ARTIFICIAL NEURAL NETWORK BASED SHORT-TERM HYDROTHERMAL SCHEDULING

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Abstract. A worldwide trend in the development of power systems is to build interconnections with the goal to achieve economical benefits. Interconnections of power systems may offer significant technical, economical and environmental advantages. A modern power system consists of a large number of Thermal and Hydal Power plants connected at various load centers through a transmission network. An important objective in the operation of such a power system is to generate and transmit power to meet the system load demand at minimum fuel cost by an optimal mix of various types of plant. In this paper Kirchmayer's method is used for hydrothermal scheduling which is a conventional method and slow. In order to overcome the disadvantage in the Kirchmayer's method, Back Propagation Neural Network (BPNN) is proposed for scheduling of Hydro-Thermal system. The result shows the effectiveness of the proposed method compared to the conventional in terms of speed and accuracy.

Keywords: Hydrothermal scheduling, Economics of power generation, Kirchmayer's method, Artificial neural networks

1. Introduction

A modern power system consists of a large number of interconnections. The main advantages of interconnection of different power generating stations is to decrease the per unit cost of electrical energy [1], decrease the reserve capacity and to provide continuity of electrical energy to the customers. The study of the problem of optimum scheduling [2] of power generation at various plants in a power system is of paramount importance, particularly where the Hydel sources are scarce and high cost of thermal generation has to be relied upon to meet the power demand. The Hydel resources being extremely limited, the worth of water is greatly increased. If optimum use is made of their limited resource in conjunction with the thermal sources, huge saving in fuel and the associated cost can be made.

The long range scheduling [3] (generally persisting from months to year) involves mainly the scheduling of water release. Long range scheduling also involves metrological and statistical analysis [4, 5, 6]. The benefit of this scheduling is to save the cost of generation, in addition to meeting the agricultural and irrigational requirements. Long range scheduling involves optimization of the operating policy in the context of major unknowns such as load, hydroelectric inflows, unit availability etc. The short range problem [7, 8] usually has an optimization interval of a day or a week. This period is normally divided in to sub-intervals for scheduled purposes. Here, the load, water inflows and unit availabilities are assumes to be known. A set of starting conditions (i.e. reservoirs levels) being given, the optimal hourly schedule can be prepared that minimizes a desired objective while meeting system constraints successfully.

Cost optimization of hydro stations can be achieved by assuming the water heads constants and converting the incremental water (i.e. fuel) rate characteristics in to incremental fuel cost curves by multiplying it with cost of water per cubic meter and applying the conventional technique of minimizing the cost function.

Different methods have been proposed for the solution of these problems in the past. Variational methods, Pontryagin maximum principle, General mathematical programming and the Dynamic programming have been used to solve the problem in different formulations. Methods based on Lagrangian multiplier and gradient search techniques for finding the most economical hydrothermal generation schedule under practical constraints have been well documented. Kirchmayer [9] utilized calculus of variation for short range scheduling problem and proposed the well known coordination equations. But this Kirchmayer's method is too slow and case sensitive method so a soft computing method is proposed in this paper using Back propagation neural network [10].

2. Optimal scheduling of power plants

Scheduling is nothing but sharing the total load and losses among the available Generators. Equal load sharing is nothing but sharing the load among the available generators equally. Optimal load scheduling is nothing but sharing the load among the available generators in cost effective manner.

The main aim in the economic dispatch problem is to minimize the total cost of generating real power at various stations while satisfying the loads and losses in the transmission line.

Optimal load scheduling can be determined using different methods and it can also be determined using Optimal Power Flow (OPF) methods. The solution of the OPF will lead to economic operation of the power plant and yield an economic dispatch of real power generation.

For the planner and operator fixed generation corresponds to a snapshot only. Planning and operating requirements very often ask for an adjustment of the generated powers according to certain criteria. One of the obvious ones is the minimum of the generating cost. The application of such a criterion immediately assumes variable input powers and bus voltages which have to be determined in such a way that a minimum of the cost of generating these powers is achieved.

3. Hydrothermal scheduling

Optimal scheduling of power plant generation is the determination of the generation for every generating unit such that the total system generation cost is minimum while satisfying the system constraints. The objective of the hydrothermal scheduling problem is to determine the water releases from each reservoir of the hydro system at each stage such that the operation cost is minimized along the planning period.

The operation cost includes fuel costs for the thermal units, import costs from neighboring systems and penalties for load shedding. The basic question in hydro thermal coordination is to find a trade-off between a relative gain associated with immediate hydro generation and the expectation of future benefits coming from storage.

