GENETIC AIDED SCHEDULING OF HYDRAULICALLY COUPLED PLANTS IN HYDRO-THERMAL COORDINATION

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***Abstract*- Scheduling of hydraulically coupled plants (HCPs) has been reckoned as one of the most difficult parts of the problem of hydro-thermal coordination. This paper presents an efficient approach to the 24-hour ahead generation scheduling of HCPs based on the genetic algorithm (GA). In this paper, the difficult water balance constraints caused by hydraulic coupling are embedded and satisfied throughout the proposed encoding and decoding algorithm. The optimal schedules of both HCPs and thermal units are concurrently obtained within the evolutionary process of artificial chromosomes. Significantly, neither reservoir successive approximation nor hydro-thermal iteration is needed. The proposed approach is applied to an actual utility system of three HCPs and 22 thermal units with great success. Results show that the new approach obtains a more highly optimal solution than the conventional dynamic programming with successive approximation (DPSA) method.**

1. INTRODUCTION

Hydroelectric scheduling plays an important role within the operation planning of a power system. The problem is mainly concerned with both hydro units scheduling and thermal units dispatching. However, when several hydro plants are located on the same river, the water outflow from one plant may be a very significant portion of the inflow to one or more other plants which are located downstream. Scheduling for these coupled hydro plants has been reckoned as a formidable task. Both electric and hydraulic couplings create a multi-dimensional, non-linear programming problem. To solve such a complex problem, several methods have been applied in the literature [1-9]. Among these methods, the *dynamic programming with successive approximation* (DPSA) method [1,3,7,9] has gained much popularity. In the successive approximation (SA) procedure, it is necessary to specify an initial "feasible schedule" for each reservoir first. Then, one reservoir is scheduled while keeping the others' schedules fixed, alternating from one reservoir to the other until the stopping rule is satisfied. The stopping rule may be the cost difference between the last two iterations within a specified tolerance and/or once a specified iteration number is exceeded.

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In the previous work [9,10], an HCP scheduling software using the DPSA method was completed and applied to the existing Taipower system of Taiwan. Since the SA technique belongs to the class of *"greedy search"* algorithms, the solution cost usually got stuck at a local optimum rather than at the global optimum. However, the optimality of solution is very important to the utility. Even a small reduction in percentage production cost may lead to a large money saving. In addition, since the SA technique dispatches only one reservoir at one time, it is not flexible enough to deal with different types of coupling constraints. Obviously, a complete and efficient algorithm for solving the scheduling problems of HCPs is still in demand.

Recently, a global optimization technique known as *genetic algorithm* (GA) has become a candidate for many optimization applications due to its flexibility and efficiency. GA is a stochastic searching algorithm. It combines an artificial survival of the fittest principle with genetic operators abstracted from nature to form a surprisingly robust mechanism that is very effective at finding optimal solutions to complex real-world problems [11,12]. GA has been successfully applied in various areas such as *loss minimization* [13], *hydrogenerator governor tuning* [14], *economic dispatch* [15], and so on.

In this paper, a new GA approach is developed for solving the 24-hour ahead scheduling problem of HCPs. One of the advantages of the new approach is the use of stochastic operators instead of deterministic rules to escape from local optimums where other methods might land, to obtain the global optimum. The difficult water balance constraints due to hydraulic coupling are embedded in the encoding chromosome string and are satisfied throughout the proposed decoding algorithm. To make the results more practical, the effects of net head and water travel time delay are also taken into account. Comparative studies on a portion of the Taipower system show that the new approach obtains lower solution cost than the conventional DPSA method.

2. PROBLEM DESCRIPTION AND FORMULATION

2.1 List of symbols

P_{hj}^t : power generation of hydro plant j in hour t

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

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

T : number of scheduling hours

N_h : number of hydro 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 reservoir j at the ending of hour t

