

# Particle Swarm Optimization for Power Dispatch with Pumped Hydro

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## 1. Introduction

Recently, a new evolutionary computation technique, known as particle swarm optimization (PSO), has become a candidate for many optimization applications due to its high-performance and flexibility. The PSO technique was developed based on the social behavior of flocking birds and schooling fish when searching for food (Kennedy & Eberhart, 1995). The PSO technique simulates the behavior of individuals in a group to maximize the species survival. Each particle "flies" in a direction that is based on its experience and that of the whole group. Individual particles move stochastically toward the position affected by the present velocity, previous best performance, and the best previous performance of the group. The PSO approach is simple in concept and easily implemented with few coding lines, meaning that many can take advantage of it. Compared with other evolutionary algorithms, the main advantages of PSO are its robustness in controlling parameters and its high computational efficiency (Kennedy & Eberhart, 2001). The PSO technique has been successfully applied in areas such as distribution state estimation (Naka et al., 2003), reactive power dispatch (Zhao et al., 2005), and electromagnetic devices design (Ho et al., 2006). In the previous effort, a PSO approach was developed to solve the capacitor allocation and dispatching problem (Kuo et al., 2005).

This chapter introduces a PSO approach for solving the power dispatch with pumped hydro (PDWPH) problem. The PDWPH has been reckoned as a difficult task within the operation planning of a power system. It aims to minimize total fuel costs for a power system while satisfying hydro and thermal constraints (Wood & Wollenberg, 1996). The optimal solution to a PDWPH problem can be obtained via exhaustive enumeration of all pumped hydro and thermal unit combinations at each time period. However, due to the computational burden, the exhaustive enumeration approach is infeasible in real applications. Conventional methods (El-Hawary & Ravindranath, 1992; Jeng et al., 1996; Allan & Roman, 1991; Al-Agtash, 2001) for solving such a non-linear, mix-integer, combinatorial optimization problem are generally based on decomposition methods that involve a hydro and a thermal sub-problem. These two sub-problems are usually coordinated by LaGrange multipliers. The optimal generation schedules for pumped hydro and thermal units are then sequentially obtained via repetitive hydro-thermal iterations. A well-recognized difficulty is that solutions to these two sub-problems can oscillate between maximum and minimum generations with slight changes of multipliers (Guan et al., 1994; Chen, 1989). Consequently,

solution cost frequently gets stuck at a local optimum rather than at the global optimum. However, obtaining an optimal solution is of priority concern to an electric utility. Even small percentage reduction in production costs typically leads to considerable savings. Obviously, a comprehensive and efficient algorithm for solving the PDWPH problem is still in demand. In the previous efforts, a dynamic programming (DP) approach (Chen, 1989) and a genetic algorithm (GA) technique (Chen & Chang, 1999) have been adopted to solve the PDWPH problem. Although the GA has been successfully applied to solve the PDWPH problem, recent studies have identified some deficiencies in GA performance. This decreased efficiency is apparent in applications in which parameters being optimized are highly correlated (Eberhart & Shi, 1998; Boeringer & Werner, 2004). Moreover, premature convergence of the GA reduces its performance and search capability (Angeline, 1998; Juang, 2004).

This work presents new solution algorithms based on a PSO technique for solving the PDWPH problem. The proposed approach combines a binary version of the PSO technique with a mutation operation. Kennedy and Eberhart first introduced the concept of binary PSO and demonstrated that a binary PSO was successfully applied to solve a discrete binary problem (Kennedy & Eberhart, 1997). In this work, since all Taipower's pumped hydro 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 generating mode. Moreover, since the basic PSO approach converges fast during the initial period and slows down in the subsequent period and sometimes lands in a local optimum, this work employs a mutation operation that speeds up convergence and escapes local optimums. Representative test results based on the actual Taipower system are presented and analyzed, illustrating the capability of the proposed PSO approach in practical applications.

## 2. Modeling and Formulation

### 2.1 List of symbols

$DR_i$	Down ramp rate limits of thermal unit $i$ .
$F_i^t (P_{si}^t)$	Production costs for $P_{si}^t$ .
$I_j^t$	Natural inflow into the upper reservoir of pumped hydro plant $j$ in hour $t$ .
$N_h$	Number of pumped hydro units.
$N_s$	Number of thermal units.
$P_{hj}^t$	Power generation (positive) or pumping (negative) of pumped hydro plant $j$ in hour $t$ .
$P_L^t$	System load demand in hour $t$ .
$P_{si}^t$	Power generation of thermal unit $i$ in hour $t$ .
$Q_j^t$	Water discharge of pumped hydro plant $j$ in hour $t$ .
$Q_{j,p}^t$	Water pumping of pumped hydro plant $j$ in hour $t$ .

