Scheduling of hydroelectric generations using artificial neural networks

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Abstract: An approach based on artificial neural networks (ANNs) is proposed for the scheduling of hydroelectric generations. The purpose of hydroelectric generation scheduling is to figure out the optimal amounts of generated powers for the hydro units in the system for the next N ($N = 24$ in the work) hours in the future. Input data include system hourly loads and the natural inflow of each reservoir. In the proposed ANN approach, a clustering ANN is first developed to identify those days with similar hourly load patterns and natural inflows. These days with similar load patterns and inflows are said to be of the same group. A total of four groups are used in the work. Then a multilayer feedforward ANN is developed for each group to reach a preliminary generation schedule for the hydro units. Since some practical constraints may be violated in the preliminary schedule, a heuristic rule based search algorithm is developed to reach a feasible sub-optimal schedule which satisfies all practical constraints. The effectiveness of th proposed approach is demonstrated by short-term hydro scheduling of Taiwan power system which consists of 10 hydro plants. It is concluded that the proposed approach is very effective in reaching proper hydro generation schedules. Moreover, the proposed approach is much faster than conventional dynamic programming approach.

List of symbols

C	= system generation cost over the study period
L_t	= system load at hour t
$COST_t(\cdot)$	= generation cost function at hour t approximated by second-order polynomial
$GTHERMAL_t$	= total generation from thermal units at hour t
Y_{it}	= water volume of reservoir i at the beginning of hour t
X_{it}	= volume of water released from reservoir i for generation during hour t
S_{it}	= spillage from reservoir i during hour t
$P_i(\cdot)$	= water-to-energy conversion function of the power plant associated with reservoir i
R_{it}	= volume of natural inflow to reservoir i during hour t
N_i	= set of the immediate upstream reservoirs of reservoir i
I	= number of reservoirs ($I = 10$ in the present work)
U	= input vector of artificial neural network
Z	= output vector of artificial neural network

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1 Introduction

The purpose of hydroelectric generation scheduling is to find the optimal amounts of generated powers for the hydro units in the study system for the next N ($N = 24$ in the present work) hours in the future. Usually, the objective function to be minimised in a hydro scheduling problem is the total fuel cost of thermal units and the practical constraints to be satisfied include power generation–load balance equations and water balance equations. Thus, the hydro scheduling problem is a typical constrained optimisation problem. Numerous approaches [1–6] have been reported in the literature to solve this problem. Quite promising results in terms of fuel cost savings have been reached in most works. However, a major disadvantage associated with these optimisation algorithm based approaches is that it usually takes a long time for these algorithms to get the desired solution.

In the present work, an approach based on artificial neural networks (ANNs) is proposed to reach the desired hydro generation schedules in an efficient manner. Artificial neural networks [8–10] have been given much attention by power engineers in the past few years. Many interesting applications of neural nets in the power field have been reported, such as load forecasting [11], power system stabiliser design [12], transient stability analysis [13], capactor control [14], and torsional oscillation analysis [15]. In artificial neural network computing, most of the time is spent on an off-line training process in which the ANN accumulates knowledge from the given input–output data pairs. Once the network is completely trained, the on-line operation would involve only a chain of simple arithmetic operations which can be completed in a very short period compared with analytical programming techniques. For a complicated constrained

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optimisation problem such as hydro scheduling problem considered in this work or unit commitment problem in power system operation, it is expected that the ANN approach will require much less computer time to get the solutions. In fact, several interesting applications of the ANN approach to unit commitment problem have been reported [16, 17].