$V_{j,sp}$: specified final water volume of reservoir j

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

Q_j^t : water discharge of hydro plant j in hour t

S_j^t : water spillage of hydro plant j in hour t

τ_{j-1} : water travel time from plant $j-1$ to plant j

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 of unit i for P_{si}^t

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

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

2.2 Hydro-thermal coordination

Presently, most methods [2] for solving the hydro-thermal coordination problem are based on decomposition approaches that involve a hydro and a thermal subproblem as shown in Fig. 1. These two subproblems are usually coordinated by LaGrange multipliers and, then, the optimal generation schedules of both hydro 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]. In the proposed GA approach, the thermal subproblem can be solved entirely independently. No multiplier coordination is required in the solution procedure, and hence the oscillation problem can be completely precluded. In the thermal subproblem, unit commitment (UC) is performed for the remaining thermal load profile (load profile minus HCP's generations), and the resulting thermal cost is returned as the "fitness" of this HCP's schedule. The optimal solutions of both hydro and thermal units are concurrently obtained within the evolutionary process of "fitness." This feature makes the proposed approach particularly attractive for coordination with any type of UC package. In this work, a dynamic programming based approach [10] is used for solving the UC task, taking into account fuel cost, start-up cost, ramp rate limits, and minimal up/down time.

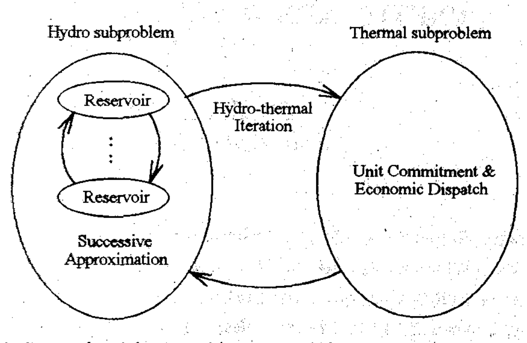

Fig. 1. Conventional decomposition approach for hydro-thermal coordination.

2.3 Equivalent hydro plant model

The number of hydro units is usually much greater than the number of hydro plants. Therefore, in practical hydro-thermal coordination problems, it is advantageous to model hydro generation at the plant (or reservoir) level to reduce the problem size. 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:

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

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

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

where coefficients α_j^{t-1}, β_j^{t-1}, and γ_j^{t-1} depend on the content of reservoir j 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 each reservoir, as shown in Fig. 2. Then, the corresponding coefficients for any reservoir volume are calculated by using a linear interpolation between the two closest volumes [3].

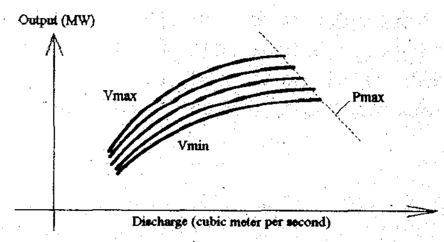

Fig. 2. Typical input-output characteristic for a variable-head hydro plant.

2.4 Objective function and constraints

The scheduling of HCPs deals with the problem of obtaining the optimal generations both for hydro 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 HCPs can be mathematically formulated as a constrained nonlinear optimization problem as follows:

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

Subject to the following constraints:

o System power balance

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

o Water dynamic balance with travel time

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

o Thermal generation and ramp rate limits

$$Max(\underline{P_{si}}, P_{si}^{t-1} - DR_{si}) \le P_{si}^t \le Min(\overline{P_{si}}, P_{si}^{t-1} + UR_{si}) \tag{6}$$

o Hydro discharge (generation) limits

$$\underline{Q_j} \le Q_j^t \le \overline{Q_j} \tag{7}$$

o Reservoir limits and specified final volume

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

$$V_j^T \le V_{j,sp} \tag{9}$$

o System spinning reserve requirement

$$\sum_{i=1}^{N_s} R_{si}^t(P_{si}^t) + \sum_{j=1}^{N_h} R_{hj}^t(P_{hj}^t) \ge R_{req}^t \tag{10}$$

In the study, the network losses in Eq. (4) are assumed to be 6% of the system load demand, a typical valve of the Taipower system.

3. OVERVIEW OF THE GENETIC ALGORITHM

The genetic algorithm (GA) is essentially a search algorithm based on the mechanics of natural selection and natural genetics. It combines solution evaluation with randomized, structured exchanges of information between solutions to obtain optimality. GA is a robust approach because no restrictions on the solution space are made during the search process. The power of this algorithm comes from its ability to exploit historical information structures from previous solution guesses in an attempt to increase performance of future solution structures [11].

By simulating "*the survival of the fittest*" criterion of Darwinian evolution among chromosome structures, the optimal solution is searched by randomized information exchange. While randomized, GA is not a simple random walk. It efficiently exploits historical information to speculate on new search points with expected improved performance. In every generation, a new set of artificial chromosomes is created using bits and pieces of the fittest of the old ones. The three prime operators associated with the GA are *reproduction*, *crossover*, and *mutation*.