Two aspects make the hydrothermal scheduling a complex problem:

- The uncertainty of inflows;
- The hydraulic coupling between hydro plants.

The operation planning of hydrothermal systems is called Hydro-Thermal Co-ordination (HTC) [11÷16] problem. This problem requires solving for the thermal unit commitments and generation dispatch as well as the hydro schedules.

The objective is to minimize thermal production cost subject to meeting the forecasted demand and other operating constraints. Also the HTC problem determines the thermal unit commitments and generation dispatch, as well as the hydro schedules, to meet the forecasted demand and other operating constraints at minimum thermal production cost.

3.1. Short term hydrothermal scheduling

In it, the load demand on the power system exhibits cyclic variation over a day or a week and the scheduling interval is either a day or a week. As the scheduling interval of short range problem is small, the solution of the short-range problem can assume the head to be fairly constant. The amount of water to be utilized for the short-range scheduling problem is known from the solution of the long-range scheduling problem.

Short-range hydro-scheduling (one day to one week) involves the hour-by-hour scheduling of all generation on a system to achieve minimum production cost for the given time period. In such a scheduling problem, the load, hydraulic inflows, and unit availabilities are assumed known. A set of starting conditions (e.g. reservoir levels) is given, and the optimal hourly schedule that minimizes a desired objective, while meeting hydraulic steam, and electric system constraints, is sought.

Part of the hydraulic constraints may involve meeting “end-point” conditions at the end of the scheduling interval in order to conform to a long-range, water-release schedule previously established

The short term hydrothermal scheduling problem is classified in to two groups:

- Fixed head Hydro-Thermal scheduling;
- Variable head Hydro-Thermal scheduling.

4. Kirchmayer’s method

In this method, equivalent cost of water (used for power generation in hydro stations) is used. Let there be α thermal power stations and (n – α) hydro power stations in a power system. Let γ_j be the equivalent cost in rupees of one cubic meter of water and be w_j the water used in cubic meters per hour for power generation in j^{th} hydro station. Let c_i be the cost of power generation is Rs./hour in i^{th} thermal power station. Then the total cost of power generation would be

$$c = \sum_{i=1}^{\alpha} c_i + \sum_{j=\alpha+1}^{n} \frac{\gamma_j \cdot w_j \cdot Rs}{hr}. \qquad (1)$$

In this method, the total cost C is minimized subject to the following equality constraint.

Load demand

$$P_D = \sum_{i}^{\alpha} P_{Ti} + \sum_{j=\alpha+1}^{n} P_{Hj} - P_L, \qquad (2)$$

where P_{Ti} - power generated by i^{th} thermal power station; P_{Hj} - power generated by j^{th} hydro power station; P_L - transmission loss.

The optimal operating state is determined by the Lagrangian method as follows.

The augmented cost function is

$$C^{*} = C - lamda\left(\sum_{i}^{\alpha} P_{Ti} + \sum_{j=\alpha+1}^{n} P_{Hj} - P_L\right), \qquad (3)$$

where C^{*} is the Lagrangian multiplier and C is as given by equation for optimality

$$\frac{\partial C}{\partial P_{Ti}} = 0, \quad i = 1, 2, 3, \cdots, \alpha$$

$$\frac{\partial C}{\partial P_{Gj}} = 0, \quad j = \alpha + 1, \cdots, n$$

Carrying out the differentiation of equation (3) results in

$$\frac{dC_i}{dP_{Hj}} + lamda \cdot \frac{dP_L}{dP_{Hj}} = lamda, \qquad i = 1, 2, \cdots, \alpha \quad (4)$$

$$\gamma_j \cdot \frac{dw_j}{dP_{Hj}} + lamda \frac{dP_L}{dP_{Hj}} = lamda, \qquad j = \alpha + 1, \cdots, n \quad (5)$$

Solution of equation yields the economically optimum thermal and hydro power generations.

If transmission loss is neglected, the equation reduces to

$$\frac{dC_i}{dP_{Ti}} = \gamma_j \cdot \frac{dw_j}{dP_{Hj}} = lamda. \qquad (6)$$

4.1. Algorithm

Step1: Read the input data C_i, W_j, γ, B-coefficient, where: C_i - fuel cost equation; W_j - water used in cubic meters per hour; γ - equivalent cost in rupees of one cubic meter of water.

Step2: Calculate the cost of power generation

$$c = \sum_{i=1}^{\alpha} C_i + \sum_{j=\alpha+1}^{n} \frac{\gamma_j \cdot W_j \cdot Rs}{hr}$$

where C_i is the cost of generation.