In the present work, a clustering ANN is first designed to identify those days with similar hourly load patterns and natural inflows. These days with similar load patterns and inflows are said to be of the same-day type. A total of four different-day type are identified in this work. For each day type, a multilayer feedforward ANN is designed to get a preliminary schedule for the hydro units. The inputs to this ANN are the hourly loads and inflows and the outputs are the hydro generation schedules. Before the ANN can be used to generate the hydro schedules, a set of input–output pairs called training patterns are first compiled. Then the connection weights of the ANN are figured out through these training patterns using the generalised delta rule [8], and the ANN can now be used to yield the hydro generation schedules. Since some practical constraints may be violated in the preliminary generation schedule reached by the multilayer feedforward ANN, a heuristic rule based search algorithm is developed to reach a feasible suboptimal schedule which satisfies all practical constraints.

2 Hydroelectric generation scheduling problem

Scheduling hydro generation is well known to be coupled with its thermal counterpart. We decouple the hydro scheduling from the thermal part by first assuming a purely thermal system. For each given load level, the lambda-iteration method is performed to solve the economic dispatch over the set of available units [2] and to evaluate the thermal generation cost to meet the load demand. In other words, we aggregate all the available thermal units into one equivalent unit and construct its generation cost function. Then, in hydro scheduling, we try to find the best way of substituting hydro for thermal energy based on this function so that the system generation cost is minimised. To do this, the study period (one day for the present work) is divided into N stages ($N = 24$ in the present case) and the hydro scheduling problem is then formulated as follows.

$$\text{minimise } C = \sum_{t=1}^{24} COST_t(GTHERMAL_t) \tag{1}$$

subject to

(i) the generation–load balance equations

$$GTHERMAL_t + \sum_i P_i(X_{it}) = L_t \quad t = 1, \ldots, 24 \tag{2}$$

(ii) the water balance equations

$$Y_{it+1} = Y_{it} + \sum_{j \in N_i} X_{jt} - X_{it} + \sum_{l \in N_i} S_{lt} - S_{it} + R_{it} \qquad i = 1, \ldots, I \qquad t = 1, \ldots, 24 \tag{3}$$

(iii) bounds on water releases

$$X_{i,min} \leqslant X_{it} \leqslant X_{i,max} \quad \text{and} \quad S_{i,min} \leqslant S_{it} \leqslant S_{i,max} \qquad i = 1, \ldots, I \tag{4}$$

(iv) bounds on a reservoir storage

$$Y_{i,min} \leqslant Y_{it} \leqslant Y_{i,max} \quad i = 1, \ldots, I \tag{5}$$

To deal with the optimisation problem some conventional approaches such as dynamic programming and linear programming can be employed. In the present work we use the ANN approach.

3 Proposed artificial neural network approach

The proposed artificial neural network approach is a three-stage process as shown in Fig. 1. The input data for the hydro scheduling problem include N ($N = 24$ in the present work) hourly loads L_t ($t = 1, 2, \ldots, 24$) and I ($I = 10$ in the present work) daily peak natural inflows for the reservoirs R_i ($i = 1, 2, \ldots, 10$). Given these hourly loads and inflows, our purpose is to determine the amount of water released for hydro generations X_{it} for each unit i such that the total fuel cost of thermal units is minimised. Of course, all practical constraints as described in eqns. 2–5 must be satisfied.

Let U be the input vector which comprises the 24 hourly loads and 10 inflows, i.e.

$$\begin{aligned} U &= [u_1 \;\; u_2 \;\; \cdots \;\; u_{24} \;\; u_{25} \;\; u_{26} \;\; \cdots \;\; u_{34}]^T \\ &= [L_1 \;\; L_2 \;\; \cdots \;\; L_{24} \;\; R_1 \;\; R_2 \;\; \cdots \;\; R_{10}]^T \end{aligned} \tag{6}$$

Let's also define Z as the output vector which comprises the volume of water released from each reservoir for hydro generation X_{it} ($i = 1, 2, \ldots, 10, t = 1, 2, \ldots, 24$)

$$\begin{aligned} Z &= [z_1 \;\; z_2 \;\; \cdots \;\; z_{240}]^T \\ &= [X_{11} \;\; \cdots \;\; X_{10,24}]^T \end{aligned} \tag{7}$$

