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Optimal Hydro-Thermal Generation Scheduling Using an Efficient Feedback Neural Network Optimization Model

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Abstract: This study demonstrates the use of a high-performance feedback neural network optimizer based on a new idea of successive approximation for finding the hourly optimal release schedules of interconnected multi-reservoir power system in such a way to minimize the overall cost of thermal generations spanned over the planning period. The main advantages of the proposed neural network optimizer over the existing neural network optimization models are that no dual variables, penalty parameters or lagrange multipliers are required. This network uses a simple structure with the least number of state variables and has better asymptotic stability. For an arbitrarily chosen initial point, the trajectory of the network converges to an optimal solution of the convex nonlinear programming problem. The proposed optimizer has been tested on a nonlinear practical system consisting of a multi-chain cascade of four linked reservoir type hydro-plants and a number of thermal units represented by a single equivalent thermal power plant and so obtained results have been validated using conventional conjugate gradient method and genetic algorithm based approach.

Key words: Constrained optimization, convergence and asymptotic stability, generation function

INTRODUCTION

Over the years, there has been a growing interest for developing fast and reliable solution techniques to find optimal operation schedules for interconnected hydro-thermal power plants. Many solution techniques, each with its specific mathematical model and computational procedure, have been reported in pertinent literature for solving this combinatorial problem (Kumar *et al*., 1979; Soares *et al*., 1980; Chand, 1981; Pereira and Pinto, 1983; Shi-Chung *et al*., 1990; Yeh *et al*., 1992; Hota *et al*., 2009; Tanju Jeewan, 2010; Chang Wenping *et al*., 2010; Amjady and Soleymanpour, 2010; Swain *et al*., 2011; Thanju and Ricardo, 2011; Jain and Sharma, 2011). Artificial neural network models have been applied to several classes of constrained optimization problems and have shown promise for solving such problems more efficiently (Tank and Hopfield, 1986; Kennedy and Chua, 1988; Shengwei and Constantinides, 1992; Maa and Shanblatt, 1992; Wang, 1994; Gong *et al*., 1996; Xin-Yu *et al*., 1996; Xia and Wang, 1998; Da-Silva *et al*., 1998; Naresh *et al*., 1999; Naresh *et al*., 2002; Leung *et al*., 2003). However, their performances are not very perfect in terms of convergence to the global optimal solution and asymptotic stability. This problem of asymptotic convergence arises particularly when infinite number of optimal solutions is involved. Further, with the use of lagrange multipliers, the number of state variables increases, thus increasing size of the neural network model.

In this study, a feedback neural network optimization model has been proposed for finding the solution of a complex short-term hydro-thermal scheduling problem. The determination of optimal release schedules involves the solution of a nonlinear programming problem. The existence of multiple interconnected reservoirs and the need for multi-period optimization characterize the scheduling problem as large-scale constrained optimization problem. The illustrious features of the proposed optimizer are that no dual variables, penalty or lagrange multipliers are required. This network optimizer consists of only the variables of the original problem. Therefore, the network has the least number of state variables, a simple structure, and a much better convergence. Based on the Lyapunov stability theory and La Salle invariance principle, the asymptotic stability of the proposed network has been strictly proved by Leung *et al*. (2003). From any initial point, the trajectory of this network converges to an optimal solution of the original programming problem.

PROBLEM FORMULATION

The short-term hydro-thermal scheduling problem can be stated as to find out water release from each

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reservoir and through each power house and the corresponding unit thermal generations over all the planning time intervals so as to minimize the total cost of fuel for thermal generations while satisfying diverse hydraulic, thermal and load balance constraints. In the considered hydro-system, there is significant delay relative to one hour time interval for water to flow from one reservoir to its immediate down stream reservoir and is taken into consideration. Typically the total planning period is one day and time interval is one hour.

