Augmented Lagrange Hopfield Network Based Method for Long-Term Hydrothermal Scheduling

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Abstract— *This paper proposes an augmented Lagrange Hopfield network (ALHN) based method for solving long-term hydrothermal scheduling problem. The main objective of the problem is to minimize total power generation cost over a scheduling period of one year while satisfying the operating constraints of the hydro and thermal plants, such as the limits on the water storages, discharges, hydro and thermal generations. The ALHN method is a combination of augmented Lagrange relaxation and continuous Hopfield neural network where the augmented Lagrange function is directly used as the energy function of the network. The effectiveness of the proposed method has been tested on two systems and the obtained results compared to those from other methods available in the literature have indicated that the proposed method is very efficient for solving long-term hydrothermal scheduling problem with good optimal solution and fast computational time.*

Keywords— **Long-term hydrothermal scheduling, augmented Lagrange Hopfield network (ALHN), fuel cost function, water storages.**

1. INTRODUCTION

Hydrothermal scheduling is designed to determine a feasible scheduling for power generation in hydro and thermal units that minimizes the operational costs of the system. Since there are many aspects to be considered, including randomness of inflow, hydraulic operational constraints, and electrical transmission constraints, the problem is usually decomposed into a series of long, mid and short-term schedules, with certain aspects represented in each term while others are neglected [1].

The long-term hydrothermal scheduling (LTHTS) problem is concerned with effective utilization of the water inflow to the various hydro reservoirs during the period of interest, usually taken as one year. The solution to this problem consists of the determination of a plant for the withdrawal of water from the hydro reservoirs for power generation throughout the period and the determination of the corresponding thermal generations so that the total cost of fuel is minimized, subject to the operating constraints of the hydro and thermal plants, such as the limits on the water storages, discharges, hydro and thermal power generations [2, 3]. In one of the earlier works [4], the hydrothermal scheduling problem was solved by forming a Lagrange function by augmenting the cost function with the equality constraints on power balance, hydro power generation and the hydro plant characteristic equations. The inequality constraints, namely, limits on water storages, hydro power generations and thermal power generations, are handled by augmenting the cost function with a penalty function. The full problem thus formulated is solved using the conjugate gradient technique. A large computer memory is required in this formulation and the convergence is dependent on the selection of penalty constants [2]. The method of feasible direction [5] was used to solve the hydrothermal scheduling problem. The fundamental principle of this technique is to find a direction of move towards the optimum value. The active constraints are included in determining the direction of move such that it always remains in the feasible domain. An important feature of the approach is its simplicity of formulation as it obviates the need of augmenting the objective function. A local variation algorithm (LVA) [2] has used the method of local variation together with participation factors and the lambda iteration method. The solution approach comprises two phases of computations. In the first phase an initial feasible hydrothermal schedule is obtained and in the second the schedule is improved iteratively to obtain an optimal hydrothermal schedule. Unlike other methods, namely, the conjugate gradient method (CGM) [4] and the feasible direction method (FDM) [5], the proposed method is simple to program, requires the least computer memory and gives an effective optimal solution in reasonable time. Another method based on lambda iteration algorithm and conjugate gradient method to compute discharge (LI-CGM) [6] has reached good quality solutions and certain convergence. J. Sasikala et al. [7] have applied lambda iteration algorithm for solving short term hydrothermal scheduling problem and compare the result from the method with optimal gamma based genetic algorithm. Augmented penalty function method (APFM) [8] has been used to solve LTHTS problem with larger scale than CGM [4] and FDM [5]. The results in terms of fuel cost and computation time have been compared to those from LVA [2]. The

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comparison has indicated that APFM [8] is less effective than LVA [2]. The Hopfield neural network (HNN) has been applied to short-term hydrothermal scheduling [9]. There are many drawbacks for such an application. The optimal solution obtained by HNN is sensitive to the selected weighting factors, so selection of the factors is a difficult task. In addition, HNN is very difficult to deal with the complicated problems with nonlinear constraints since the problem constraints have to be linearized before implementing in HNN. Furthermore, for a large-scale system HNN must take long computational time for convergence.