Reproduction is simply an operation whereby an old chromosome is copied into a "mating pool" according to its fitness value. More highly fitted chromosomes (i.e., with better values of the objective function) receive a greater number of copies in the next generation. Copying chromosomes according to their fitness values means that chromosomes with a higher value have a higher probability of contributing one or more offspring in the next generation.

Crossover is an extremely important component of the GA. It is a structured recombination operation. This operation is similar to that of two scientists exchanging information. This study applies a new crossover technique known as "*uniform crossover*". The uniform crossover exchange bits, according to a randomly generated mask, between the parent chromosomes to create two new chromosomes. The '1' in the random mask means bits swapping and the '0' means bits replicating, as shown in Fig. 3. Syswerda [16] showed that the convergence speed of the uniform crossover is faster than the popular *one-point crossover* and *two-point crossover* techniques.

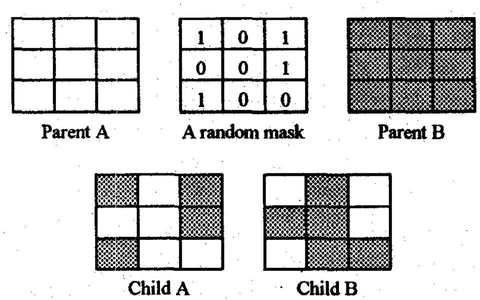

Fig. 3. The uniform crossover.

Although reproduction and crossover effectively search and recombine existing chromosomes, they do not create any new genetic material in the population. Mutation is capable of overcoming this shortcoming. It is an occasional (with small probability) random alternation of a chromosome position, as shown in Fig. 4. This provides background variation and occasionally introduces beneficial materials into the population.

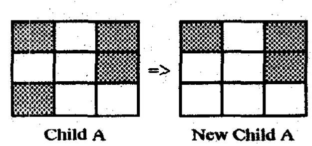

Fig. 4. The mutation.

4. GENETIC ALGORITHM SOLUTION METHODOLOGY

The solution methodology for solving the scheduling problems of HCPs by the proposed GA approach is outlined in the flowchart in Fig. 5 and will be described in detail later.

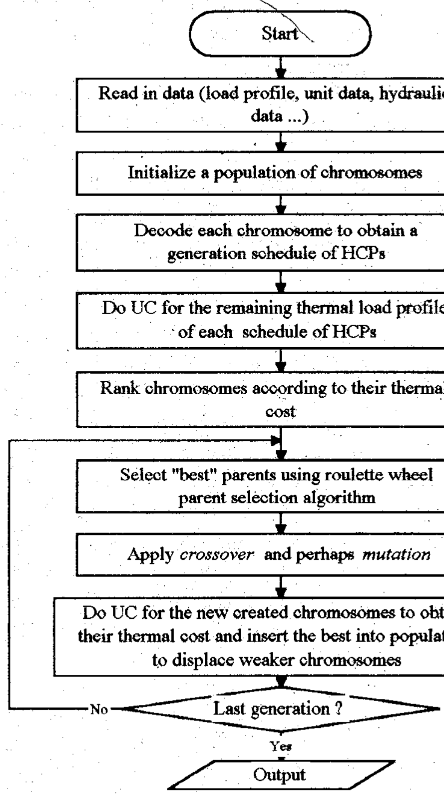

Fig. 5. General flow chart of the proposed approach.

4.1 Encoding

Implementation of a problem in a GA starts from the parameter encoding, i.e., the representation of the problem. The encoding must be carefully designed to utilize the GA's ability to efficiently transfer information between chromosome strings and objective function of a problem. For ease of exposition, consider a river system consisting of three HCPs, as shown in Fig. 6. The two-dimensional encoding scheme that translates the encoded parameter-water discharges of each plant into their binary representation is shown in Fig. 7. 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 chromosome string contains 3×24 genes to represent the solution for the hourly discharge schedule of the three plants in a 24-hour period. Each gene is assigned the same number of five bits to represent a normalized water discharge q_j^t. The resolution is equal to $1/2^5$ of the discharge difference from minimum to maximum.