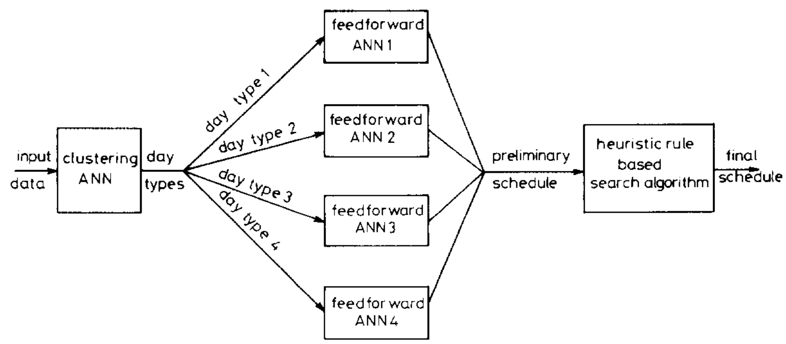

Fig. 1 *Proposed artificial neural network approach*

The basic idea behind the proposed ANN approach is that the output vectors Z_1 and Z_2 for two days with similar input vectors U_1 and U_2 tend to be similar to each other. In other words, it is very natural for system operators to adopt similar hydro schedules for two days with similar loads and inflows. Thus, we propose to adopt a clustering ANN at the first stage to identify those days with similar input patterns (similar hourly loads and inflows). These days with similar input patterns are said to of the same day type.

One important issue which must be addressed in identifying the day types using the clustering ANN is how many day types should be used. In the present work, the operators' experience is employed as a guideline in choosing the number of day types for the clustering ANN. Through an interview with the experienced opertors at Taiwan Power Company, it is recommended that the following four types of days should be included.

type 1: weekdays with heavy inflows

type 2: weekdays with normal inflows

type 3: weekends (including holidays) with heavy inflows

type 4: weekends with normal inflows

Details of the clustering ANN are described in Section 4.

Now, the days of the same-day type are expected to have similar input patterns. To reach a preliminary hydro schedule for a day with given hourly loads and inflows, we propose to design a multilayer feedforward ANN for each day type. Therefore, we have a total of four feedforward ANNs with each ANN being capable of yielding the desired hydro schedules for the days of a certain day type. The inputs to any ANN are the 24 hourly loads and 10 inflows and the outputs contain the preliminary volumes of released water X_{it}. The multilayer feedforward ANN is briefly described in Section 5.

Since some practical constraints as described in eqns. 2–5 may be violated in the preliminary hydro schedules, a heuristic rule based search algorithm is proposed to modify the preliminary schedules to reach the resultant feasible solutions. Details of the search algorithm is described in Section 6.

4 Clustering ANN for day type identification

In the design of the clustering ANN, a set of 240 input vectors with each vector described by eqn. 6 are first compiled. This set of input vectors are referred to as the training set. Note that each input vector contains the 24 hourly loads and 10 inflows for a particular day. Let the ith input vector U_i ($i = 1, 2, \ldots, 240$) be denoted as

$$U_i = [u_{i1} \quad u_{i2} \quad \cdots \quad u_{ik} \quad \cdots \quad u_{i,34}]^T \tag{8}$$

To identify these days with similar input patterns, define the Euclidean distance measure d_{ij} between two vectors U_i and U_j as

$$\begin{aligned} d_{ij} &= \|U_i - U_j\| = \sqrt{[(U_i - U_j)^t(U_i - U_j)]} \\ &= \left(\sum_{k=1}^{34} (u_{ik} - u_{jk})^2 \right)^{1/2} \end{aligned} \tag{9}$$

If d_{ij} is less than a threshold d_τ, the two input vectors U_i and U_j are said to be of the same cluster and the two days with the two input vectors are said to be of the same-day type. Note that the threshold d_τ must be determined via a trial-and-error to classify the 240 input vectors into four clusters with each cluster containing the input patterns for those days of a particular day type as described in Section 3. The clustering algorithm is described as follows.