Objective function and constraints: The objective function is taken as to minimize the summation of the fuel cost for all the thermal units over the complete planning period. The unit fuel cost is generally assumed to be a quadratic function of unit thermal power. Mathematically the cost function is expressed as (Naresh *et al*., 1999):

$$F = Min \sum_{j \in N_t} Fj\left(P_{g\,j}^{\;k}\right)$$

$$F = Min \sum_{k=1}^{k} \sum_{j=1}^{N_t} a_j \left(P_{g\,j}^{\;k}\right)^2 + b_j \left(P_{g\,j}^{\;k}\right) + c_j$$

subject to

Generation-load balance equation: Generation of energy in a power system has to be equal to the load (including losses). This equality constraint for time interval k is expressed as:

$$\sum_{j=1}^{N_t} P_{g\,j}^{\;k} + \sum_{i=1}^{N} P_{h\,i}^{\;k} = P_d^k + P_1^k$$

Water balance equation for reservoir plants: Reservoir water balance or continuity equation is expressed as equality constraint. Mathematically the dynamic behavior of reservoirs is expressed as:

$$x_i^k = x_i^{k-1} + y_i^k - q_i^k + \sum_{m \in R_u} \left(q_m^{\;k-\tau_i^m}\right)$$

where,

$$q_i^k = z_i^k + v_i^k \quad \text{and} \quad q_m^{k-\tau_i^m} = z_m^{k-\tau_i^m} + v_m^{k-\tau_i^m}$$

Spillage modeling: Spillage is allowed only when water release from the reservoir exceeds the maximum discharge limit through the turbines. Water spilled from reservoir during time interval k is written as follows:

$$v_i^k = \left\{ q_i^k - \bar{z}_i ,\ if\ q_i^k \geq \bar{z}_i \right\}$$

otherwise spill is zero.

Thermal power limits: There are upper and lower limits for the thermal units to generate power. These inequality constraints are expressed as:

$$P_{g\,j}^{\min} \leq P_{g\,j}^{k} \leq P_{g\,j}^{\max};\ \ j \in N_t$$

Bounds on reservoir storage and water discharge: For reservoir I,

$$x_{i,\min} \leq x_i^k \leq x_{i,\max};\ i = 1,2,3,\ \ldots,\ N$$

Net reservoir release may also be constrained between maximum and minimum limits.

$$q_{i,\min} \leq q_i^k \leq q_{i,\max};\ i = 1,2,3,\ldots,\ N$$

Hydro power limits: The bound constraints on hydropower generation which sets the hydro-generator limits are also included. The inequality is expressed as:

$$P_{h_i}^{\min} \leq P_{h_i}^{k} \leq P_{h_i}^{\max}, i = 1,2,\ldots, N$$

Hydro-power output characteristics: Hydropower generation is a function of net head and turbine discharge. Constant water head is generally assumed in short period scheduling formulation. However, this assumption is true only in case of large capacity reservoirs. Head variation cannot be ignored if there is strong relationship between inflow and capacity. Since net head is a function of volume of stored water, hydropower generation can be written in terms of release variables and storage, and the frequently used expression is (Soares *et al*., 1980; Pereira and Pinto, 1983; Shi-Chung *et al*., 1990 ; Yeh *et al*., 1992; Tank and Hopfield, 1986; Kennedy and Chua, 1988; Shengwei and Constantinides, 1992; Maa and Shanblatt, 1992; Wang, 1994; Gong *et al*., 1996; Xin-Yu *et al*., 1996; Xia and Wang, 1998; Da-Silva *et al*., 1998; Naresh *et al*., 1999; Naresh *et al*., 2002):

$$P_{hi}^k = C_{1i}\left(x_i^k\right)^2 + C_{2i}\left(q_i^k\right)^2 + C_{3i}\left(x_i^k\right)\left(q_i^k\right) + C_{4i} x_i^k + C_{5i}\left(q_i^k\right) + C_{6i}; \qquad i \in N$$

It may be noted here that in order to meet out the final reservoir storages i.e., to satisfy an equality constraint,, a dependent interval is chosen randomly and releasevariable vector defined as:

$$Q = [Q_1, Q_2, \ldots, Q_j, \ldots, Q_N]$$

where,

$$Q_j = \left[q_j^1, q_j^2, \ldots, q_j^{d-1}, q_j^{d+1}, \ldots, q_j^k, \ldots, q_j^K\right]$$