Step3: The main objective is to minimize the cost of generation. Objective function for minimizing the total cost of generation is given by $\sum_{i=1}^{\alpha} \int_{i}^{T} C_i dt$.

Step4: Read the load demand (Pd).

Step5: The optimal operating state is determined using equation (3).

Step6: Differentiate the above function results in equations (4) and (5).

Step7: By using the load balance equation form another equation

$$P_{Ti} + P_{GH} = P_{\text{load}} + P_{\text{loss}}. \qquad (7)$$

Step8: By solving equations (4), (5) and (7), obtain the P_{Ti}, P_{Hj} values.

Step9: Calculate operating cost of the total system.

Step10: Display the results.

5. Back propagation neural network

Back Propagation is a systematic method for training multilayer artificial networks. It is a multilayer forward network using extend gradient-descent based delta-learning rule, commonly known as back propagation rule. Back propagation provides a computationally efficient method for changing the weights in a feed forward network, with differential activation function units, to learn a training set of input-output examples. Being a gradient descent method it minimizes the total squared error of the output computed by net. The network is trained by supervised learning method. The aim of this network is to train the net to achieve a balance between the ability to respond correctly to the input patterns that are used for training and the ability to provide good responses to the input that are similar.

5.1. Back propagation algorithm

Initialization of the weights

Step1: Initialize weights to small random values.

Step2: While stopping condition is false do Steps 3-10.

Step3: For each training pair do steps 4-9.

Feed Forward

Step4: Each hidden unit receives the input signal X_i and transmits the signals to all units in the layer above i.e. hidden units.

Step5: Each hidden unit sums its weighted input signals

$$Z_{-inj} = Voj + \sum_{i=1}^{n} \left(X_i \cdot V_{ij}\right), \qquad (8)$$

applying activation function for to get output

$$Z_i = f\left(Z_{-inj}\right), \qquad (9)$$

Step6: Each output unit sums its weighted input signals

$$Y_{-inj} = W_{ok} + \sum_{j=1}^{p} \left(Z_j \cdot W_{jk}\right), \qquad (10)$$

and apply activation function to calculate output

$$Y_k = f\left(Y_{-inj}\right). \qquad (11)$$

Back Propagation of errors

Step7: Each output unit receives a target pattern corresponding to an input pattern, error information term is calculated as

$$\Delta_k = \left(t_k - y_k\right) \cdot f\left(Y_{-ink}\right). \qquad (12)$$

Step8: Each hidden unit sums its delta from units in the layer above

$$\delta_{-inj} = \sum_{k=1}^{m} \delta_j \cdot W_{jk} . \qquad (13)$$

The error information term is calculated as

$$\delta_j = \delta_{-inj} \cdot f(Z_{-inj}). \quad (14)$$

Updation of the weights

Step9: Each unit updates its bias and weights.

The weight correction term is given by

$$\Delta W_{jk} = alpha \cdot \delta_k \cdot Z_j, \quad (15)$$

and the bias correction term is given by

$$\Delta W_{ok} = alpha \cdot \delta_k, \quad (16)$$

Therefore

$$W_{jk}(new) = W_{jk}(old) + \Delta W_{jk},$$
$$W_{ok}(new) = W_{ok}(old) + \Delta W_{ok}. \quad (17)$$

Each hidden unit updates its bias and weights.

The weight correction term is given by

$$\Delta V_{ij} = alpha \cdot \delta_j \cdot X_i, \quad (18)$$

and the bias correction term is given by

$$\Delta V_{ok} = alpha \cdot \delta_j, \quad (19)$$

The weights between input and hidden layer can be updated as follows

$$V_{ij}(new) = V_{ij}(old) + \Delta V_{ij},$$
$$V_{oj}(new) = V_{oj}(old) + \Delta V_{oj}. \quad (20)$$

Step10: Test stopping condition.

5.3. Merits of Back Propagation Algorithm

- The mathematical formula present here, can be applied to any network and does not require any special mention of the features of the function to be learnt.
- The computing is reduced if the weights chosen are small at the beginning.
- The batch update of weights, which provides a smoothing effect on the weight correction terms.

5.4. Proposed Neural Network

The neural network proposed will have two input neurons, two middle layer neurons, two output neurons and one bias neuron. The inputs for the neural network are load demand and loss. The outputs are Thermal and Hydal power generations. The network is trained with Back Propagation Algorithm using Gradient Descent method.