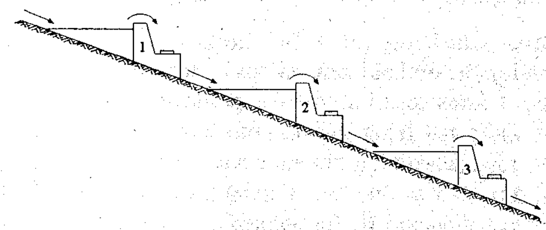

Fig. 6. Hydraulically coupled plants.

	q_1^t					q_2^t					q_3^t				
H 1	1	0	0	1	1	0	0	1	0	1	1	0	1	0	0
O 2	0	1	1	0	0	1	0	0	1	1	0	1	1	0	1
U :			:					:					:		
R 24	0	0	1	0	1	0	1	0	1	1	0	1	1	1	0

Fig. 7. The proposed encoding scheme.

4.2 Decoding

Evaluation of a chromosome is accomplished by decoding the encoded chromosome string and computing the chromosome's fitness value using the decoded parameter. The detailed decoding procedure is summarized in the following stages:

1. Decode each gene of the chromosome string to obtain the normalized discharge q_j^t in decimal values:

	Plant j				
Hour t	b_1	b_2	b_3	b_4	b_5
	$\times$	$\times$	$\times$	$\times$	$\times$
	2^{-1}	2^{-2}	2^{-3}	2^{-4}	2^{-5}

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

2. Calculate the upper and lower boundaries of the discharge: Because of the hydraulic coupling, the discharge of an HCP is constrained by: a) the discharge limits of that plant, b) the storage limits of the reservoir of that plant, c) the storage limits of the reservoir of the downstream plant. Combining these constraints, the upper and lower bounds of the discharge of plant j in hour t can be derived as:

$$\overline{Q_j^t} = Min[\overline{Q_j}, (V_j^{t-1} + Q_{j-1}^{t-\tau_{j-1}} + I_j^t - \underline{V_j}), (-V_{j+1}^{t-1} - I_{j+1}^t + \overline{Q_{j+1}} + \overline{V_{j+1}})] \tag{11}$$

$$\underline{Q_j^t} = Max[\underline{Q_j}, (V_j^{t-1} + Q_{j-1}^{t-\tau_{j-1}} + I_j^t - \overline{V_j}), (-V_{j+1}^{t-1} - I_{j+1}^t + \underline{Q_{j+1}} + \underline{V_{j+1}})] \tag{12}$$

where $\overline{Q_j^t}$ and $\underline{Q_j^t}$ denote, respectively, the upper and lower bounds of Q_j^t.

3. Translate the normalized value q_j^t to the actual value Q_j^t:

$$Q_j^t = \underline{Q_j^t} + q_j^t(\overline{Q_j^t} - \underline{Q_j^t}) \tag{13}$$

4. Calculate the generation output P_{hj}^t using (2).
5. Continue the computation for each plant from upstream to downstream, and for hour 1 to hour 24.
6. Calculate the remaining thermal load profile:

$$P_{rm}^t = P_L^t - \sum_{j=1}^{3} P_{hj}^t \qquad t = 1,2,\ldots,24 \tag{14}$$

where P_{rm}^t is the remaining thermal load in hour t.
7. Do thermal unit commitment for the remaining thermal load profile, and return the corresponding thermal cost.

In the proposed approach, the thermal subproblem can be solved entirely independently. Each chromosome represents a complete discharge schedule of HCPs. The UC package was executed to calculate the corresponding thermal cost of this discharge schedule. Then, the genetic iterations proceed to search the optimal chromosome (discharge schedule) which has the lowest thermal cost. The searching procedure will stop when a specified number of generations (500 generations in the study) is exceeded.

4.3 The excessive discharge penalty cost and fitness function

Implementation of an optimization problem in a genetic algorithm is realized within the evolutionary process of a fitness function. Since the objective function is the minimal thermal cost, HCPs will discharge the water energy of reservoirs as much as possible to yield more hydro generation. The decision of the daily storage target of a reservoir is a rather complex task. It involves meteorological forecasting, water supply, statistical analyses, and others. Power utility usually has its own decision rule. In this work, the final volume of each reservoir is a read-in data and is specified to be the same as the initial volume in the example case. When the final reservoir volumes are specified, excessive discharge of water in the current day will result in an additional thermal cost in the next day. Therefore, the penalty cost of excessive discharge must be included in the fitness function:

$$PNT = \sum_{j=1}^{3} (\alpha_j^T Q_{j,ex}^2 + \beta_j^T Q_{j,ex} + \gamma_j^T) \times IC \tag{15}$$

where PNT is the penalty cost of an HCP's schedule with excessive discharge, $Q_{j,ex}$ is the total excessive discharge of plant j and all its upstream plants, and IC is the incremental cost per MW of the most expensive thermal unit.