- $R_{hj}^t(P_{hj}^t)$  Spinning reserve contribution of pumped hydro plant  $j$  for  $P_{hj}^t$ .
- $R_{req}^t$  System's spinning reserve requirements in hour  $t$ .
- $R_{si}^t(P_{si}^t)$  Spinning reserve contribution of thermal unit  $i$  for  $P_{si}^t$ .
- $S_j^t$  Water spillage of pumped hydro plant  $j$  in hour  $t$ .
- $T$  Number of scheduling hours.
- $UR_i$  Up ramp rate limits of thermal unit  $i$ .
- $V_j^t$  Water volume of the upper reservoirs of plant  $j$  at the end of hour  $t$ .
- $V_{j,l}^t$  Water volume of the lower reservoirs of plant  $j$  at the end of hour  $t$ .
- $v_i^k$  Velocity of particle  $i$  at iteration  $k$ .
- $x_i^k$  Position (coordinate) of particle  $i$  at iteration  $k$ .

## 2.2 Modeling a pumped hydro plant

A pumped hydro plant, which consists of an upper and a lower reservoir, is designed to save fuel costs by generating during peak load hours with water in the upper reservoir, which is pumped up from the lower reservoir to the upper reservoir during light load hours (Fig. 1).

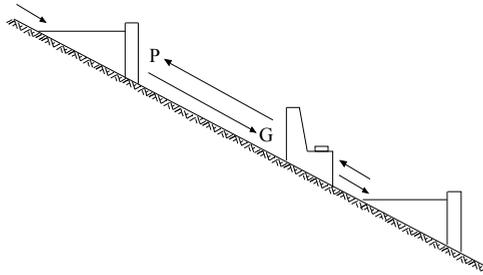


Figure 1. Pumped hydro plant

In generating mode, the equivalent-plant model can be derived using an off-line mathematical procedure that maximizes total plant generation output under different water discharge rates (Wood & Wollenberg, 1996). The generation output of an equivalent pumped hydro plant is a function of water discharged through turbines and the content (or the net head) of the upper reservoir. The general form is expressed as

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

The quadratic discharge-generation function, considering the net head effect, utilized in this work as a good approximation of pumped hydro plant generation characteristics is given as

$$P_{hj}^t = \alpha_j^{t-1} Q_j^{t2} + \beta_j^{t-1} Q_j^t + \gamma_j^{t-1} \quad (2)$$

where coefficients  $\alpha_j^{t-1}$ ,  $\beta_j^{t-1}$ , and  $\gamma_j^{t-1}$  depend on the content of the upper reservoir at the end of hour  $t-1$ . In this work, the read-in data includes five groups of  $\alpha$ ,  $\beta$ ,  $\gamma$  coefficients that are associated with different storage volume, from minimum to maximum, for the upper reservoir (first quadrant in Fig. 2). Then, the corresponding coefficients for any reservoir volume are calculated using a linear interpolation (Chen, 1989) between the two closest volume.

In pumping mode, since all Taipower's pumped hydro units are designed for constant power pumping, the characteristic function of a pumped hydro plant is a discrete distribution (third quadrant in Fig. 2).

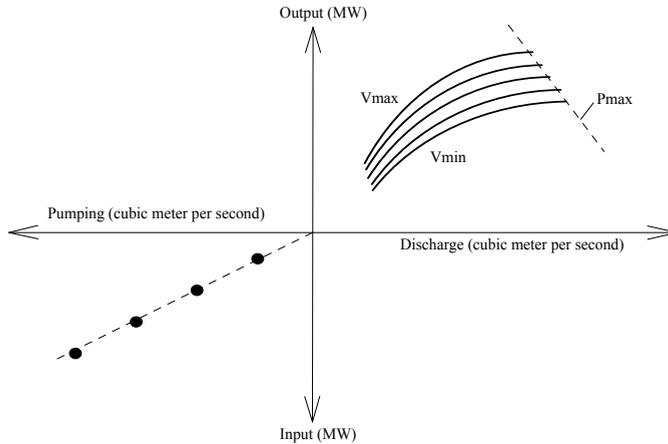


Figure 2. Typical input-output characteristic for a pumped hydro plant

**2.3 Objective function and constraints**

The pumped hydro scheduling attempts seeking the optimal generation schedules for both pumped hydro and thermal units while satisfying various hydro and thermal constraints. With division of the total scheduling time into a set of short time intervals, say, one hour as one time interval, the pumped hydro scheduling can be mathematically formulated as a constrained nonlinear optimization problem as follows:

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

Subject to the following constraints:

*System power balance*

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

*Water dynamic balance*

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

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

Thermal generation and ramp rate limits

$$\text{Max}(\underline{P}_{si}, P_{si}^{t-1} - DR_i) \leq P_{si}^t \leq \text{Min}(\overline{P}_{si}, P_{si}^{t-1} + UR_i) \quad (7)$$

Water discharge limits

$$\underline{Q}_j \leq Q_j^t \leq \overline{Q}_j \quad (8)$$

Water pumping limits

$$\underline{Q}_{j,p} \leq Q_{j,p}^t \leq \overline{Q}_{j,p} \quad (9)$$

Reservoir limits

$$\underline{V}_j \leq V_j^t \leq \overline{V}_j \quad (10)$$

$$\underline{V}_{j,l} \leq V_{j,l}^t \leq \overline{V}_{j,l} \quad (11)$$

System's spinning reserve requirements

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

### 3. Refined PSO Solution Methodology

#### 3.1 Basic PSO technique

Consider an optimization problem of  $D$  variables. A swarm of  $N$  particles is initialized in which each particle is assigned a random position in the  $D$ -dimensional hyperspace such that each particle's position corresponds to a candidate solution for the optimization problem. Let  $x$  denote a particle's position (coordinate) and  $v$  denote the particle's flight velocity over a solution space. Each individual  $x$  in the swarm is scored using a scoring function that obtains a score (fitness value) representing how good it solves the problem. The best previous position of a particle is  $Pbest$ . The index of the best particle among all particles in the swarm is  $Gbest$ . Each particle records its own personal best position ( $Pbest$ ), and knows the best positions found by all particles in the swarm ( $Gbest$ ). Then, all particles that fly over the  $D$ -dimensional solution space are subject to updated rules for new positions, until the global optimal position is found. Velocity and position of a particle are updated by the following stochastic and deterministic update rules:

$$v_i^{k+1} = wv_i^k + c_1 \text{Rand}() \times (Pbest_i^k - x_i^k) + c_2 \text{Rand}() \times (Gbest^k - x_i^k) \quad (13)$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \quad (14)$$

where  $w$  is an inertia weight,  $c_1$  and  $c_2$  are acceleration constants, and  $\text{Rand}()$  is a random number between 0 and 1.

Equation (13) indicates that the velocity of a particle is modified according to three components. The first component is its previous velocity,  $v_i^k$ , scaled by an inertia,  $w$ . This component is often known as “habitual behavior.” The second component is a linear attraction toward its previous best position,  $Pbest_i^k$ , scaled by the product of an acceleration constant,  $c_1$ , and a random number. Note that a different random number is assigned for each dimension. This component is often known as “memory” or “self-knowledge.” The third component is a linear attraction toward the global best position,  $Gbest^k$ , scaled by the product of an acceleration constant,  $c_2$ , and a random number. This component is often known as “team work” or “social knowledge.” Fig. 3 illustrates a search mechanism of a PSO technique using the velocity update rule (13) and the position update rule (14).