Therefore, Q is now a vector consisting of n = N(K-1) independent variables. The discharge in the d^{th} (dependent) interval is then calculated by:

$$q_j^d = x_j^K - x_j^0 - \sum_{\substack{k=1 \\ k \neq d}}^{K} q_j^k + \sum_{k=1}^{K} y_j^k + \sum_{m \in R_u} \left(q_m^{k-\tau_i^m} \right)$$

In this way, number of independent variables is reduced by the value equal to the number of reservoirs N nd equality constraints to meet out the final storage targets are always satisfied. By introducing this modeling strategy, probability of optimizing the objective function in the feasible region is augmented. In other words, the fixed value equality constraints can be expressed in terms of definite range of water release rate variables and so can be handled easily.

SOLUTION TECHNIQUE

Leung *et al*. (2003) introduced a High Performance feedback Optimization Neural Network (HPONN) and this model exhibits capability in solving constrained linear, convex non-linear programming problems having both linear and nonlinear, equality and inequality constraints. In order to formulate an optimization problem in terms of a neural network, the important step is to construct an appropriate energy function L(Q,M,) such that the lowest energy state corresponds to the intended optimal solution Q^r. Based on the energy function, we construct a gradient system of differential equations that corresponds to a neural network. Consider a scheduling problem P with linear/nonlinear objective function with equality and inequality constraints. Mathematically the problem can be represented as Minimize F(Q), subject to inequality and equality constraints;

$$g_i(Q) \leq 0; \; h_j(Q) = 0 \qquad (1)$$

where, $Q = [Q_1, Q_2, ..., Q_n]^T$ is a vector of n variables of problem i = 1,2, ..., m, m = 6(K)(N) + 2K, j = 1, 2, ... N and n = (K)(N). The function F(Q) is a nonlinear function of variables F(Q) and g(Q) are twice continuously differentiable convex functions and $h_j(Q) = a_j^T Q - b_j$ and the, vectors $\{a_j\}$ are linearly independent. Let:

$$g(Q) = \left(g_1(Q), g_2(Q), \ldots, g_m(Q)\right)^T.$$

$$A = \begin{bmatrix} a_1^T \\ a_2^T \\ a_3^T \\ . \\ . \\ . \\ a_j^T \end{bmatrix}, \; b = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ . \\ . \\ . \\ b_j \end{bmatrix}$$

Now the problem can be re-written as:

$$\min F(Q)$$
$$\text{s.t., } g(Q) \leq 0, \; AQ = b \qquad (2)$$

Let M_1 be the lower bound of the optimal value of scheduling problem, i.e $M_1 \leq F(Q^*)$, where Q* is an optimal solution problem . Let $d(Q, M_1) = F(Q) - M_1$ and $F(Q, M_1) = d(Q, M_1)\,[d(Q, M_1) + |d(Q, M_1)|\,]/2$ then $F(Q, M_1)$ anon-negative, continuously differentiable, and convex function, and is locally Lipschitz continuous.

$$\Delta F(Q, M_1) = \begin{cases} 2d(Q, M_1)\nabla F(Q), & if\, d(Q, M_1) \geq 0 \\ 0, & if\; d(Q, M_1) \prec 0 \end{cases} \qquad (3)$$