Step 1: Start with no cluster prototype vectors

Step 2: Let $I = (i_1, i_2, \ldots, i_m)$ be the next input vector

Step 3: If there are any prototype vectors, find $T = (t_1, t_2, \ldots, t_n)$ to minimise $d(T, I) = \|T - I\| = (\sum (t_n - i_n)^2)^{1/2}$

Step 4: If $d(T, I) > d_\tau$, a specified threshold or if there are no cluster prototype vectors yet, create a new cluster with prototype vector I. Output the index of this cluster. Then go to Step 2

Step 5: Otherwise, update T as $T = (1 - \lambda) \times T + \lambda \times I$. Output T's index. Go to Step 2.

In the clustering algorithm, a threshold d_τ is first assigned. Each pattern belongs to only one cluster. Overlapping is not allowed in this algorithm.

After the clustering process is completed, there are four clusters of input patterns. The input patterns for those days of the same-day type are put in the same cluster. Now, for an input vector U which is not in the training set, compute the Euclidean distance measure between this vector U and the patterns in the four clusters. The cluster with minimal distance is assigned to the vector U. The day type for the input vector U can then be identified.

5 Multilayer feedforward ANN for determination of preliminary schedule

It is observed from Fig. 1 that four multilayer feedforward artificial neural networks ANN1, ANN2, ANN3, and ANN4 are needed for the input patterns which belong to day types 1, 2, 3, and 4, respectively, to reach preliminary hydro schedules.

The nodes in the input layer receive input signals from the outside would and directly pass the signals to the nodes in the next layer. In this paper, the 24 hourly loads L_t ($t = 1, 2, \ldots, 24$) and 10 natural inflows R_i ($i = 1, 2, \ldots, 10$) are taken as the inputs of the neural networks.

The nodes in the output layer provide the desired hydro generation schedule which is characterised by the volumes of water released from the reservoirs X_{it}. Therefore 240 output nodes are needed. In addition to the input layer and output layer, one or more hidden layers are needed. The nodes in the hidden layer take signals from the nodes in the input layer and send their outputs to the nodes in the next layer when computations within the nodes have been completed. In the present work, only one hidden layer is employed.

The design of an artificial network involves two major phases: training and testing. In the training process, we try to determine the connection weights using a set of input–output patterns in the training set. Once the connection weights have been worked out, the performance of the neural network is tested using patterns both within and outside the training set. The speed and accuracy of the test results are evaluated to decide whether modification of the neural network structure (number of hidden layers and hidden nodes per layer) or further training of the neural network is necessary. Once the speed and accuracy of the ANN meet the requirement of the present application, it can be employed to evaluate hydro generation scheduling in real-time situations.

The first step in neural network training is to compile the training patterns in the training set. In the present, each training pattern comprises 34 input variables and 240 output variables. For each input pattern U, the corresponding hydro generation schedule Z is obtained offline by using differential dynamic programming (DDP) technique [7]. A major advantage of the DDP algorithm is that the curse of dimensionality in conventional DP algorithm can be avoided while the system dynamics can still be exploited explicitly. But it suffers from computational inefficiency. The efficiency can be improved by the proposed ANN approach. Two DDP algorithms have been developed for problems with linear constraints [6, 18]. Note that all computations in creating the training patterns are performed off-line. Therefore time is not a crucial factor at this stage.

With these training patterns at hand, one can proceed to work out a proper set of connection weight that can best fit the input–output patterns in the training set. A commonly used approach is the generalised delta rule [8] which is used in this paper.

After the connection weights have been determined, the ANN can be employed to determine a preliminary hydro schedule for a given load pattern and natural inflows. Four neural networks are required as we have to determine hydro schedules for input patterns which are classified to four different day types.