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

$$FIT(i) = \frac{1}{1 + k(\frac{cost(1)}{cost(i)} - 1)} \tag{16}$$

where *cost(i)* is the corresponding thermal cost plus the excessive discharge penalty cost of the i-th chromosome, and *cost (1)* is the cost of the highest ranking chromosome, namely, the presently best chromosome, and k is a scaling constant (k=50 in this study). Taking the penalty cost into account, excessive discharge can be avoided in the final solution.

4.4 Reproduction and parameter selection

When the fitness of each chromosome is calculated and is sorted in descending order, the "*roulette wheel parent selection*" technique [12] is used to select the "best" parents for crossover and mutation according to their fitness. It consists of the following steps:

1. Sum the fitness of all chromosomes in the population; call it the FITSUM.
2. Generate a random number, p, between 0 and FITSUM.
3. Return the first chromosome whose fitness, added to the fitness of preceding chromosomes, is greater than or equal to p.

Like other stochastic methods, the GA has a number of parameters that must be selected. These include the size of the population, the probability of crossover, and the probability of mutation. Usually, a relatively small size of population, high crossover probability, and low mutation probability is recommended. According to the authors' experiments, the following values of parameters are appropriate: size of population = 30; probability of crossover = 0.8; probability of mutation = 0.1

5. CASE STUDY

The proposed approach was implemented in a software and tested on a portion of the Taipower generation system, which consists of 22 thermal units and the Ta-Chia river hydro system with three reservoirs. It can also be applied to the system including more than one river chain by considering one river chain at a time. This software was written in Salford Fortran language and executed on a 486-33 personal computer.

Fig. 8 is a schematic diagram of the Ta-Chia river hydro system, which consists of three HCPs. The Ta-Chia river system is the most important hydroelectric resource in Taiwan, and accounts for 35% of the total of Taipower's hydro generation. Furthermore, the Ta-Chia plants are the dominant sources of system spinning reserve due to their fast response characteristics. Detailed characteristic data of these plants are given in Table 1. Besides the common constraints listed in Section 2, the Taipower system has the following unique characteristics that increase the difficulty of the problem.

1. Chin-Shan is a must-run unit, because it is connected to Taipower's Automatic Generation Control (AGC) system. But, it has only a small reservoir.
2. There is a one-hour water travel time delay between the Chin-Shan and Ku-Kuan plants.
3. The 300MW system spinning reserve requirement must be satisfied.
4. The large load fluctuation at the noon break hours can not be completely handled by thermal units due to their ramp rate limits.

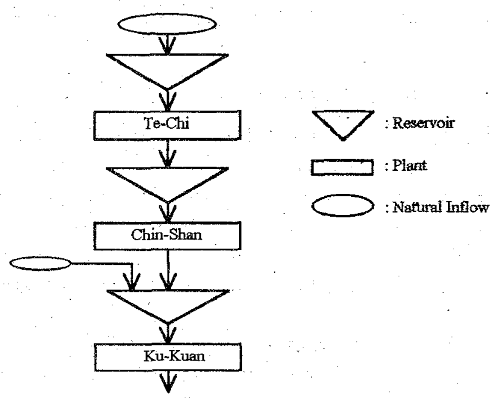

Fig. 8. The Ta-Chia river hydroelectric system.

Table 1. Characteristic of Ta-Chia river system

Plant Iden.	Maximal Output (MW)	Minimal Output (MW)	Maximal Discharge (m^3/s)	Maximal Storage ($k \times m^3$)	Natural Inflow (m^3/s)
Te-Chi	234	60	177	254420	58
Chin-Shan	360	40	150	427	-
Ku-Kuan	180	30	73	7960	6
Total	774 MW				

The software is tested on a summer weekday whose load profile, as shown in Fig. 9, is obtained by subtracting the expected generation output of other river chains and base load units from the actual system load profile. The optimal schedules of both HCPs and thermal units are obtained within 5 minutes, well satisfied the Taipower's requirement. At present, Taipower has its own scheduling algorithm, based on the DPSA method [10]. Throughout the study, the DPSA method is then used as the main benchmark of comparison for the proposed approach. Test results are schematically shown in Fig. 10 and Fig. 11. Fig. 10 shows the total generation profile created by the proposed approach and the one created by the DPSA method. Fig. 11 shows the optimal hourly MW schedules for the individual plants by the proposed approach.

