Hydroelectric generation scheduling using self-organizing feature maps

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Abstract

An approach based on self-organizing feature maps is proposed for the scheduling of hydroelectric generations. The purpose of hydroelectric generation scheduling is to figure out the optimal amount of generated powers for the hydro units in the system for the next N ($N = 24$ in this work) hours in the future. In the proposed approach, self-organizing feature maps are developed in order to reach preliminary generation schedules. Since some practical constraints may be violated in the preliminary schedule, a heuristic rule based search algorithm is developed to reach a feasible suboptimal schedule which satisfies all practical constraints. The effectiveness of the proposed approach is demonstrated by short-term hydro scheduling of Taiwan power system which consists of ten hydro plants. It is concluded from the results that the proposed approach is very effective in reaching proper hydro generation schedules.

Keywords: Hydroelectric generation scheduling; Load data classification; Neural networks

1. Introduction

The purpose of hydroelectric generation scheduling is to find the optimal amount 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 minimized in the hydro scheduling problem is the total fuel cost of the thermal units and the practical constraints to be satisfied include power generation–load balance equations and water balance equations, etc. Thus, the hydro scheduling problem is a typical constrained optimization problem. Numerous approaches [1–9] 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 optimization 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 self-organizing feature maps is proposed in order to reach the desired hydro generation scheduled in an efficient manner. Artificial neural networks (ANNs) [10, 11] 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 [12], power system stabilizer design [13], torsional oscillation analysis [14], unit commitment [15] and security assessment [16–18]. A major advantage of the ANN approach is that the domain knowledge is distributed in the neurons and information processing is carried out in a parallel-distributed manner. Therefore, it is rather efficient for the ANN to reach the desired solutions. For a complicated constrained optimization problem such as the hydro scheduling problem considered in this work in power system operation, it is expected that the ANN approach will require much less computer time to get the solutions.

In this paper, we decided to use Kohonen's self-organizing neural net to speed up hydro generation scheduling. Kohonen's self-organizing neural net is based on clustering ANNs in which the training patterns in the training set are classified into several groups according to the hourly load patterns. The basic idea is to put those patterns with similar load patterns in the same cluster. After the training patterns have been clustered into several groups, the desired hydro schedules for a given day can be obtained by first comparing the load pattern for the day with those in the various groups identified by using the training patterns. The group of

training patterns whose load patterns are most similar to the load pattern for the day under study are identified as the target cluster. A preliminary schedule is obtained by averaging the hydro schedules for the patterns in the target cluster. In order to compare the results for the schedules, the Euclidean clustering algorithm is also employed.

Since some practical constraints may be violated in the preliminary schedule reached by the ANN method mentioned above, a heuristic rule based search algorithm is developed to reach a feasible suboptimal schedule which satisfies all practical constraints.

In the next section, the hydroelectric generation scheduling problem is briefly described. In Section 3, an overview of the proposed approach is introduced. The details of Kohonen's self-organizing neural net and Euclidean clustering, used for reaching a preliminary hydro generation schedule, are described in Section 4. The resultant schedule is obtained by using the heuristic rule based search algorithm described in Section 5. Finally, the effectiveness of the proposed ANN approach is demonstrated by the hydro scheduling of Taiwan power system which consists of four Ta-Chia River cascaded plants, three Cho-Shui River plants, and three hydraulically independent plants. It is concluded from the results that proper hydro generation schedules can be obtained by using the proposed Kononen neural network in a very efficient manner.

2. The hydroelectric generation scheduling problem

Scheduling hydro generation is well known to be coupled with its thermal counterpart. Under present Taiwan Power Company (TPC) system operation conditions, short-term commitment changes are not allowed for most of the base-load and medium-load thermal units. The scheduling of hourly thermal generation is thus reduced to an economic dispatch problem, in which the thermal unit commitment aspect can be ignored. To meet the spinning reserve requirement, TPC keeps a certain percentage of the available thermal capacities (committed units and all the peaking units) as the spinning reserve. According to the aforementioned operation of the TPC system, the coupling between hydro and thermal generation scheduling is through the constraint that the total generation should meet the system load.