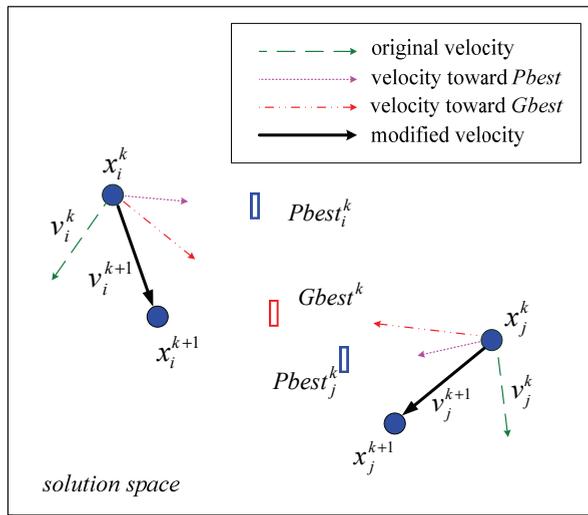


Figure 3. Searching mechanism of a PSO

Acceleration constants  $c_1$  and  $c_2$  represent the weights of the stochastic acceleration terms that push a particle toward  $Pbest$  and  $Gbest$ , respectively. Small values allow a particle to roam far from target regions. Conversely, large values result in the abrupt movement of particles toward target regions. In this work, constants  $c_1$  and  $c_2$  are both set at 2.0, following the typical practice in (Eberhart & Shi, 2001). Suitable correction of inertia  $w$  in (13) provides a balance between global and local explorations, thereby reducing the number of iterations when finding a sufficiently optimal solution. An inertia correction function called “inertia weight approach (IWA)” (Kennedy & Eberhart, 2001) is utilized in this work. During the IWA, the inertia weight  $w$  is modified according to the following equation:

$$w = w_{max} - \frac{w_{max} - w_{min}}{Itr_{max}} \times Itr \quad (15)$$

where  $w_{max}$  and  $w_{min}$  are the initial and final inertia weights,  $Itr_{max}$  is the maximum number of iteration, and  $Itr$  is the current number of iteration.

### 3.2 Binary encoding

For exposition ease, consider a pumped hydro plant with four units. Fig. 4 presents a particle string that translates the encoded parameter-water discharges of each plant into their binary representations.

<i>Hour</i>	1	2	.....	24
	1 0 0 0 1	0 0 0 1 1		1 0 0 1 0

Figure 4. Particle string for a pumped hydro plant with four units

Using a plant’s water discharge instead of the plant’s generation output, the encoded parameter is more beneficial when dealing with difficult water balance constraints. Each particle string contains 24 sub-strings that represent the solution for hourly discharge/pumping schedules of the pumped hydro plant during a 24-hour period. Each sub-string is assigned the same number of five bits. The first bit is used to identify whether the plant is in generating or pumping mode. The remaining four bits are used to represent a normalized water discharge,  $q_j^t$ , in generating mode, or the number of pumping units in pumping mode. In generating mode, the resolution equals  $1/2^4$  of the discharge difference from minimum to maximum.

### 3.3 Decoding of particle string

A particle within a binary PSO approach is evaluated through decoding the encoded particle string and computing the string’s scoring function using the decoded parameter. The following steps summarize the detailed decoding procedure.

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

<i>Hour t</i>				
$b_1$	$b_2$	$b_3$	$b_4$	$b_5$
$b_2=b_3=b_4=b_5="0" \Rightarrow$ "idle mode"				
$b_1="0" \Rightarrow$ "pumping mode"				
$b_1="1" \Rightarrow$ "generating mode"				

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

Step 3. Decode the remaining four bits of the sub-string to calculate the number of pumping units,  $N_p^t$ , and the total volume of pumped water,  $Q_{j,p}^t$ :

<i>Hour t</i>				
0	$b_2$	$b_3$	$b_4$	$b_5$

$$N_p^t = \sum_{i=2}^5 (b_i) \quad b_i \in \{0, 1\} \tag{16}$$

$$Q_{j,p}^t = Q_{j,sp} \times N_p^t \tag{17}$$

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

Step 4. Calculate the upper boundary of pumped water:

$$\overline{Q}_{j,p}^t = \text{Min}[\overline{Q}_{j,p}, (V_{j,l}^{t-1} - \underline{V}_{j,l})] \quad (18)$$

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

Step 5. Calculate the MW power for pumping:

$$P_{hj}^t = -(P_{j,sp} \times N_p^t) \quad (19)$$

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

Step 6. Decode the remaining four bits of the sub-string to obtain a normalized discharge,  $q_j^t$ , in decimal values:

<i>Hour t</i>				
1	$b_2$	$b_3$	$b_4$	$b_5$
	×	×	×	×
	$2^{-1}$	$2^{-2}$	$2^{-3}$	$2^{-4}$

$$q_j^t = \sum_{i=2}^5 (b_i \times 2^{-(i-1)}) \quad b_i \in \{0, 1\} \quad (20)$$

Step 7. Calculate the upper boundary of discharge:

$$\overline{Q}_j^t = \text{Min}[\overline{Q}_j, (\overline{V}_{j,l} - V_{j,l}^{t-1})] \quad (21)$$

Step 8. Translate the normalized value,  $q_j^t$ , to the actual value,  $Q_j^t$ :

$$Q_j^t = \underline{Q}_j + q_j^t (\overline{Q}_j^t - \underline{Q}_j) \quad (22)$$

Step 9. Calculate the generation output,  $P_{hj}^t$ , using (2).

