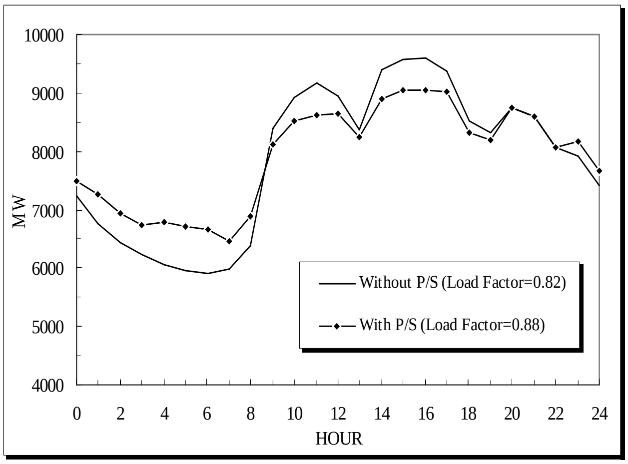

Fig. 9. Remaining thermal load profile.

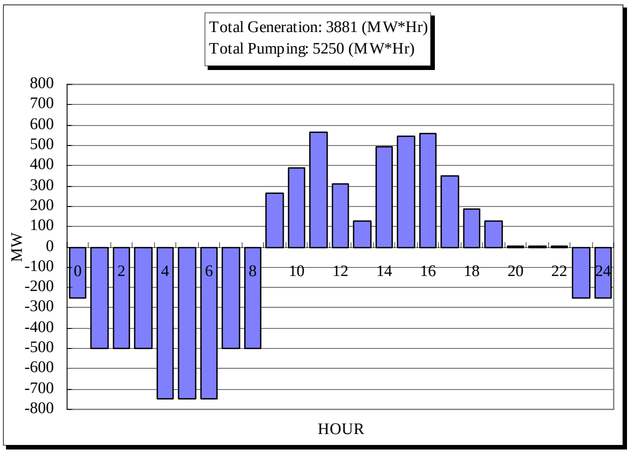

Fig. 7. Generation/pumping profile obtained using the proposed RBPSO method.

4.2 Comparison with Existing Methods

This section describes further how the proposed approach and existing methods differ in performance, in order to highlight the merit of RBPSO. This work adopts a DP method [7] and a GA method [12] as the benchmark for comparison.

Test results are schematically shown in Fig. 10 and Fig. 11. Fig. 10 shows the total generating/pumping profile obtained using a DP method. Fig. 11 shows the total generating/pumping profile obtained using a GA method. Table 2 summarizes the performance comparison between the proposed RBPSO and other two methods. Notably, the proposed RBPSO approach has better cost saving and execution time than the other two existing methods.

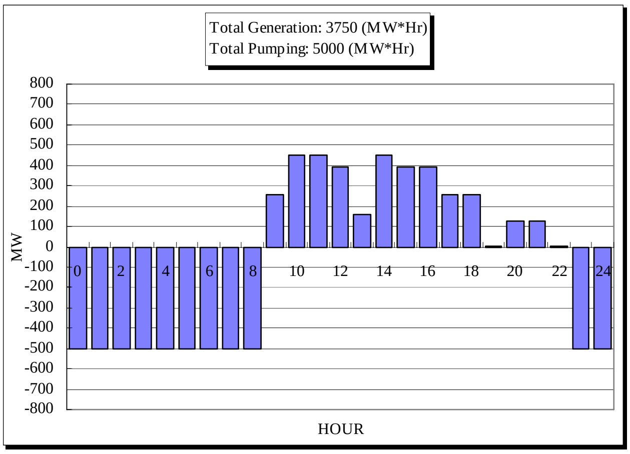

Fig. 10. Generation/pumping profile obtained using DP method.

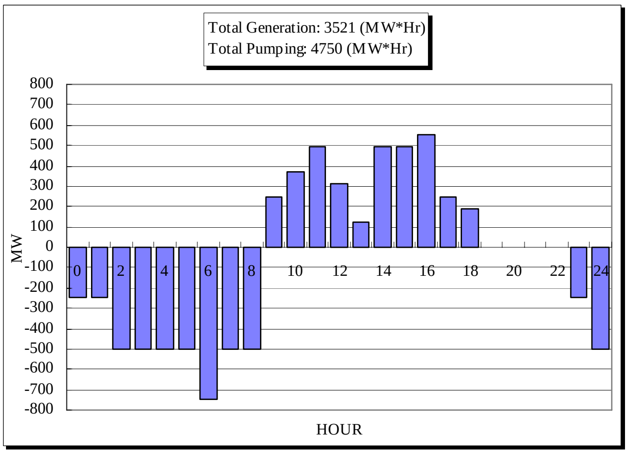

Fig. 11. Generation/pumping profile obtained using GA method.

Table 2. Performance Comparison with Existing Methods.

Method	Load Factor	Cost Saving* (10^3 NT$)	Executing Time (sec.)
DP [7]	0.87	5,641	336
GA [12]	0.87	5,738	164
Proposed RBPSO Method	0.88	5,906	152

* Cost Saving = (cost without P/S) - (cost with P/S)

5 Conclusion

This paper presents a new RBPSO methodology and its application in the P/S units scheduling problem of the daily power system operation. One of the advantages of the proposed approach is the flexibility of PSO for modeling various constraints. The difficult water dynamic balance constraints are embedded and satisfied throughout the proposed binary string encoding and decoding algorithms. The effect of net head was also considered. Numerical results from an actual utility system indicate the attractive properties of the RBPSO approach in practical application, which are a highly optimal solution and more robust convergence behavior.

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