From the above study, several interesting and important observations can be summarized as follows:

1. Both total HCP generation profiles basically follow the load fluctuation that is consistent with our economic expectation. However, an additional cost saving of 173 thousand NT dollars has been realized by the proposed approach.
2. The reason the HCPs are not generating to their maximum in peak-hours is due to the system spinning reserve requirement.
3. Due to the large-head-small-tail characteristic of the Ta-Chia river, the downstream Ku-Kuan plant generates electricity at full capacity in most hours in order not to spill the valuable water resource.
4. Te-Chi has to generate (discharge) at an off-peak hour (2:00 AM) to keep Chin-Shan always on-line without violating the storage limitations of the small Chin-Shan reservoir.

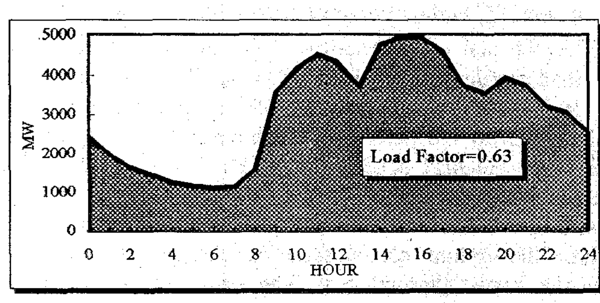

Fig. 9. A summer weekday load profile.

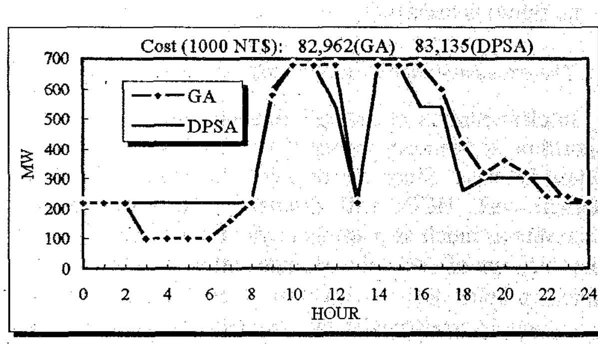

Fig. 10. Contrast of two generation profiles.

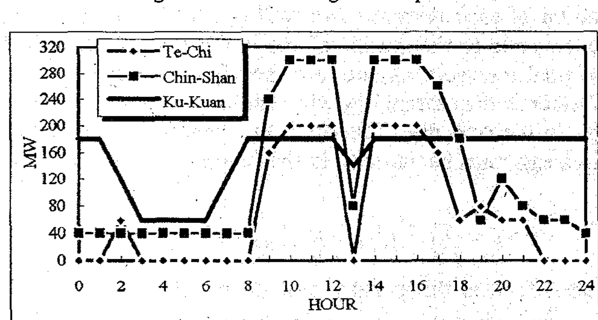

Fig. 11. Optimal MW schedules for individual plant by the GA approach.

To further investigate the convergence behavior for both GA and DPSA methods, two additional runs are conducted for each method. Different random initial populations are given for the GA method, and different initial "feasible schedules" are given for the DPSA method. Table 2 shows the test results. The evolutionary process of the GA method is depicted in Fig. 12. Throughout the experiment results, we find that the final solution of the DPSA method is obviously different for various "initial feasible schedules". Note that the final solution always got stuck at the local optimal point which is the nearest from the initial point. Since the final solution strongly depends on the initial schedule, the user may thus need expertise to set a good "initial schedule" in order to obtain a better solution. By contrast, GA searches for many optimal solutions in parallel and hops randomly from point to point, thus it can escape from local optimal points where other algorithms might land. Therefore, the global optimal solution can be approached with high probability for different "random populations", as shown in Fig. 12.

Table 2. Comparison of the solution costs.

	Cost (1000 NT$)	
	GA	DPSA
Base Case (BC)	82,962	83,135
Additional Run 1 (AR 1)	82,965	83,186
Additional Run 2 (AR 2)	82,958	83,247

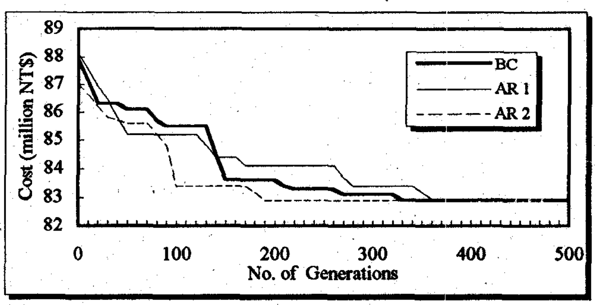

Fig. 12. The evolutionary process of the proposed approach.