We decouple the hydro scheduling from the thermal part by first establishing the generation cost function of meeting the system load by purely thermal generation. For each given load level, the lambda-iteration method is performed to solve the economic dispatch over the set of available units [1] and to evaluate the thermal generation cost in order 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 minimized. In TPC's hydro system, there is no significant delay relative to the one-hour time increment for water to flow from one reservoir to its immediate downstream neighbor. To do this, the study period (one day for the present work) is divided into N stages ($N = 24$ in the present study) and the hydro scheduling problem is then formulated as follows.

$$\text{Minimize } C = \sum_{t=1}^{24} \text{COST}_t(\text{GTHERMAL}_t) \quad (1)$$

subject to

(1) the generation-load balance equations

$$\text{GTHERMAL}_t + \sum_i P_i(X_{it}) = L_t \quad (2)$$

$$t = 1, 2, \dots, 24$$

(2) the water balance equations

$$Y_{i,t+1} = Y_{it} + \sum_{j \in N_i} X_{jt} - X_{it} + \sum_{l \in N_i} S_{lt} - S_{it} + R_{it} \quad (3)$$

$$i = 1, 2, \dots, I; \quad t = 1, 2, \dots, 24$$

(3) bounds on water releases

$$X_{i,\min} \leq X_{it} \leq X_{i,\max} \quad \text{and} \quad S_{i,\min} \leq S_{it} \leq S_{i,\max} \quad (4)$$

$$i = 1, 2, \dots, I$$

(4) bounds on reservoir storage

$$Y_{i,\min} \leq Y_{it} \leq Y_{i,\max} \quad i = 1, 2, \dots, I \quad (5)$$

(5) the spinning reserve requirement

$$\sum_i [P_i(X_{i,\max}) - P_i(X_{it})] \geq \text{SR}_t \quad t = 1, 2, \dots, 24 \quad (6)$$

with the following nomenclature.

C	system generation cost over study period
$\text{COST}_t(.)$	generation cost function at hour t which is approximated by a second-order polynomial
GTHERMAL_t	total generation from thermal units at hour t
I	number of reservoirs ($I = 10$ in present work)
L_t	system load at hour t
N_i	set of reservoirs immediately upstream of reservoir i
$P_i(.)$	water-to-energy conversion function of power plant associated with reservoir i
R_{it}	volume of natural inflow to reservoir i during hour t
S_{it}	spillage from reservoir i during hour t

SR_t	hydro spinning reserve requirement at hour t
X_{it}	volume of water released from reservoir i for generation during hour t
Y_{it}	water volume of reservoir i at beginning of hour t

Note that Y_{i1} and Y_{i25} are the given initial and final water volumes of reservoir i .

To deal with the optimization problem, some conventional approaches such as dynamic and linear programming can be employed. In the present work, we decided to use Kohonen's neural network.

3. The proposed solution method

The proposed artificial neural network approach is a two-stage process as shown in Fig. 1.

The input data for the hydro scheduling problem are N ($N=24$ in this work) hourly loads L_t ($t=1, 2, \dots, 24$). Given these hourly loads, 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 the thermal units is minimized. Of course, all practical constraints as described in Eqs. (2)–(6) must be satisfied.