Step 10. Calculate the remaining thermal loads,  $P_{rm}^t$ :

$$P_{rm}^t = P_L^t - P_{hj}^t \quad (23)$$

Step 11. Continue with computations of the 10 steps from hour 1 to hour 24.

Step 12. Perform the unit commitment (UC) for the remaining thermal load profile, and return the corresponding thermal cost. In this work, a UC package based on the neural network (Chen & Chen, 2006) is used to perform the UC task taking into account fuel costs, start-up costs, ramp rate limits, and minimal uptime/downtime constraints.

Step 13. Translate the corresponding thermal cost into the score of the  $i$ -th particle using a scoring function (details are found in the next Section).

Step 14. Repeat these 13 steps for each particle from the first to last particle.

### 3.4 Scoring function

The scoring function adopted is based on the corresponding thermal production cost. To emphasize the “best” particles and speed up convergence of the evolutionary process, the scoring function is normalized into a range of 0-1. The scoring function for the  $i$ -th particle in the swarm is defined as

$$SCORE(i) = \frac{I}{1 + k_i \left( \frac{cost(i)}{cost(Gbest)} - I \right)} \quad (24)$$

where  $SCORE(i)$  is the score (fitness value) of the  $i$ -th particle;  $cost(i)$  is the corresponding thermal cost of the  $i$ -th particle;  $cost(Gbest)$  is the cost of the highest ranking particle string, namely, the current best particle; and,  $k_i$  is a scaling constant ( $k_i = 100$  in this study).

### 3.5 Mutation operation

The basic PSO approach typically converges rapidly during the initial search period and then slows. Then, checking the positions of particles showed that the particles were very tightly clustered around a local optimum, and the particle velocities were almost zero. This phenomenon resulted in a slow convergence and trapped the whole swarm at a local optimum. Mutation operation is capable of overcoming this shortcoming. Mutation operation is an occasional (with a small probability) random alternation of the  $Gbest$  string, as shown in Fig. 5. This work integrates a PSO technique with a mutation operation providing background variation and occasionally introduces beneficial materials into the swarm to speed up convergence and escape local optimums.

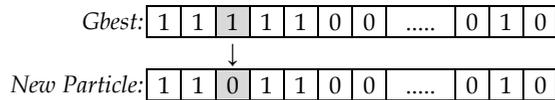


Figure 5. Mutation operation

The solution methodology for solving the pumped hydro scheduling problem using the proposed approach is outlined in the general flow chart (Fig. 6).

## 4. Test Results

The proposed approach was implemented on a MATLAB software and executed on a Pentium IV 3.0GHz personal computer. Then, the proposed approach was tested for a portion of the Taipower system, which consists of 34 thermal units and the Ming-Hu pumped hydro plant with four units. In addition to the typical constraints listed in Section 2, the Taipower system has three additional features that increase problem difficulty.

- The Taipower system is an isolated system. Thus it is self-sufficient at all times. The 300MW system's spinning reserve requirement must be satisfied each hour.
- Thermal units, due to their ramp rate limits, have difficulty handling large load fluctuations, especially at noon lunch break.
- The lower reservoir of Ming-Hu pumped hydro plant has only a small storage volume. Table 1 presents detailed data for the Ming-Hu pumped hydro plant. The thermal system consists of 34 thermal units: 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 (Chen & Chang, 1995).