Then construct the energy function:

$$L(Q, M_1) = F(Q, M_1) + \frac{1}{2} g(Q)^T \left[g(Q) + |g(Q)|\right] + \frac{1}{2}\|AQ - b\|^2 \qquad (4)$$

where, $Q = [Q_1, Q_2, ..., Q_n]^T$ and $|Q| = [|Q_1|, |Q_2|, ..., |Q_n|\,]^T$ we obtain that $L(Q, M_1)$ is a non-negative, continuously differentiable, and convex function. Let Q* be an optimal solution of the convex nonlinear programming problem $M_1 \leq F(Q^*)$ and then $L(Q, M_1)$ has a minimum point and is a minimum point and min $L(Q, M_1) \leq L(Q^*, M_1)$. $\nabla L(Q, M_1) = 0 \Leftrightarrow Q$ is a minimum point of $L(Q, M_1)$ is equal to that of its minimum points (optimal solutions). $L(Q, M_1)$ is a non-negative, continuously differentiable, and convex function. Hence, an equilibrium point of $L(Q, M_1)$ is just equivalent to one of the minimum points. Based on these results, a neural network for solving the minimum point of $L(Q, M_1)$ can then be constructed as:

$$\frac{dQ}{dt} = -\nabla L(Q, M_1)$$

It is a sub-network for solving convex nonlinear programming problem. By computing the gradient of $L(Q, M_1)$, the previous equation can be written in detail as:

$$\frac{dQ}{dt} = -\nabla F\left(Q, M_1\right) - \nabla g\left(Q\right)^T \left[g(Q) + \left|g(Q)\right|\right] - A^T\left(AQ - b\right) \quad (5)$$

It has been proven by Leung *et al*. (2003), that the neural network (5) is Lyapunov stable, and it converges to an exact solution of L(Q, M_1) in the large. Especially when L(Q, M_1) has a unique minimum point Q_1^* i.e., there exists a unique equilibrium point Q_1^* in network (5), then Q_1^* is globally, uniformly, and asymptotically stable. When L(Q, M_1) has infinitely many optimal solutions, then given an arbitrary initial point Q^0, the trajectory of neural network (5) converges to one of its optimal solutions.

Convergence condition: Suppose that Q* is an optimal solution of problem and M_1 is an estimated value of the lower bound of its optimal value, i.e., $M_1 \leq F(Q^*)$ the energy function sequence is:

$$L\left(Q, M_r\right) = F\left(Q, M_r\right) + \frac{1}{2} g\left(Q\right)^T \left[g(Q) + \left|g(Q\right|\right] + \frac{1}{2}\left\|AQ - b\right\|^2, r = 1,2,\ldots \quad (6)$$

and $F(Q, M_r) = d(Q, M_r)\,[d(Q, M_r) + |d(Q, M_r)|\,]^2$, and Q^r the minimum point of L(Q, M_r), then $M_r \leq M_{r+1}$, $M_r \leq f(Q^*)$ and $f(Q^r) \leq f(Q^*)$; Also $\{M_r\}$ has the limiting point M*, that is $\lim_{r\to+\infty} M_r = M^*$ the sequence $\{Q^r\}$ has limiting point $\overline{Q}$; any limiting point $\overline{Q}$ of $\{Q^r\}$ satisfies f(Q) = f(Q*) = M*, that is, every limiting point of $\{Q^r\}$ is the optimal solution of problem; meanwhile, the limit value f($\overline{Q}$) of the sequence $\{f(Q^r)\}$ and that of $\{M^r\}$ are the optimal value of problem. It has been clearly proven $\forall Q^0$, the corresponding trajectory of neural network (5) converges to one minimum point of L(Q, M_1)Also it has been show that any minimum point of L(Q, M_1) is stable. On this basis the trajectory of neural network (5) converges to a minimum point Q^1 of L(Q ,M_1). Let:

$$M_2 = M_1 + \sqrt{L\left(Q^1 M_1\right)},$$

then by convergence theorem $M_2 \leq F\left(Q^*\right)$.