Let U be the input vector which comprises the 24 hourly loads, that is,

$$U = [u_1, u_2, \dots, u_{24}]^t = [L_1, L_2, \dots, L_{24}]^t \quad (7)$$

Let us also define Z as the output vector which comprises the volume of water released from each reservoir for hydro generation X_{it} ($i=1, 2, \dots, 10$; $t=1, 2, \dots, 24$):

$$Z = [z_1, z_2, \dots, z_{240}]^t = [X_{11}, \dots, X_{10,24}]^t \quad (8)$$

Before the ANN can be used to generate the hydro schedules, a set of training patterns is first compiled. For the purpose of this work, a total of 92 historical load records in the summer season of 1990 was collected. From these load patterns, that for the first day of each month was reserved as a test pattern. This leaves only 89 patterns as training patterns. These load patterns are the inputs to the ANN. Let the i th input vector U_i ($i=1, 2, \dots, 89$) be denoted as

$$U_i = [u_{i1}, u_{i2}, \dots, u_{i24}]^t \quad (9)$$

Fig. 1. The proposed solution method.

Fig. 2. A clustering of two-dimensional points.

For the 89 load patterns, the corresponding water release schedules which were obtained by using constrained differential dynamic programming [9] are also compiled as the outputs of the training patterns. Thus, we have 89 input–output pairs.

To reach the preliminary hydro schedule for the day with given hourly loads, a clustering ANN is developed. The purpose of clustering is to separate patterns into groups. Fig. 2 shows a conceptual clustering figure. It is observed from Fig. 2 that points of two-dimensional patterns are grouped into clusters according to their geometric similarity. Note that there is no overlapping in Fig. 2. In other words, every pattern belongs to one and only one group. In the present work, each load pattern is described by a 24-dimensional vector and we are going to group the 89 load patterns into clusters. Two means of clustering, Kohonen's neural network and Euclidean clustering, will be employed. Details of the two clustering algorithms will be described in Sections 4.1 and 4.2, respectively. For the load pattern under study, U_f , a group can be found which is most similar to the study pattern among those created at load pattern clustering. Let us identify this group as G . Thus, the average of the Z vectors which are associated with the U patterns in the group G should contain valuable information with regard to the described schedule for the study pattern U_f . Let O_f be this average vector. In other words,

$$O_f = \text{average}(Z_m | U_m \in G) \quad (10)$$

where Z_m is the schedule vector corresponding to load pattern U_m in group G . Note that the vector O_f gives the desired preliminary hydro schedules for the day under study. In other words, the hourly water releases for the ten hydro plants are the elements of the vector O_f .

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

4. Clustering by Kohonen's neural net and the Euclidean algorithm

4.1. Kohonen's self-organizing neural net for load data classification

The unsupervised learning ANN, Kohonen's self-organizing feature map, was employed to classify the 89 load patterns.

The self-organizing feature map originated from the observation that the fine structure of the cerebral cortex in the brain is self-organized during training. It maps the N -dimensional inputs $[u_1, u_2, \dots, u_{24}]^t$ onto the M output nodes ($M = 11 \times 11 = 121$ in our study), as shown in Fig. 3. The output nodes are arranged on a two-dimensional grid-like network. Each output node is described by a pair of rectangular coordinates. A salient characteristic of the Kohonen net is that the mapping is topologically conservative, which means that 'similar' input vectors in its N -dimensional space will be mapped to the nodes within a neighborhood on the two-dimensional grid. Using this feature, typical applications of Kohonen's net are pattern clustering or pattern classification.

Between every output node and every input node there is a weighted synaptic connection w_{ij} . To each output node, its weight vector W_j acts as a templet or exemplar. The degree of activation of each node is directly dependent on the similarity between this templet and the present input pattern.

As an input pattern presented at the input nodes, the activation value a_j of node j was given by the following formula:

$$a_j = \frac{1}{\|U - W_j\|} \quad (11)$$

where U is the input pattern vector, which is a 24-hour load record in our study, and $W_j = [w_{1j}, w_{2j}, \dots, w_{24j}]^t$ is the connection weight vector for output node j ($j = 1, 2, \dots, 121$).

Fig. 3. Kohonen's self-organizing feature map.

When an input pattern is presented to the neural net, the neural net computes the activation value for each output node based on the present connection weights. The input pattern is said to be mapped to the output node with the maximum activation value.