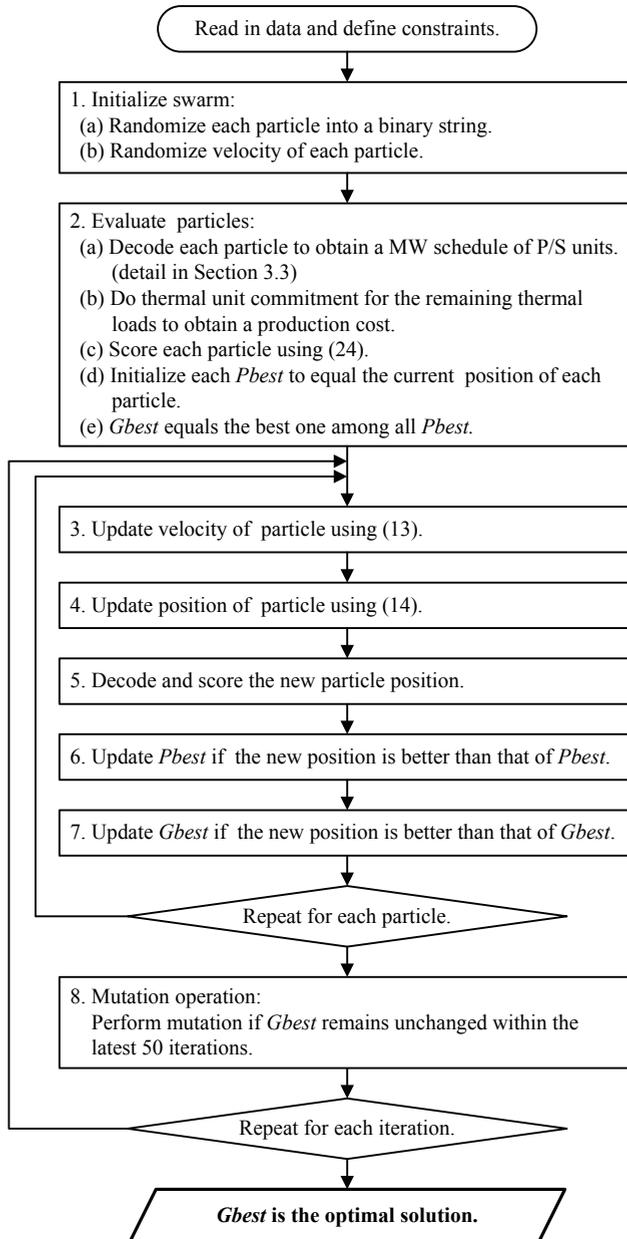


Figure 6. General flow chart of the proposed approach

Installed Capacity	Maximal Discharge (m <sup>3</sup> /s)	Maximal Pumping (m <sup>3</sup> /s)	Lower Reservoir		Efficiency
			Maximal Storage (10 <sup>3</sup> m <sup>3</sup> )	Minimal Storage (10 <sup>3</sup> m <sup>3</sup> )	
250MW×4	380	249	9,756	1,478	≈ 0.74

Table 1. Characteristics of the Ming-Hu pumped hydro plant

The proposed approach was tested on a summer weekday whose load profile (Fig. 7) was obtained by subtracting expected generation output of other hydro plants and nuclear units from the actual system load profile. Fig. 8 and 9 present schematics of test results. Fig. 8 shows the total generation/pumping schedules created by the proposed approach. Fig. 9 shows the remaining thermal load profiles. The optimal schedules for pumped hydro units and thermal units are obtained within 3 minutes, satisfying Taipower's time requirement. To investigate further how the proposed approach and existing methods differ in performance, this work adopts a DP method (Chen, 1989) and a GA method (Chen & Chang, 1999) as the benchmark for comparison. Table 2 summarizes the test results obtained using these three methods.

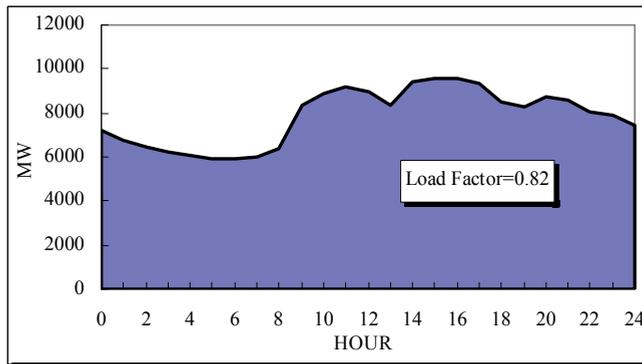


Figure 7. Summer weekday load profile

Several interesting and important observations are derived from this study and are summarized as follows:

- The generation/pumping profile generally follows the load fluctuation, a finding that is consistent with economic expectations. The Ming-Hu pumped hydro plant generates 3,893 MWh power during peak load hours and pumps up 5,250 MWh power during light load hours, resulting in a cost saving of NT\$5.91 million in one day, where cost saving = (cost without pumped hydro) - (cost with pumped hydro).
- The pumped hydro units are the primary source of system spinning reserve due to their fast response characteristics. The system's spinning reserve requirement accounts for the fact that pumped hydro units do not generate power at their maximum during peak load hours.
- Variation of water storage in the small lower reservoir is always retained within the maximum and minimum boundaries. The final volume returns to the same as the initial volume.
- The load factor is improved from 0.82 to 0.88 due to the contribution of the four pumped hydro units.