Construct the energy function:

$$L\left(Q, M_2\right) = F\left(Q, M_2\right) + \frac{1}{2} g\left(Q\right)^T \left[g(Q) + \left|g(Q)\right|\right] + \frac{1}{2}\left\|AQ - b\right\|^2 \quad (7)$$

and the corresponding neural network for obtaining its minimum points becomes:

$$\frac{dQ}{dt} = -\nabla L\left(Q, M_2\right)$$

$$\frac{dQ}{dt} = -\nabla F\left(Q, M_2\right) - \nabla g\left(Q\right)^T \left[g\left(Q\right) + \left|g\left(Q\right)\right|\right] - A^T\left(AQ - b\right)$$

Replacing M_1 with M_2 in convergence theorem results, the trajectory of the network (8) by same indication, converges to a minimum point Q^2 of L(Q, M_2). Let:

$$M_3 = M_2 + \sqrt{L\left(Q^2, M_2\right)}$$

and then by convergence theorem $M_3 \leq F(Q^*)$. The energy function L(Q, M_3) can be constructed and the corresponding neural network for solving its minimum point. The remainder can be deduced by analogy.
In general, let:

$$M_{r+1} = M_r + \sqrt{L\left(Q^r, M_r\right)}$$

then by convergence theorem $M_{r+1} \leq F(Q^*)$ and construct the energy function:

$$L\left(Q, M_r\right) = F\left(Q, M_r\right) + \frac{1}{2} g\left(Q\right)^T \left[g\left(Q\right) + \left|g\left(Q\right)\right|\right] + \frac{1}{2}\left\|AQ - b\right\|^2 \quad (9)$$

and the corresponding neural networks for obtaining its minimum points are:

$$\frac{dQ}{dt} = -\nabla L\left(Q, M_r\right) = -\nabla F\left(Q, M_r\right) - \nabla g\left(Q\right)^T \left[g(Q) + \left|g(Q)\right|\right] - A^T\left(AQ - b\right) \quad (10)$$

Similarly, replacing M_1 with, Mr it follows that the trajectory of the network (10) converges to a minimum point Q^r of L(Q, M_r) Hence, the neural network, which is a feedback network, for solving nonlinear programming problem is constructed as:

$$\dot{Q} = \frac{dQ}{dt} = -\nabla F\left(Q, M_r\right) - \nabla\left[g\left(Q\right)^T \left|g\left(Q\right)\right|\right] - A^T\left(AQ - b\right); \qquad r = 1,2,\ldots \quad (11)$$

$$Q(0) = Q^{r-1}$$

where the parameter $M_1 \leq F(Q^*)$ and

$$M_{r+1} = M_r + \sqrt{L\left(Q^r, M_r\right)}$$

in this network must be determined by the equilibrium point Q^r and the parameter M_r in the mentioned network.

By convergence theorem, every limiting point of the sequence $\{Q^r\}$ produced by the feedback neural network (11) is the optimal solution of problem and the limiting values of the sequence $\{F(Q^r)\}$ and $\{M_r\}$ is its optimal value. The differential equations (10) and (11) for neural network dynamics are non-linear and can be solved with the help of fourth order Runge - Kutte method (Gerald and Wheatley, 1989).

Solution algorithm:

- Assume initial values arbitrarily for water discharge rate variable vector Q.
- Set r = 1, initialize lower bound $M_r < F(Q^*)$ time step Δt, tolerance values ϵ_1 and ϵ_2.
- Calculate reservoir storage, hydropower generations using current values of water discharge rates.
- Compute the gradient vector of objective function $\nabla F(Q, M_r)$ using Eq. (3) and gradient matrix ∇g of the of the constraint functions.
- Calculate new values of water discharge rates using the equation $Q(t+\Delta t) = Q(t) - \Delta t.Q$
- Compute Euclidian norm of Q i.e.,

$$S = \|Q\|^2 = \sum_{i=1}^{n} Q_i^2$$

- Check for equilibrium: if $S < \epsilon_1$, then $Q^r = Q$ and compute the energy function $L(Q^r, M_r)$ using Eq. (9) and go to step 6; otherwise let $t = t + \Delta t$ and go to step 3.
- If $L(Q^r, M_r) < \epsilon_2$, then print the output results and stop; otherwise update;

$$M_{r+1} = M_r + \sqrt{L\left(Q, M_r\right)}$$

increment r = r + 1 and go to step 3.