Kohonen suggested that the connection weights be initialized to small random values. The approach works well for the cases where the input vectors are widely spread over the whole pattern space. But the input vectors in the present work are restricted to a small portion of the space. Therefore, we proposed to set the initial weight vectors to be around the means of these vectors. In other words, we first define

$$W'_j = \text{means of } (U_i, i = 1, 2, \dots, 89) \quad (12)$$

$$j = 1, 2, \dots, M$$

Then we perturb W'_j with a random noise as follows:

$$W_j = W'_j + [5r \times \text{variance of } (U_i, i = 1, 2, \dots, 89)]$$

$$j = 1, 2, \dots, M \quad (13)$$

where r is a random number uniformly distributed in the range -0.5 to 0.5 .

During the learning process, the output nodes are activated by input vectors. At every presentation of input vectors, the mapped node which has the maximum activation value is identified, and the weight vectors of the mapped node and its neighbors are updated by the following formula:

$$W_j(t+1) = W_j(t)(1-\eta) + U\eta \quad (14)$$

where U is the present input vector and η is a step size which is decreasing during the learning process.

The range of the neighborhood of updating initially covers a wide range and shrinks by iterations. Finally, only the weights of the mapped node are updated.

After enough input pattern vectors have been presented, input patterns with similar features will be mapped to the same output unit or to output units within a small neighborhood.

4.2. The Euclidean clustering algorithm for load data classification

In order to compare the results for the schedules, the Euclidean clustering algorithm was also used to classify the 89 load patterns.

To identify 89 load patterns with similar input patterns, let us define the Euclidean distance measure d_{ij} between two vectors U_i and U_j as

$$d_{ij} = \|U_i - U_j\| = [(U_i - U_j)^t (U_i - U_j)]^{1/2}$$

$$= \left[\sum_{k=1}^{24} (u_{ik} - u_{jk})^2 \right]^{1/2} \quad (15)$$

If d_{ij} is less than a threshold d_c , the two input vectors U_i and U_j are said to be of the same cluster and the two

Fig. 4. Two clusters which contain similar patterns.

days with the two input vectors are said to be similar. Fig. 4. depicts the situation with two clusters. The threshold d_τ in Fig. 4 must be chosen to be greater than typical intra-cluster distances and smaller than inter-cluster distances. Also, each pattern belongs to only one cluster. Overlapping is not allowed in this algorithm.

After the clustering process is completed, we get several clusters of input patterns. Now, for an input vector U which is not in the training set, we compute the Euclidean distance measure between this vector U and the patterns in the several clusters. The cluster with minimal distance is assigned to the vector U . The cluster for the input vector U can then be identified.

5. The heuristic rule based search algorithm

In the preliminary schedule reached by the ANN approaches, some practical constraints such as water release bounds, available water limits and the hydro spinning reserve requirement 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.

(1) Heuristic rule for water release bounds

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

Let $X_{it} = X_{i, \min}$ if $X_{it} < X_{i, \min}$

($i = 1, 2, \dots, 10; t = 1, 2, \dots, 24$)

Table 1
Hydro system data

Reservoir	Storage (km ³)		Plant	Water release (m ³ /s)	
	Lower bound	Upper bound		Lower bound	Upper bound
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	1342	I-Hsing	0	31.7

(2) Heuristic rule for available water limits

Reduce a small amount of the released water from X_{it} during the off-peak period until

$$\sum_{t=1}^{24} X_{it} = Q_i \quad (i = 1, 2, \dots, 10) \quad \text{if} \quad \sum_{t=1}^{24} X_{it} > Q_i$$

where Q_i is the total available water volume for reservoir i over the study period.