6. CONCLUSIONS

This paper presents a genetic aided methodology of scheduling HCPs in the daily hydro-thermal coordination. The difficult water balance constraints due to hydraulic coupling are embedded and satisfied throughout the proposed encoding and decoding algorithms. The effects of net head and water travel time were also considered. Numerical results from an actual utility system indicate the attractive properties of the GA approach in practical application, namely, a highly optimal solution cost and more robust convergence behavior.

Although the paper includes the analysis and results for one day study, the presented method can be extended to study a period of one week without any increase in conceptual complexity. However, it does drastically increase the computational efforts required.

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REFERENCES

[1] Wood, A.J. and B.F. Wollenberg, *Power Generation, Operation, and control*, John Wiley & Sons, New York, 1984.

[2] El-Hawary, M.E., "An overview of scheduling functions in hydro-thermal electric power systems," Proceedings of the 1991 IASTED International Conference, pp.1-37, March, 1991.

[3] Ruzic, S., et al., "A flexible approach to short-term hydro-thermal coordination," Part I & II, IEEE Paper 94 SM 563-7 & 564-5 PWRS, Presented at the IEEE/PES 1994 Summer Meeting.

[4] Guan, X., and P.B. Luh, "Nonlinear approximation method in Lagrangian relaxation-based algorithm for hydrothermal scheduling," IEEE Paper 94 SM 562-9 PWRS, Presented at the IEEE/PES 1994 Summer Meeting.

[5] Rux, L.M., "An incremental economic dispatch method for cascaded hydroelectric power plants," IEEE Trans. on Power Systems, Vol. 8, No. 3, pp.1266-1273, August 1993.

[6] Amado, S.M. and C.C. Ribeiro, "Short-term generation scheduling of hydraulic multi-reservoir multi-area interconnected systems," IEEE Trans. on Power Systems, Vol. 2, No. 3, pp.758-763, 1987.

[7] Yang, J.S. and N. Chen, "Short term hydrothermal coordination using multi-pass dynamic programming," IEEE Trans. on Power Systems, Vol. 4, No. 3, pp.1050-1056, August 1989.

[8] Wu, R.N., et al., "An investigation of the accuracy and the characteristics of the peak-shaving method applied to production cost calculations," IEEE Trans. on Power Systems, Vol. 4, No. 3, pp.1043-1049, August 1989.

[9] Chen, P.H., *Generation Scheduling of Hydraulically Coupled Plants*, Master Thesis in Electrical Engineering, National Tsing-Hua University, 1989.

[10] Sun, D.I., et al., "Generating units (hydro; thermal; and pumped-storage) optimal dispatch," Annual Research and Development Report, Taipower, pp. 1-81, 1988.

[11] Goldberg, D.E., *Genetic Algorithm in Search, Optimization, and Machine Learning*, Addison-Wesley, 1989.

[12] Davis, L., *Handbook of Genetic Algorithms*, Van Nostrand Reinhold, 1991.

[13] Nara, K., et al., "Implementation of genetic algorithm for distribution systems loss minimum reconfiguration," IEEE Trans. on Power Systems, Vol. 7, No. 3, pp. 1044-1050, August 1992.

[14] Lansberry, J.E. and L. Wozniak, "Adaptive hydrogenerator governor tuning with a genetic algorithm," IEEE Trans. on Energy Conversion, Vol. 9, No. 1, pp. 179-183, March 1994.

[15] Walters, D.C., and G.B. Sheble, "Genetic algorithm solution of economic dispatch with valve point loading," IEEE Trans. on Power Systems, Vol. 8, No. 3, pp.1325-1332, August 1993.

[16] Syswerda, G., "Uniform crossover in genetic algorithms," Proceedings of the 3rd International Conference on Genetic Algorithms, pp. 2-9, June 1989.

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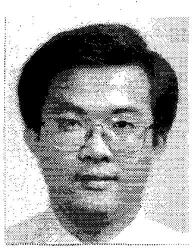

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