6 Heuristic rule based search algorithm for determination of final schedule

In the preliminary schedule reached by the multilayer feedforward ANN, some practical constraints such as water release bounds and available water limits may be violated. In this case, the following heuristic rules can be applied to refine the preliminary schedule and to reach the final hydro schedule.

(i) Heuristic rule on water release bounds

Let $X_{it} = X_{i,max}$ if $X_{it} > X_{i,max}$

Let $X_{it} = X_{i,min}$ if $X_{it} < X_{i,min}$ ($i = 1, 2, \ldots, 10$, $t = 1, 2, \ldots, 24$)

(ii) Heuristic rule on water available limits

Reduce a small amount of released water from X_{it} during off-peak period until $\sum_{t=1}^{24} X_{it} = Q_i$ ($i = 1, 2, \ldots, 10$) if $\sum_{t=1}^{24} X_{it} > Q_i$ where Q_i is the total available water volume for reservoir i over the study period. Increase a small amount of released water from X_{it} during peaking hours until $\sum_{t=1}^{24} X_{it} = Q_i$ ($i = 1, 2, \ldots, 10$) if $\sum_{t=1}^{24} X_{it} < Q_i$.

7 Example

To demonstrate the effectiveness of the proposed ANN approach, hydroelectric generation scheduling is performed on Taiwan power system which consists of four Ta-Chia River cascaded plants, three Cho-Shui River plants (including a large pumped storage plant and two cascaded hydro plants) and three hydraulically independent plants. The schematic diagram of hydro plants along both Cho-Shui River and Ta-Chia River is shown in Fig. 2. For the case of the one hour time increment considered in this work, there is no significant delay in water reaching a reservoir from its immediate upstream neighbour.

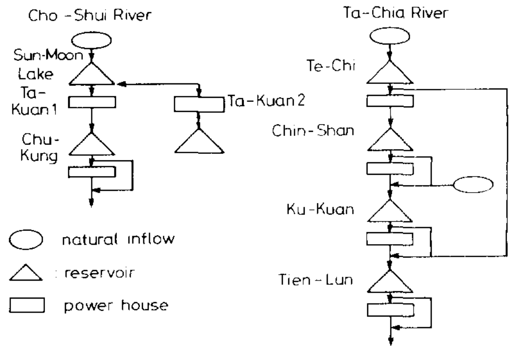

Fig. 2 *Schematic diagram of Cho-Shui River and Ta-Chia River*

The hydro system data and reservoir operating parameter used for the present work are presented in Table 1 and Table 2, respectively.

Table 2: Reservoir operating parameter

Reservoir	Initial volume	Final volume	Natural inflow (case 3)	Natural inflow (case 7)
	km^3	km^3	m^3/s	m^3/s
Sun-Moon	89640	89640	30.55	29.39
Storage Pond	8316	8316	0	0
Chu-Kung	72	72	0	0
Te-Chi	184107	184107	40.3	41.5
Chin-Shan	540	540	0	0
Ku-Kuan	5400	5400	13.7	13.2
Tien-Lun	144	144	0	0
Li-Wu	144	144	26	26.2
Lung-Chien	54	54	8.5	8.4
I-Hsing	180	180	30.5	30.1

In the training process, 60 training patterns for each day type are selected from the operating record of Taiwan Power Company (TPC) to determine the connection weights of the neural network. To examine the convergence characteristics of the training algorithms, the root mean squared error (RMSE) in the learning process are depicted in Fig. 3. The training conditions of the four different feedforward neural networks are summarised in Table 3. The convergence criterion is defined as RMSE $\leqslant 0.0001$ for each ANN. From the results in Fig. 3 and Table 3, it is observed that it takes longer time for ANN1 and ANN2 to converge than it takes for ANN3 and ANN4. This is due to the fact that ANN1 and