Increase a small amount of the released water from X_{it} during peak hours until

$$\sum_{t=1}^{24} X_{it} = Q_i \quad (i = 1, 2, \dots, 10) \quad \text{if} \quad \sum_{t=1}^{24} X_{it} < Q_i$$

(3) Heuristic rule for hydro spinning reserve requirement

Reduce a small amount of released water from X_{it} until

$$\sum_i [P_i(X_{i, \max}) - P_i(X_{it})] \geq \text{SR}_t \quad (t = 1, 2, \dots, 24)$$

if

$$\sum_i [P_i(X_{i, \max}) - P_i(X_{it})] < \text{SR}_t$$

6. Example

To demonstrate the effectiveness of the proposed ANN approach, hydroelectric generation scheduling was performed on Taiwan power system which consists of four Ta-Chia River cascaded plants, three Cho-Shui plants and three hydraulically independent plants. The schematic diagrams of the hydro plants along the Cho-Shui and Ta-Chia Rivers are shown in Fig. 5. The hydro system data used for this work are presented in Table 1. A total of 92 historical load records in the summer season of 1990 was collected. Among these load patterns, the load record for the first day of each month was reserved as a test pattern. Fig. 6 depicts the system's hourly load curves for the three test load patterns.

Fig. 5. Schematic diagrams of Cho-Shui and Ta-Chia Rivers.

The 89 load records were used to train the Kohonen net. After 800 iterations of the presentations, the neural net mapped these patterns onto the 11×11 grid as shown in Fig. 7. The numbers labeled on each node of Fig. 7 indicates the number of input patterns mapped to that node. By using the trained net with its weight connection, we can map the three reserved vectors onto the output nodes. Thus, to each vector with its mapped node, the similar patterns within the 89 records can be found by collecting those records that map themselves onto the same output node or its neighbors. To pick the neighbors of a node, we selected the nine nodes which

Fig. 6. Daily system load profiles: —, 6/1/90 (Fri.); - - -, 7/1/90 (Sun.); . . . , 8/1/90 (Wed.).

	1	2	3	4	5	6	7	8	9	10	11
1	3	2	2	1	1	1	0	1	0	1	0
2	1	0	1	0	1	2	0	1	0	0	0
3	1	1	1	1	0	0	1	0	1	1	2
4	0	0	1	0	2	1	2	2	1	1	1
5	2	0	0	2	1	0	4	1	1	2	1
6	0	1	1	0	0	0	2	2	1	0	0
7	1	1	0	0	3	0	0	0	0	0	0
8	1	1	0	0	1	2	1	2	0	0	1
9	0	0	1	1	0	0	0	0	0	2	0
10	1	1	1	1	0	1	3	0	1	0	0
11	0	0	0	0	0	0	0	0	1	1	1

Fig. 7. The mapped net of the 89 patterns.

form a rectangle with the mapped node as its center. In our study, the reserved three load patterns were used to test the proposed algorithm. For example, since the record of 1 August 1990 maps to the node with coordinates (1, 2), all records mapped to nodes (1, 1), (1, 3), (2, 1), (2, 2), (2, 3), (11, 1), (11, 2) and (11, 3) are selected as a cluster. The greater the number of nodes that are selected as neighbors, the more patterns will be included in a cluster. Note that overlapping of clusters is allowed here. After obtaining the preliminary schedules of the three test records by averaging the vectors of the associated clusters, the heuristic rule based search algorithm was executed to reach the final schedules.

The 89 load records were also clustered by using the Euclidean clustering algorithm described in Section 4.2. Table 2 shows the results of a typical clustering for a d_c of 0.3. It was noticed that the number of clusters increases if the value of d_c in the algorithm is decreased. For a day in the future with the forecasted load pattern U_f , the Euclidean distances between this study pattern

Table 2

A typical clustering (clusters : number of vectors)

1:8	4:3	7:2	10:1
2:3	5:32	8:12	11:1
3:3	6:7	9:17

Fig. 8. Comparison of hydro generation schedules for the case of 1 June 1990 (Fri.): —, DDP; - - -, EA-HA; - · -, KA-HA.

and the patterns in several clusters can be calculated and then it can be associated with the cluster with minimum distance. We obtain the corresponding average vector O_i as a preliminary schedule. Then, the heuristic rule based search algorithm is also executed to give the final schedules.