In this paper, a new improvement of continuous Hopfield neural network, called Augmented Lagrange Hopfield network (ALHN) has been proposed for solving long-term hydrothermal scheduling problem. ALHN is a combination of augmented Lagrange relaxation and continuous Hopfield neural network where the augmented Lagrange function is directly used as the energy function of the continuous Hopfield network. On the contrary to HNN, ALHN can obtain the fast convergence for not only simple systems but also large-scale and complicated systems. In order to verify the effectiveness of ALHN two systems are used to perform and the obtained results are compared to those from LVA [2], CGM [4], FDM [5], LI-CGM [6] and APFM [8].

2. PROBLEM FORMULATION

The availability of limited amount of hydroelectric energy, in the form of stored water in the system reservoirs makes the optimal operation complex, because of the link between an operating decision in a given stage and the future consequences of this decision in subsequent stages. Further, it is impossible to have perfect forecasts of the future inflow as well as the load variation during a given period. Therefore, for long term storage regulation, it becomes necessary to account for the random nature of the load and river inflow. A hydrothermal system is considered with N_1 thermal and N_2 hydro plants. The problem is visualized as an M stage decision process by subdividing the planning period into M sub-intervals.

2.1. Thermal fuel cost

The objective function, which is the fuel cost of the thermal plants, is as follows:

$$F_{sm} = a_s + b_s P_{sm} + c_s P_{sm}^2 \tag{1}$$

2.2. Constraints

Load demand

$$P_{Lm} + P_{Dm} - \sum_{s=1}^{N1} P_{sm} - \sum_{h=1}^{N2} P_{hm} = 0 \tag{2}$$

$$P_{Lm} = \sum_{i=1}^{N_1+N_2} \sum_{j=1}^{N_1+N_2} P_{im} B_{ij} P_{jm} + \sum_{i=1}^{N_1+N_2} B_{0i} P_{im} + B_{00} \tag{3}$$

Storage continuity constraint

$$X_{hm} - X_{hm-1} - J_{hm} + q_{hm} = 0, \;\; m = 1, 2, ..., M \tag{4}$$

The limits on the storage level in the reservoirs

$$X_h^{\max} \le X_{hm} \le X_h^{\min} \tag{5}$$

Total volume of water available constraint

$$X_{h0} - X_{hM} + \sum_{m=1}^{M} j_{hm} - \sum_{m=1}^{M} q_{hm} = 0 \tag{6}$$

The limits on water discharge

$$q_h^{\max} \le q_{hm} \le q_h^{\min} \tag{7}$$

Hydro generation

$$P_{hm} = h_{0h}(1 + 0.5e(X_{hm} + X_{hm-1}))(q_{hm} - \rho_h) \tag{8}$$

Generator operating limits

$$P_s^{\min} \le P_{sm} \le P_s^{\max} \tag{9}$$

$$P_h^{\min} \le P_{hm} \le P_h^{\max} \tag{10}$$

3. ALHN BASED METHOD FOR THE PROBLEM

3.1 ALHN for Optimal Solutions

The augmented Lagrange function L of the problem is formulated as follows:

$$\begin{aligned} L = & \sum_{m=1}^{M} T_m \; [\sum_{s=1}^{N1} F_s(P_{sm})] + \sum_{m=1}^{M} \lambda_m (P_{Lm} + P_{Dm} - \sum_{s=1}^{N1} P_{sm} - \sum_{h=1}^{N2} P_{hm}) \\ & + \sum_{h=1}^{N2} \sum_{m=1}^{M} \beta_{hm} (X_{hm} - X_{hm-1} - J_{hm} + q_{hm}) \\ & + \sum_{h=1}^{N2} \sum_{m=1}^{M} \gamma_{hm} \begin{pmatrix} (P_{hm} - h_{0h}(1 + 0.5e(X_{hm} + X_{hm-1})) \\ (q_{hm} - \rho_h) \end{pmatrix} \\ & + \mu_h \sum_{h=1}^{N2} (X_{h0} - X_{hM} + \sum_{m=1}^{M} j_{hm} - \sum_{m=1}^{M} q_{hm}) \\ & + \frac{1}{2} \sum_{m=1}^{M} \beta_{1,m} \left(P_{Lm} + P_{Dm} - \sum_{s=1}^{M} P_{sm} - \sum_{h=1}^{N2} P_{hm} \right)^2 \\ & + \frac{1}{2} \sum_{h=1}^{N2} \sum_{m=1}^{M} \beta_{2,hm} \left(X_{hm} - X_{hm-1} - J_{hm} + q_{hm} \right)^2 \\ & + \frac{1}{2} \sum_{h=1}^{N2} \sum_{m=1}^{M} \beta_{3,hm} \begin{pmatrix} P_{hm} - h_{0h}(1 + 0.5e(X_{hm} + X_{hm-1})) \\ (q_{hm} - \rho_h) \end{pmatrix}^2 \\ & + \frac{1}{2} \beta_{4,h} \sum_{h=1}^{N2} (X_{h0} - X_{hM} + \sum_{m=1}^{M} j_{hm} - \sum_{m=1}^{M} q_{hm})^2 \end{aligned} \tag{11}$$

where λ_m, β_{hm}, μ_h and γ_{hm} are Lagrange multipliers, $\beta_{1,m}$, $\beta_{2,hm}$, $\beta_{3,hm}$ and $\beta_{4,h}$ are penalty factors.

The energy function E of the problem is described in terms of neurons is determined as:

$$E = \sum_{m=1}^{M}\sum_{s=1}^{N_1} t_m \left(a_s + b_s V_{p,sm} + c_s V_{p,sm}^2\right)$$
$$+ \sum_{m=1}^{M} V_{\lambda,m} (P_{Lm} + P_{Dm} - \sum_{s=1}^{N1} V_{P,sm} - \sum_{h=1}^{N2} V_{P,hm})$$
$$+ \sum_{h=1}^{N2}\sum_{m=1}^{M} V_{\beta,hm} (V_{X,hm} - V_{X,hm-1} - J_{hm} + V_{q,hm})$$
$$+ \sum_{h=1}^{N2}\sum_{m=1}^{M} V_{\gamma,hm} \begin{Bmatrix} V_{P,hm} - h_{0h}(1+0.5e\times \\ (V_{X,hm} + V_{X,hm-1}))(V_{q,hm} - \rho_h) \end{Bmatrix}$$
$$+ V_{\mu h} \sum_{h=1}^{N2} (X_{h0} - X_{hM} + \sum_{m=1}^{M} j_{hm} - \sum_{m=1}^{M} V_{qhm})$$
$$+ \frac{1}{2}\sum_{m=1}^{M} \beta_{1,m} \left(P_{Lm} + P_{Dm} - \sum_{s=1}^{M} V_{P,sm} - \sum_{h=1}^{N2} V_{P,hm} \right)^2$$
$$+ \frac{1}{2}\sum_{h=1}^{N2}\sum_{m=1}^{M} \beta_{2,hm} \left(V_{X,hm} - V_{X,hm-1} - J_{hm} + V_{q,hm}\right)^2$$
$$+ \frac{1}{2}\sum_{h=1}^{N2}\sum_{m=1}^{M} \beta_{3,hm} \begin{pmatrix} V_{P,hm} - h_{0h}(1+0.5e\times \\ (V_{X,hm} + V_{X,hm-1}))(V_{q,hm} - \rho_h) \end{pmatrix}^2$$
$$+ \frac{1}{2}\beta_{4,h} \sum_{h=1}^{N2} (X_{h0} - X_{hM} + \sum_{m=1}^{M} j_{hm} - \sum_{m=1}^{M} V_{qhm})^2$$
$$+ \sum_{m=1}^{M} \left(\sum_{s=1}^{N_1} \int_0^{V_{P,sm}} g^{-1}(V)dV + \sum_{h=1}^{N_2} \int_0^{V_{P,hm}} g^{-1}(V)dV \right) \quad (12)$$
$$+ \sum_{m=1}^{M} \left(\sum_{s=1}^{N_1} \int_0^{V_{X,hm}} g^{-1}(V)dV + \sum_{h=1}^{N_2} \int_0^{V_{q,hm}} g^{-1}(V)dV \right)$$