- e. Notably, both cost saving and execution time for the proposed approach are superior to either a DP or a GA method.

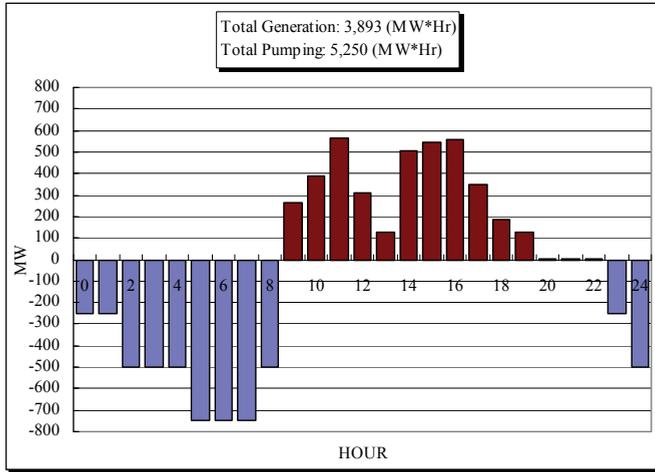


Figure 8. Hourly generation/pumping schedules

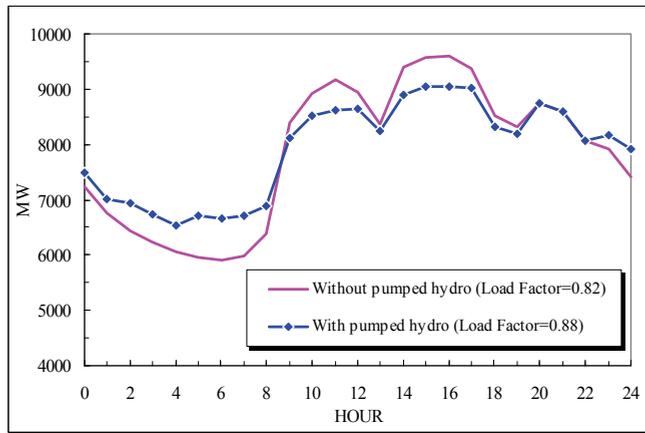


Figure 9. Contrast of two remaining thermal load profiles

Method	Load Factor	Cost Saving (10 <sup>3</sup> NT\$)	Execution Time (second)
DP	0.87	5,641	336
GA	0.87	5,738	164
RPSO	0.88	5,906	127

Table 2. Performance comparison with existing methods

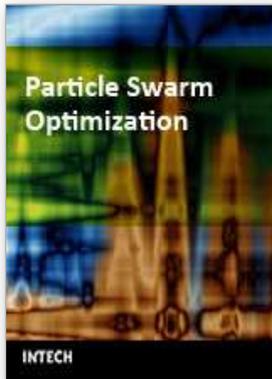
## 5. Conclusion

This work presents a novel methodology based on a refined PSO approach for solving the power dispatch with pumped hydro problem. An advantage of the proposed technique is the flexibility of PSO for modeling various constraints. The difficult water dynamic balance constraints are embedded and satisfied throughout the proposed encoding/decoding algorithms. The effect of net head, constant power pumping characteristic, thermal ramp rate limits, minimal uptime/downtime constraints, and system's spinning reserve requirements are all considered in this work to make the scheduling more practical. Numerical results for an actual utility system indicate that the proposed approach has highly attractive properties, a highly optimal solution and robust convergence behavior for practical applications.

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## **Particle Swarm Optimization**

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Particle swarm optimization (PSO) is a population based stochastic optimization technique influenced by the social behavior of bird flocking or fish schooling. PSO shares many similarities with evolutionary computation techniques such as Genetic Algorithms (GA). The system is initialized with a population of random solutions and searches for optima by updating generations. However, unlike GA, PSO has no evolution operators such as crossover and mutation. In PSO, the potential solutions, called particles, fly through the problem space by following the current optimum particles. This book represents the contributions of the top researchers in this field and will serve as a valuable tool for professionals in this interdisciplinary field.

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