The hydro generations over the 24-hour scheduling period from the three approaches which include differential dynamic programming (DDP), Kohonen's ANN-heuristic algorithm (KA-HA) and the Euclidean algorithm-heuristic algorithm (EA-HA) are compared in Figs. 8, 9 and 10 for the system load profiles of 1 June, 1 July and 1 August 1990, respectively. Details of the released water schedule for each hydro plant are not given due to limited space. The total fuel costs of the thermal units for these schedules and the CPU times required by the three approaches are summarized in Table 3. All our numerical computations were performed on a Sun workstation.

From the above results, the following observations and discussions can be made.

(1) It is found from the results in Figs. 8–10 that the proposed ANN approach gives hydro generation schedules which are very similar to the optimal schedules obtained by the DDP algorithm.

(2) It is observed from the results in Table 3 that the fuel costs for the schedules from the ANN approach are close to those for the optimal schedules from the DDP approach. However, the ANN approach requires much

Fig. 9. Comparison of hydro generation schedules for the case of 1 July 1990 (Sun.): —, DDP; - - -, EA-HA; - · -, KA-HA.

Fig. 10. Comparison of hydro generation schedules for the case of 1 August 1990 (Wed.): —, DDP; - - -, EA-HA; - · -, KA-HA.

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 ANNs in a very efficient manner.

(3) Kohonen's net clustering is preferable to the Euclidean one due to its flexibility. First of all, the self-organizing feature map is visually easier to understand, as shown in Fig. 3. Secondly, overlapping is allowed in the former and the range and size of a cluster is user-defined. Take the case of 1 July as an example. On comparing the scheduling results in Fig. 9 and Table 3, it is found that the Euclidean clustering gives more different schedules. The day happens to be a Sunday. In fact, there are only two patterns in the nearest group from Euclidean clustering. This will not occur in self-organized clustering in which we have the freedom to select the neighbors of its mapped nodes.

Table 3
Comparison of the results

Date	Solution by DDP		Solution by EA–HA			Solution by KA–HA		
	Time (s)	Cost (NT\$)	Time (s)	Cost (NT\$)	Difference ^a (%)	Time (s)	Cost (NT\$)	Difference ^a (%)
1 June 1990 (Fri.)	148.01	159146592	0.31	159238416	0.05770	0.31	159234272	0.05509
1 July 1990 (Sun.)	133.01	123179936	0.30	123255640	0.06146	0.31	123230224	0.04082
1 Aug. 1990 (Wed.)	159.54	168468384	0.32	168513424	0.02674	0.33	168509528	0.02442

$$^a\text{Difference} = \frac{(\text{cost of schedule}) - (\text{cost from DDP algorithm})}{\text{cost from DDP algorithm}} \times 100\%$$

(4) As far as the training time is concerned, the time spent by the Euclidean algorithm to cluster 89 patterns is about 30 seconds. The value for the Kohonen self-organizing feature map is about 20 minutes.

(5) We demonstrate the proposed method by using ten hydro plants. It is not difficult to employ the clustering ANN approach on a larger scale and for more complex problems. Basically, the clustering algorithms are insensitive to the scale of problems.

7. Conclusions

A new technique using self-organizing feature maps has been proposed for short-term hydroelectric generation scheduling of a power system. In this approach, we first employ the method to obtain a preliminary schedule for the hydro units. Kohonen clustering, which is used to classify load patterns into groups, is developed. In each case, a preliminary schedule is obtained by averaging optimal schedules in the group. Then the schedule is refined by a heuristic rule based search algorithm in order 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 was 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 to get the generation schedules than the differential dynamic programming method.

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