TEST SYSTEM

The test system shown in Fig. 1 has been used to evaluate the performance of feedback neural network optimizer. The load demand, hydro unit power generation coefficients, river inflows and reservoir limits for the test network are referred from (Orero and Irving, 1998). The water transportation delays considered are $\tau^1_3 = 2$ h, $\tau^3_3 =$ 3 h and $\tau^4_3 = 4$ h, where τ^m_i the water travel is time from reservoir m to reservoir i. The composite thermal plant fuel cost coefficients taken a, b, c are 0.002, 19.2 and 5000.0, respectively. Maximum and minimum limits on equivalent thermal power generation are 2500 and 500 MW, respectively. From problem formulation, it is clear that in this system there will be 192 inequality constraints to satisfy water release limits and 192 inequality constraints to satisfy the storage limits from upper as well as lower bound. In addition to these there are 192 inequality constraints to satisfy hydro power generator limits and 48 inequality constraints corresponding to bounds on equivalent thermal power generator limits. So in all there will be 614 inequality constraints. Equality constraints are not directly handled but considered implicitly as explained in problem formulation.

Simulation results and discussion: In the short term hydrothermal scheduling problem, the two important parameters that can be allowed to vary are the satisfaction of the final reservoir storage levels and the cost of thermal generation. Although these two objectives are conflicting yet by using modified modeling strategy and tuned parameter values best of both variables can be obtained. With the given data, the proposed HPONN algorithm coded in C ++ was simulated. Taking initial values for Δt: integration step size, M_r: lower bound of optimal value, ϵ_1 and ϵ_2: convergence tolerance values. Different combination of the values of parameters have been tried to check the performance of the proposed technique for the considered problem. By the trial and error procedure, with step size $\Delta t = 0.01$, $M_r = 900000$ i.e. as a lower bound of the optimal value, $\epsilon_1 = 0.000001$ and $\epsilon_2 = 0.0001$, optimization run was carried out.

Figure 2 shows the variation of the scheduling cost with the number of iterations. Initially the trajectory starts with cost function value equal to 985520 and sharply reduces and stabilizes to a value 926700. Actually the feedback optimization neural network solves this problem through the process in which the feedback information of states Q^r and M_r is used to adjust M_r to M_{r+1} such that M_r and $F(Q^r)$ successively approximate $F(Q^*)$. The final stable value of the objective function indicates that the thermal generation cost has been minimized and there was no considerable violation of the storage constraints. The feasibility and efficiency of the proposed feedback neural network has been validated by comparing the results obtained by this method with the results obtained using genetic algorithm approach (Orero *et al*., 1998) and conventional Augmented Lagrange Multiplier Method (ALMM) (Mokhtar *et al*., 1993). Figure 3 shows the variation of the scheduling cost with the number of iterations using GA and better performance in terms of hydro-thermal scheduling cost value and convergence in proposed approach has been observed. It can be easily demonstrated that with proper selection of time step size and lower bound of the optimal value M_r, best optimal results corresponding to constraints satisfaction are obtained with the proposed new optimizer.

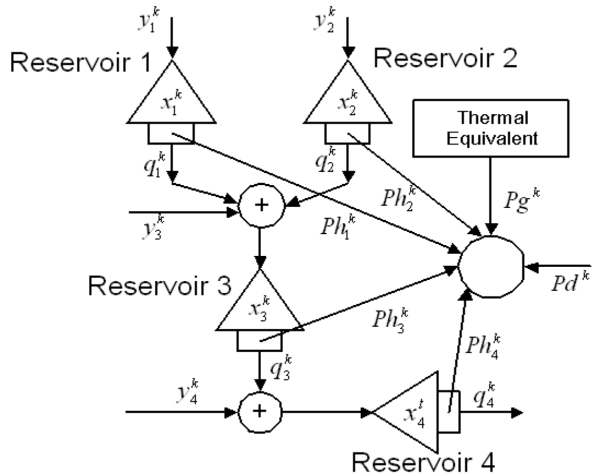

Fig. 1: Test system to evaluate the performance of feedback neural network optimize