where $V_{\lambda,m}$, $V_{\beta,hm}$, $V_{\gamma,hm}$ and $V_{\mu,h}$ are the outputs of the multiplier neurons associated with power balance and water constraints, respectively; $V_{P,hm}$, $V_{P,sm}$, $V_{X,hm}$ and $V_{q,hm}$ are the outputs of continuous neurons *hm*, *sm*, *hm* and *hm* representing P_{hm}, P_{sm}, $X_{,hm}$ and q_{hm} respectively.

The dynamics of the model for updating neuron inputs are defined as follows:

$$\frac{dU_{P,sm}}{dt} = -\frac{\partial E}{\partial V_{P,sm}} \quad (13)$$

$$\frac{dU_{P,hm}}{dt} = -\frac{\partial E}{\partial V_{P,hm}} \quad (14)$$

$$\frac{dU_{X,hm}}{dt} = -\left(\frac{\partial E}{\partial V_{X,hm}}\right)_{m \neq M} \quad (15)$$

$$\frac{dU_{q,hm}}{dt} = -\left(\frac{\partial E}{\partial V_{q,hm}}\right)_{m \neq 1} \quad (16)$$

$$\frac{dU_{\lambda m}}{dt} = +\frac{\partial E}{\partial V_{\lambda m}} \quad (17)$$

$$\frac{dU_{\beta hm}}{dt} = +\frac{\partial E}{\partial V_{\beta hm}} \quad (18)$$

$$\frac{dU_{\gamma hm}}{dt} = +\frac{\partial E}{\partial V_{\gamma hm}} \quad (19)$$

$$\frac{dU_{\mu h}}{dt} = +\frac{\partial E}{\partial V_{\mu h}} \quad (20)$$

The inputs of neurons at step *n* are updated:

$$U_{P,sm}^{(n)} = U_{P,sm}^{(n-1)} - \alpha_{P,sm}\frac{\partial E}{\partial V_{P,sm}} \quad (21)$$

$$U_{P,hm}^{(n)} = U_{P,hm}^{(n-1)} - \alpha_{P,hm}\frac{\partial E}{\partial V_{P,hm}} \quad (22)$$

$$U_{X,hm}^{(n)} = U_{X,hm}^{(n-1)} + \alpha_{X,hm}\frac{\partial E}{\partial V_{X,hm}} \quad (23)$$

$$U_{q,hm}^{(n)} = U_{q,hm}^{(n-1)} + \alpha_{q,hm}\frac{\partial E}{\partial V_{q,hm}} \quad (24)$$

$$U_{\lambda,m}^{(n)} = U_{\lambda,m}^{(n-1)} + \alpha_{\lambda,m}\frac{\partial E}{\partial V_{\lambda,m}} \quad (25)$$

$$U_{\gamma,hm}^{(n)} = U_{\gamma,hm}^{(n-1)} + \alpha_{\gamma,hm}\frac{\partial E}{\partial V_{\gamma,hm}} \quad (26)$$

$$U_{\beta,hm}^{(n)} = U_{\beta,hm}^{(n-1)} + \alpha_{\beta,hm}\frac{\partial E}{\partial V_{\beta,hm}} \quad (27)$$

$$U_{\mu,h}^{(n)} = U_{\mu,h}^{(n-1)} + \alpha_{\mu,h}\frac{\partial E}{\partial V_{\mu,h}} \quad (28)$$

where $U_{\lambda,m}$, $U_{\beta,hm}$, $U_{\gamma,hm}$ and $U_{\mu,h}$ are the inputs of the multiplier neurons; $U_{P,hm}$, $U_{P,sm}$, $U_{X,hm}$ and $U_{q,hm}$ are the inputs of continuous neurons. $\alpha_{\lambda,m}$, $\alpha_{\gamma,hm}$, $\alpha_{\beta,hm}$ and $\alpha_{\mu,h}$ are step sizes for updating the inputs of multiplier neurons; and $\alpha_{P,sm}$, $\alpha_{P,hm}$ $\alpha_{X,hm}$ and $\alpha_{q,hm}$ are step sizes for updating the inputs of continuous neurons.