In the proposed method the output of each neuron can be determined using sigmoid activation function. Error will be calculated between expected output and actual output. Error is back propagated and weights are adjusted in such a way that actual value move towards the expected value, means error is back propagated until the actual output is equal to desired output. In the process if actual output is equal to the desired output then the neural network is said to be trained. The proposed neural network is as shown in Figure 1.

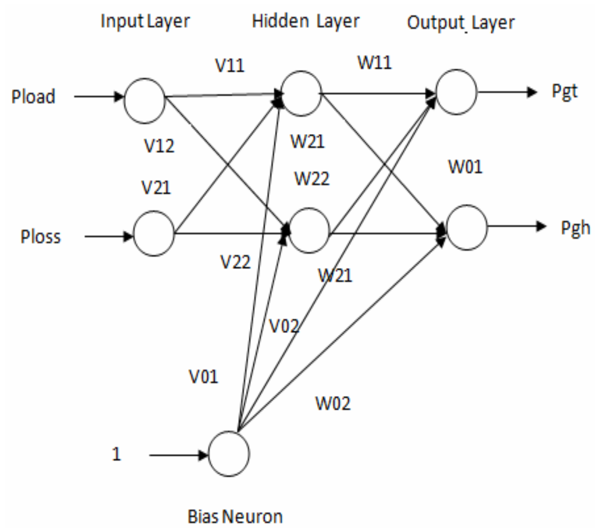

Figure 1. Proposed Back Propagation Neural Network

The above network is trained by using 150 training patterns and it takes 129.01198 sec time for training. It has taken 11976 iterations to train. After training, load demand and power loss if given as inputs with in very less time as compared to Kirchmayer's method it will give the results. While training the graph between error and number of iterations is as shown in Figure 2.

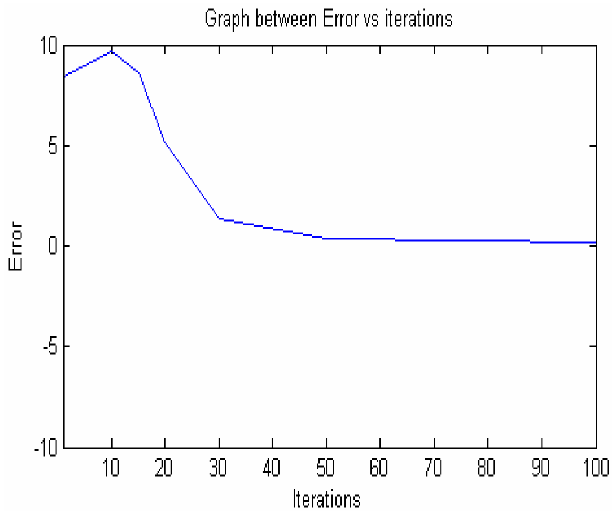

Figure 2. Graph between Error and number of iterations

6. Results

The following table shows how the load is scheduled between Thermal and Hydal power plants with Kirchmayer's method and proposed method, when different loads are applied and it is observed from the table the effectiveness of proposed method.

Table 1. Comparison Table

Inputs		Kirchmayer's method			Back Propagation Neural Network Training Time = 129.01198 s		
Load Demand	Losses	Hydro Power	Thermal Power	Execution Time, [s]	Hydro Power	Thermal Power	Execution Time, [s]
0.1	0.054575	0.092921	0.010204	0.13329	0.0906635	0.0129615	0.03207
0.146667	0.083089	0.1369	0.020132	0.135709	0.125876	0.0217131	0.032798
0.3	0.191294	0.283815	0.08053	0.134908	0.28055	0.0823413	0.033804
0.366667	0.245491	0.348919	0.120243	0.131658	0.352249	0.124018	0.032201
0.426667	0.298083	0.408104	0.163541	0.132977	0.413756	0.167547	0.032788
0.48	0.348031	0.461188	0.208494	0.132611	0.465918	0.210423	0.033111
0.7	0.586347	0.686347	0.460838	0.13626	0.68198	0.451874	0.03018
0.78	0.686432	0.76763	0.581633	0.134275	0.771155	0.586198	0.032486
0.88	0.821924	0.87257	0.768064	0.133662	0.879087	0.77866	0.032057

7. Conclusion

Hydro thermal scheduling is determined for the given load by using conventional method i.e. Kirchmayer's method and Back Propagation Neural Network method. The results shows that Kirchmayer's method is too slow than Back Propagation Neural Network (BPNN) method. BPNN gives fast and accurate results when compared to Kirchmayer's method. In future this work may be extended using Radial Basis Function neural network.

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