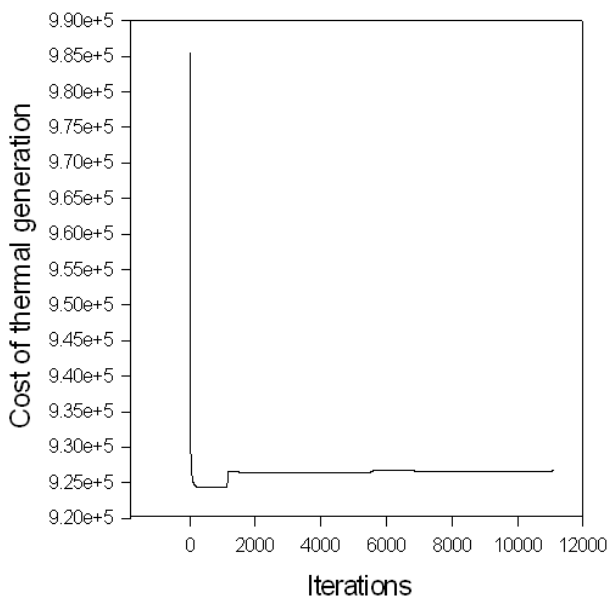

Fig. 2: Variation of hydrothermal scheduling cost with the number of iterations with HPONN

It is also desirable that the end period coupling constraint has to be satisfied for all the reservoirs so that the user of the reservoir after the planning horizon is not penalized. Therefore the terminal state condition $x^K_i = x^0_i$ is also examined and it is found that the exact terminal state has been obtained. The terminal storage vector is obtained as [120, 70, 170, 140]. It is also valuable to provide as an output, quantities such as plant storage levels, total thermal generation and hydro unit power outputs, during each time interval. These quantities are calculated using the water discharge rates, the hourly river inflows, water transport delays and the load demand at each time interval, over the scheduling period. The optimal plant release schedules, storage schedules and generation (hydro and thermal) schedules for short-term hydrothermal scheduling using feedback neural network optimizer are depicted in Table 1.

The production cost of thermal generations obtained and time taken on Pentium IV, 3.2 GHz clock, 512 RAM by the three methods are depicted in Table 2. A familiar conjugate gradient approach ALMM takes very less number of iterations to solve this problem. We have considered ALMM as reference for the solution of this problem and number of iterations taken for convergence process is not comparable with the HPONN and GA approaches. However a notable point regarding neural

Table 1: HPONN Hydro- thermal scheduling results

Hour	Q1	Q2	Q3	Q4	S1	S2	S3	S4	HG	TG
1	9.3	6.00	26.26	13.00	100.66	82.00	151.84	109.80	333.27	1036.73
2	9.1	6.00	25.29	13.00	100.48	84.00	134.75	99.20	321.16	1068.84
3	8.9	6.10	24.30	13.00	99.55	86.90	123.79	87.80	309.96	1050.04
4	8.6	6.14	23.15	13.00	97.92	89.76	117.81	74.80	297.68	992.32
5	8.3	6.18	21.97	13.00	95.59	91.58	113.78	88.06	319.27	970.73
6	8.2	6.38	20.67	13.00	94.35	92.20	111.83	100.35	341.56	1068.44
7	8.3	6.77	19.32	13.00	94.04	91.42	110.00	111.65	363.09	1286.91
8	8.5	7.39	18.05	13.00	94.49	91.03	108.36	121.81	384.10	1615.9
9	8.7	7.90	17.04	13.00	95.78	91.13	107.02	130.78	400.91	1839.09
10	8.7	8.22	16.30	13.00	98.01	91.91	107.03	138.44	414.21	1905.79
11	8.7	8.31	15.74	13.00	101.28	92.60	108.40	144.76	423.83	1806.17
12	8.7	8.59	15.15	13.00	102.55	92.01	111.93	149.81	432.95	1877.0
13	8.6	8.69	16.38	13.00	104.94	91.32	116.49	153.85	435.62	1794.38
14	8.5	8.92	17.30	13.00	108.39	91.40	119.23	157.15	438.76	1761.24
15	8.4	9.13	17.63	13.00	110.98	91.27	121.81	159.89	441.84	1688.1
16	8.2	9.30	16.79	15.04	112.77	89.97	124.25	160.00	464.43	1605.5
17	8.1	9.66	15.75	16.38	113.67	87.31	127.83	160.00	479.65	1650.35
18	7.9	10.0	316.46	17.30	113.73	83.28	130.72	160.00	84.511	1655.49
19	7.8	11.0	15.32	17.91	112.86	79.22	133.81	159.71	493.66	1746.34
20	8.0	11.8	14.19	19.40	110.80	75.39	138.21	157.11	505.17	1774.83
21	5.0	6.00	10.00	13.00	112.80	78.39	148.11	159.86	403.89	1836.11
22	7.8	10.3	10.00	20.77	112.97	77.08	159.23	155.54	509.23	1610.77
23	6.0	11.1	10.32	21.92	115.91	73.97	166.73	148.94	497.54	1352.46
24	5.9	11.9	10.56	23.14	120.00	70.00	170.00	140.00	491.97	1098.03