The outputs of continuous neurons and multiplier neurons:

$$V_{P,sm} = \left(P_s^{\max} - P_s^{\min}\right)\left(\frac{1+\tanh\left(\sigma U_{P,sm}\right)}{2}\right) + P_s^{\min} \quad (29)$$

$$V_{P,hm} = \left(P_h^{\max} - P_h^{\min}\right)\left(\frac{1+\tanh\left(\sigma U_{P,hm}\right)}{2}\right) + P_h^{\min} \quad (30)$$

$$V_{X,hm} = \left(X_h^{\max} - X_h^{\min}\right)\left(\frac{1+\tanh\left(\sigma U_{X,hm}\right)}{2}\right) + X_h^{\min} \quad (31)$$

$$V_{q,hm} = \left(q_h^{\max} - q_h^{\min}\right)\left(\frac{1+\tanh\left(\sigma U_{q,hm}\right)}{2}\right) + q_h^{\min} \quad (32)$$

$$V_{\lambda m} = U_{\lambda m} \quad (33)$$

$$V_{\gamma,hm} = U_{\gamma,hm} \quad (34)$$

$$V_{\beta,hm} = U_{\beta,hm} \quad (35)$$

$$V_{\mu,h} = U_{\mu,h} \quad (36)$$

where σ is slope of sigmoid function that determines the shape of the sigmoid function [10].

3.1.1 Initialization

The initial outputs of continuous neurons are set at their middle limits and the multiplier neurons are set as follows:

$$V_{P,sm}^{(0)} = \left(P_s^{\max} + P_s^{\min}\right)/2 \quad (37)$$

$$V_{P,hm}^{(0)} = \left(P_h^{\max} + P_h^{\min}\right)/2 \quad (38)$$

$$V_{X,hm}^{(0)} = \left(X_h^{\max} + X_h^{\min}\right)/2 \quad (39)$$

$$V_{q,hm}^{(0)} = \left(q_h^{\max} + q_h^{\min}\right)/2 \quad (40)$$

$$V_{\lambda m}^{(0)} = \frac{1}{N_1}\sum_{s=1}^{N_1} \frac{t_{sm}\left(b_s + 2c_s V_{P,sm}^{(0)}\right)}{1 - \frac{\partial P_{Lm}}{\partial V_{P,sm}}} \quad (41)$$

$$V_{\gamma h}^{(0)} = \frac{1}{N_2}\sum_{h=1}^{N_2} V_{\lambda m}^{(0)}\left(1 - \frac{\partial P_{Lm}}{\partial V_{P,hm}}\right) \quad (42)$$

$$V_{\beta,h1} = V_{\gamma,m}.h_{0h}\{1 + 0.5e(2V_{X,hm-1} + J_{hm} - 2V_{q,hm}\} \quad (43)$$

$$V_{\beta,hm+1|m\geq 1}^{(0)} = \begin{pmatrix} V_{\beta,hm}^{(0)} - V_{\gamma,hm}^{(0)}\{0.5h_{0h}e(V_{q,hm}^{(0)} - \rho)\} \\ -V_{\gamma,hm+1}^{(0)}\{0.5h_{0h}e(V_{q,hm+1}^{(0)} - \rho)\} \end{pmatrix} \quad (44)$$

3.1.2 Selection of Parameters

By experiment, the value of σ is fixed at 100 for all test systems. The other parameters will vary depending on the data of the considered systems.

3.1.3 Termination Criteria

The algorithm of ALHN will be terminated when either maximum error Err_{max} is lower than a predefined threshold ε or maximum number of iterations N_{max} is reached.

3.1.4 Overall procedure

The overall algorithm of the ALHN for finding an optimal solution for the HTS problem is as follows.

Step 1: Select parameters for the model in Section 3.1.2.