Table 1: Hydro system data

Reservoir	Storage lower bound	Storage upper bound	Plant	Water release lower bound	Water release upper bound
	km^3	km^3		m^3/s	m^3/s
Sun-Moon	13269	155685	Ta-Kuan 2	−249	380
Storage Pond	1565	9407	Ta-Kuan 1	0	50
Chu-Kung	1.6	105	Chu-Kung	0	45
Te-Chi	89886	243120	Te-Chi	0	217.5
Chin-Shan	26	647	Chin-Shan	0	174.8
Ku-Kuan	101	6563	Ku-Kuan	0	133.6
Tien-Lun	90	560	Tien-Lun	0	68
Li-Wu	0	340	Li-Wu	0	36.7
Lung-Chien	0	202	Lung-Chien	0	13.2
I-Hsing	0	1343	I-Hsing	0	31.7

ANN2 are employed to deal with hydro scheduling for weekdays when the load patterns experience large fluctuation between peaking hours and off-peak period. In

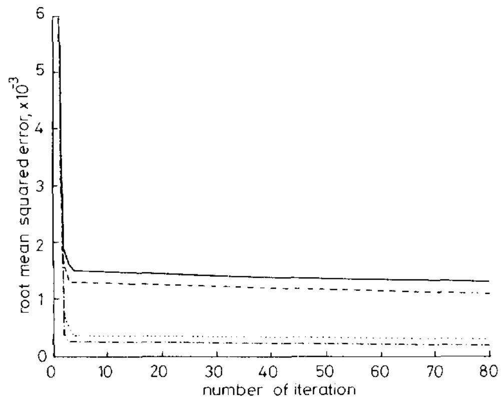

Fig. 3 *RMS errors at first 80 iterations*
——— ANN1
– – – – ANN2
······ ANN3
—·— ANN4

Table 3: Training conditions of four different feedforward neural networks (RMSE ≤ 0.0001)

Feedforward neural network	Learning rate	Momentum rate	Number of iterations	Learning time
				s
ANN1	0.9	0.7	12375	58345
ANN2	0.9	0.7	11250	54132
ANN3	0.9	0.7	925	4375
ANN4	0.9	0.7	609	2895

this case, the generated powers for hydro units and thermal units change significantly from off-peak period to peaking hours. Therefore it takes larger time to train a neural network with such patterns. All our numerical computations are performed on a Sun workstation.

Once the ANN has been trained, the efficiency and accuracy of the proposed approach can be evaluated by examining the hydro generation schedules for 10 hourly load-inflow patterns. The system's hourly load curves for two of the 10 cases (cases 3 and 7) are depicted in Fig. 4.

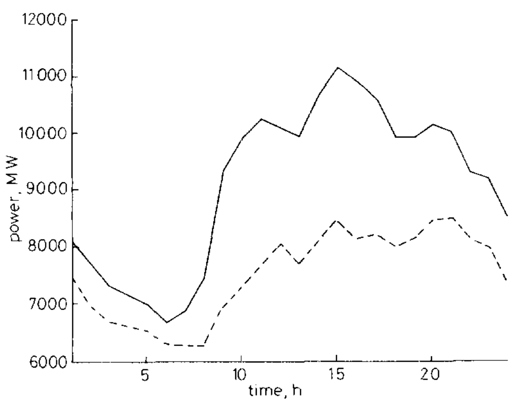

Fig. 4 *Daily system load profiles*
——— case 3
– – – – case 7

The hydro generations over the 24 hour scheduling period from three different approaches, i.e. the DDP approach, the proposed ANN approach and the nearest neighbour approach, are compared in Figs. 5 and 6 for

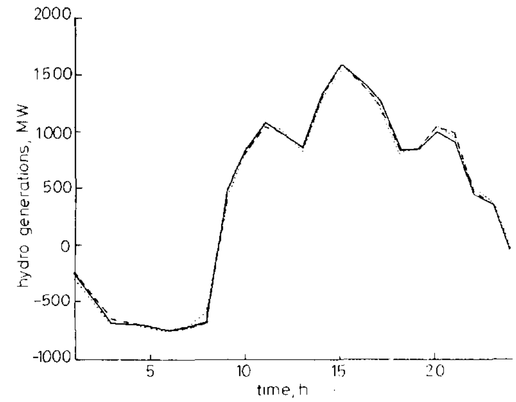

Fig. 5 *Comparison of hydro generation schedules for case 3*
——— DDP
– – – – proposed approach
······ nearest neighbour approach