Table 2: Cost and time comparison

	HPONN	ALMM	GA
With time delays	926700	926702	926707
Time taken in seconds	258.84	39	368

network optimizer is that, the nature of the network is essentially similar to parallel processing. Therefore, it provides a convenient way to realize its operation by the use of fast transputers. Such a hardware implementation will be bound to provide extremely fast computation for the optimal scheduling problems.

CONCLUSION

In hydro-thermal scheduling problem, the complexity introduced by the cascade nature of the hydraulic network, the scheduling time linkage, non-linear relationships in the problem variables and the water transport delay factors, has made the problem very difficult to solve using standard optimization methods. The algorithm presented in this paper can handle very large problems and can be used to solve any scheduling problem in practice. This feedback neural network has been developed based on the idea of successive approximation to the optimal value of the linear/ nonlinear programming problem from the same value as mentioned. This network has the least number of state variables i.e. the only variables of the original programming problem and a much better convergence. A practical nonlinear hydro-thermal test system has been solved successfully and quite promising results have been obtained.

NOMENCLATURE

q^k_i	Release from reservoir i during time K
y^k_i	Side inflow to reservoir i during time K
$x_{i,\,min}$	Lower limit on the stored water in reservoir i during time k
$x_{i,\,man}$	Upper limit on the stored water in reservoir i during time k
x^k_i	Volume of water in reservoir i during time step k
$q_{i,\,man}$	Maximum limit on release of reservoir i during K
$q_{i,\,min}$	Minimum limit on release of reservoir i during time K
N	Total number of reservoirs in linked system
X^K_i	End period storage for reservoir i
x^0_i	Initial storage for reservoir i
k, K	Time index, scheduling period
u^k_p	Release from upstream reservoir p during time k
R_u	Upstream plant index
τ^m_i	Water travel time from reservoir m to reservoir i
$C_{1i}, C_{2i}, C_{3i}, \ldots C_{6i}$	Co-efficients of power generation function for i^{th} hydro-plant
F	System generation cost function
F_j	Fuel cost of j^{th} thermal unit
$P_{g_j}^{k}$	j^{th} thermal unit generation at time k
N_t	Total number of thermal plants
a_j, b_j, c_j	Thermal generation coefficients of j^{th} unit

P^k_d Load demand during interval k
P^k_l Losses during interval k
$P_{h_i}^{\ k}$ Power generation of i hydro plant at instant k
$P_{geq}^{\ k}$ Equivalent thermal generation in interval k
α, β, γ Equivalent thermal generation coefficients
z^k_i Turbine discharge rate for reservoir ith at time k
v^k_i Volume of spilled from i^{th} reservoir at time k
$\overline{z}_i$ Maximum allowable water discharge rate through turbine for reservoir i
$\underline{z}_i$ Minimum allowable water discharge rate through turbine for reservoir i

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