Step 2: Initialize inputs and outputs of all neurons using (37)-(44) as in Section 3.1.1.

Step 3: Set $n = 1$.

Step 4: Calculate dynamics of neurons using (13)-(20).

Step 5: Update inputs of neurons using (21)-(28).

Step 6: Calculate output of neurons using (29)-(36).

Step 7: Calculate errors as in section 3.1.3.

Step 8: If $Err_{max} > \varepsilon$ and $n < N_{max}$, $n = n + 1$ and return to Step 4. Otherwise, stop.

4. NUMERICAL RESULTS

The proposed algorithm has been coded in Matlab 7.2 programming language and executed on an Intel(R) Core (TM)2 Duo CPU T7250 @2.00 GHz PC.

4.1. The first system

The first example chosen consists of a system with two hydro plants and two thermal plants. The incremental costs of the thermal plants are [2, 4]:

$$dF_1 / dP_1 = 0.8 + 0.04P_1$$
$$dF_2 / dP_2 = 0.78 + 0.06P_2$$

The water inflows in p.u. during the 12 time intervals, the rest of data relating to the expressions for the hydro plants, initial and final storage of the reservoirs and the transmission loss formula matrix are also given in [2, 4]. Load demand for all the time intervals is 8.0p.u. The optimal solutions are given in table 1. Clearly, all generations of each plant for 12 time intervals are the same because of the same load demand of 8.0 pu for all time intervals. The results comparisons in terms of total fuel cost and computation time among ALHN and other methods for the first system are given in the table 2. CGM [4] and FDM [5] have approximate fuel cost and higher than LVA [2] and ALHN. ALHN has the best solution compared to the all ones.

4.2. The second system

The second system has three hydro plants and four thermal plants. The complete data for the second system are from [6, 8]. The optimal solutions from ALHN are given in table 3. The result comparison in terms of total fuel cost and computation time among ALHN and other methods are given in table 4. The cost from ALHN is much less than LI-CGM [6] and APFM [8] but higher than LVA [2].

Clearly, at the both systems, ALHN is much faster than all methods. LVA [2] has been implemented on a 32-bit PRIME 2250 system with 1 MB. There is no computer reported in [4, 5, 6, 8]. Although ALHN has been executed in the better CPU than other methods, computation time of within 2 seconds for each system has also indicated that ALHN is an effective method to solve long term hydrothermal scheduling problem.

Table 1. Optimal solutions using ALHN for the first system.

		Thermal generations		Hydro generations		Water discharge		
m	P_{Dm} (pu)	P_{s1m} (pu)	P_{s2m} (pu)	P_{h1m} (pu)	P_{h2m} (pu)	P_{Lm} (pu)	q_{h1m} (pu)	q_{h2m} (pu)
1	8	2.7288	2.0413	2.2586	1.8843	0.9132	0.7564	1.521
2	8	2.7288	2.0413	2.2586	1.8843	0.9132	0.8227	0.9922
3	8	2.7288	2.0413	2.2586	1.8843	0.9132	0.9969	0.997
4	8	2.7288	2.0413	2.2586	1.8843	0.9132	1.1451	1.5588
5	8	2.7288	2.0413	2.2586	1.8843	0.9132	1.2927	2.4323
6	8	2.7288	2.0413	2.2586	1.8843	0.9132	1.534	2.8734
7	8	2.7288	2.0413	2.2586	1.8843	0.9132	1.6401	2.047
8	8	2.7288	2.0413	2.2586	1.8843	0.9132	1.2486	0.5795
9	8	2.7288	2.0413	2.2586	1.8843	0.9132	0.8853	0.5007
10	8	2.7288	2.0413	2.2586	1.8843	0.9132	0.6376	0.5
11	8	2.7288	2.0413	2.2586	1.8843	0.9132	0.5332	0.5
12	8	2.7288	2.0413	2.2586	1.8843	0.9132	0.5127	0.5

Table 2. Result comparison for the first system

Method	LVA [2]	CGM [4]	FDM [5]	ALHN
Cost ($)	48.6685	48.7512	48.7488	48.5907
CPU time (s)	67	123	102	2.3