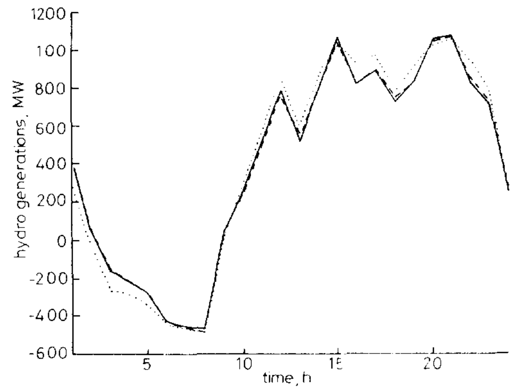

Fig. 6 *Comparison of hydro generation schedules for case 7*
——— DDP
– – – – proposed approach
······ nearest neighbour approach

cases 3 and 7, respectively. The total fuel costs of thermal units for these schedules and the CPU time required by the three approaches are summarised in Table 4.

In Table 4, input patterns (hourly load-inflow patterns) in case 1 and case 2 are within the training set. After the clustering algorithm is used for a d_r of 0.35, it is found that the case 1 and case 2 belong to day type 2 and day type 4, respectively. As a result, the multilayer feedforward ANN2 and ANN4 are employed to determine the preliminary schedules. Table 5 gives the water release of Te-Chi hydro plant from the ANN for the preschedule and the ANN heuristic algorithm (ANN-HA) for the final schedule. It is observed from Table 5 that the violations in the preliminary schedule are small, but the solution is infeasible.

We apply the simple heuristic rules to reach a feasible solution. Detail of the released water schedule for each hydro plant are not given. It is observed from the results in Table 4 that the fuel costs for the schedules from the proposed approach are very close to those for the

Table 4: Comparison of results

Case	Solution by DDP		Solution by nearest neighbour approach			Solution by proposed approach		
	CPU time	Fuel cost	CPU time	Fuel cost	cost difference	CPU time	Fuel cost	cost difference
	s	NT$	s	NT$		s	NT$	
1	126.89	125 200 584	0.43	125 200 584	—	0.55	125 214 435	0.011 06%
2	112.37	95 177 008	0.42	95 177 008	—	0.56	95 177 951	0.000 99%
3	137.46	125 001 848	0.43	125 092 256	0.072 33%	0.56	125 028 447	0.021 27%
4	142.57	124 975 637	0.43	125 061 748	0.068 90%	0.55	124 996 451	0.016 65%
5	152.21	123 325 048	0.43	123 417 243	0.074 76%	0.54	123 345 239	0.016 37%
6	150.28	123 783 681	0.42	123 858 470	0.060 42%	0.56	123 805 673	0.017 77%
7	118.42	94 997 264	0.43	95 065 061	0.071 37%	0.55	95 011 032	0.014 49%
8	122.81	95 068 673	0.42	95 158 572	0.094 56%	0.54	95 080 783	0.012 74%
9	113.75	95 186 936	0.41	95 268 581	0.085 77%	0.56	95 199 725	0.013 44%
10	115.37	95 572 579	0.42	95 636 937	0.067 34%	0.56	95 586 469	0.014 53%

$$\text{Cost difference} = \frac{(\text{cost of schedule}) - (\text{cost of DDP algorithm})}{\text{cost from DDP algorithm}} \times 100\%$$

Table 5: Water release of Te-Chi hydro plant from ANN (preschedule) and ANN-HA (final schedule)

hour	ANN	ANN-HA
h	m^3/s	m^3/s
1	2.7	0.0
2	−3.2	0.0
3	2.2	0.0
4	−2.2	0.0
5	−4.1	0.0
6	1.3	0.0
7	2.9	0.0
8	−0.8	0.0
9	30.2	27.9
10	52.8	52.6
11	53.9	54.1
12	52.4	52.3
13	45.3	43.2
14	67.7	68.9
15	77.2	79.3
16	76.7	77.9
17	58.3	59.3
18	41.2	38.5
19	43.3	41.7
20	52.1	51.8
21	43.0	41.4
22	31.2	27.7
23	26.0	21.8
24	9.4	4.1

optimal schedules from the DDP approach. It is concluded that the ANNs have been trained very well in this application. It is also observed that the nearest neighbour approach gives exactly the same schedule as that obtained by the DDP approach in case 1 and case 2 since the two cases are within the training set and the solution from the DDP approach will be picked out by the nearest neighbour approach.

The input patterns in cases 3–10 in Table 4 are not within the training set. It is found from the results in Table 4 and Figs. 5 and 6 that the fuel costs of the schedules from the proposed approach are closer to those from the DDP approach than those from the nearest neighbour approach. In other words, the proposed approach can give better results than the nearest neighbour approach. However, the two approaches require much less computer time than the DDP approach. In fact, a major advantage of the ANN approach is that the desired solution can be reached by the ANN in a very efficient manner for on-line operation.

In the present work, the input patterns are classified into four clusters according to the types of day. Four different feedforward neural networks (ANN1, ANN2, ANN3 and ANN4) are designed to reach hydro schedules for the input patterns of day types 1, 2, 3 and 4, respectively. It is interesting to examine how the resultant schedules will be changed if we do not classify the input patterns into four clusters and use only one feedforward ANN to generate the preliminary schedules. We refer to this approach as the modified approach. The fuel costs of the schedules from the modified approach are compared with those from the DDP approach and the proposed ANN approach in Table 6.

Table 6: Comparison of fuel costs

Case	DDP approach	Proposed approach	Modified approach
	NT$	NT$	NT$
1	125 200 584	125 214 435	125 289 837
2	95 177 008	95 177 951	95 302 092
3	125 001 848	125 028 447	125 094 691
4	124 975 637	124 996 451	125 068 543
5	123 325 048	123 345 239	123 430 369
6	123 783 681	123 805 673	123 885 752
7	94 997 264	95 011 032	95 121 850
8	95 068 673	95 080 783	95 181 673
9	95 186 936	95 199 725	95 327 883
10	95 572 579	95 586 469	95 712 685

It is observed from the results in Table 6 that the fuel costs from the modified approach are higher than those from the proposed ANN approach. It is concluded that the modified approach will generate a hydro schedule which is different from the optimal schedule generated by the DDP algorithm while the proposed ANN will generate a schedule which is close to the optimal schedule. The main reason why the proposed ANN approach is superior to the modified approach is that the ANN in the proposed approach needs to deal with similar input patterns of the same day type only while the ANN in the modified approach must treat different input patterns of all day types.

8 Conclusions

A novel technique using artificial neural networks has been proposed for short term hydroelectric generation scheduling of a power system. A clustering ANN is developed to classify all days to be scheduled into four clusters based on the hourly load and inflow pattern of the day. A multilayer feedforward ANN is designed for the days in a cluster. The feedforward ANN takes the hourly loads and inflows as its input and generates a preliminary hydro generation schedule. The schedule is refined by a heuristic rule based search algorithm to reach the final hydro schedule which satisfies all practical constraints.

To demonstrate the effectiveness of the proposed ANN approach, hydroelectric generation scheduling of

Taiwan power system is performed. It is concluded that the hydro schedules generated by the ANN approach are very close to the optimal schedules reached by the differential dynamic programming method. A major advantage of the ANN approach is that it takes much less computer time for the ANN approach to get the generation schedules than the differential dynamic programming method.

9 References

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