Table 3. Optimal solutions using ALHN for the second system

Thermal generation						Hydro generation			
m	P_{Dm} (MW)	P_{1m} (MW)	P_{2m} (MW)	P_{3m} (MW)	P_{4m} (MW)	P_{1m} (MW)	P_{2m} (MW)	P_{3m} (MW)	P_{Lm} (MW)
1	200	60.8542	50.664	36.334	36.334	13.151	8.0765	0	5.414
2	210	51.6357	42.803	30.5587	30.5587	0.0501	0.2097	61.3109	7.1265
3	205	61.411	51.1399	36.6831	36.6831	6.8325	12.6364	5.1273	5.5145
4	180	50.8341	42.1179	30.053	30.053	9.8902	13.5418	7.3799	3.87
5	195	51.2462	42.4688	30.3113	30.3113	16.0372	17.0841	11.7342	4.1932
6	200	45.7969	37.8322	26.8955	26.8955	25.1512	23.1856	18.2849	4.0417
7	220	43.4586	35.8453	25.4298	25.4298	38.0488	29.0992	27.6018	4.9133
8	204	28.3794	23.0685	15.9782	15.9782	53.7104	33.2545	38.8607	5.2299
9	189	16.3886	12.9543	8.4642	8.4642	66.8045	34.7673	47.4905	6.3328
10	199	18.5544	14.778	9.8211	9.8211	71.4077	33.9512	47.5099	6.8433
11	207	20.38	16.3164	10.965	10.965	75.9744	33.9168	45.7446	7.2622
12	198	13.9493	10.9016	6.9356	6.9356	85.747	33.2368	48.572	8.2771

Table 4. Result comparison for the second system

Method	LVA [2]	LI-CGM [6]	APFM [8]	ALHN
Cost ($)	6234.38	6800.129	6992.73	6777
CPU time (s)	110	-	203	2.2

5. CONCLUSION

In this paper, the proposed Augmented Lagrange Hopfield Network based method is effectively implemented for solving the long-term hydro-thermal scheduling problem. ALHN is a continuous Hopfield neural network with its energy function based on augmented Lagrange function. The ALHN method can find an optimal solution for an optimization in a very fast manner. The effectiveness of the proposed method has been verified through two test systems where the first one consist of two thermal plants and two hydropower plants and the second one has four thermal plants and three hydropower plants. The two systems are scheduled in twelve subintervals. The obtained results compared to those from other methods. The result comparison has indicated that the proposed method can obtain better optimal solutions than other methods. Moreover, the ALHN proposed method also takes the short computation time to get convergence for system ranging from small to larger scale. Therefore, the proposed ALHN method is a promising method for solving long-term hydro-thermal scheduling problem.

NOMENCLATURE

a_s, b_s, c_s	Cost coefficients for thermal unit *s*,
N_1, N_2	Number of thermal and hydro plants.
M	Number of time intervals for scheduling horizon.
P_{Dm}	Load demand of the system during subinterval *m*
P_{hm}	Generation output of hydro unit *h* during subinterval *m*
P_h^{min}, P_h^{max}	Lower and upper generation limits of hydro unit *h*
P_{Lm}	Transmission loss of the system during subinterval *m*
P_{sm}	Generation output of thermal unit *s* during sub-interval *m*
B_{ij}, B_{0i}, B_{00}	Loss formula coefficients of transmission system.
P_s^{min}, P_s^{max}	Lower and upper generation limits of thermal unit *s*
T_m	Duration of subinterval *m*
X_{hm}	Water storage for the *hth* hydro plant during the *mth* sub-interval
J_{hm}	Water inflow into the reservoir for the *hth* hydro plant during the *mth* sub-interval
q_{hm}	Water discharge through the *hth* hydro plant during the *mth* sub-interval
h_{0h}	Basic head of *hth* hydro plant
ρ_h	The non-effective water discharge of the *hth* hydro plant.
e	The water head correction factor to account for variation in head with storage of the *hth* hydro plant.

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