OPTIMAL SCHEDULING OF SHORT -RANGE FIXED HEAD HYDRO-THERMAL SYSTEMS

Thesis submitted in partial fulfillment of the requirements for the award of degree of

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in
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By:
Sarbjeet Kaur
(Regn. No. 80641021)

Under the supervision of:
Mrs. Manbir Kaur
Assistant professor

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ELECTRICAL & INSTRUMENTATION ENGINEERING DEPARTMENT
THAPAR UNIVERSITY
PATIALA – 147004

Certificate

I hereby certify that the work which is being presented in the thesis entitled, **"Optimal Scheduling of Short Range Fixed Head Hydro thermal Systems"**, in partial fulfillment of the requirements for the award of degree of Master of Engineering in *Power Systems & Electric Drives* submitted in Electrical & Instrumentation Engineering Department of Thapar University, Patiala, is an authentic record of my own work carried out under the supervision of **Mrs. Manbir kaur**. The matter presented in this thesis has not been submitted for the award of any other degree of this or any other university, except as reported in text and references.

Kaur

(Sarbjeet kaur)
Regn.No.80641021

This is to certify that the above statement made by the candidate is correct and true to the best of my knowledge.

Manbir kaur
10.7.08

(Mrs. Manbir kaur)
Assistant Professor
Electrical and Instrumentation Engg. Department
Thapar University
Patiala

Countersigned by

S. Ghosh

(Dr. Smarajit Ghosh)
Professor and Head
Electrical and Instrumentation Engg. Department
Thapar University
Patiala.

RK Sharma

(Dr.R.K.Sharma)
Dean (Academic Affairs)
Thapar University,
Patiala.

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Abstract

Optimum scheduling of power plant generation is of great importance to electric utility systems. The optimal scheduling of an electric power system is the determination of the generation for every plant such that the total system generation cost is minimum while satisfying the system constrains. However due to insignificant marginal cost of hydroelectric power, the problem of minimizing the operational cost of a hydrothermal system essentially reduces to that of minimizing the fuel cost for thermal plants under the constraints of the generating limits and water available. The problem of optimal economic operation of hydrothermal electric power systems with fixed head hydro plants is considered. The implementation is based on a Approximate Newton's iterative procedure, with special initial guess and sparsity-based matrix manipulations to obtain improved convergence properties. Approximate Newton Raphson method is developed and demonstrated to solve the hydrothermal scheduling problem with quadratic thermal cost function together with and without valve point loading effect. ANN (artificial neural network) models are faster as compared to conventional method (Approximate Newton Raphson Method) and provide accurate result as close to the conventional methods. Here error back propagation method is used to solve the hydro thermal scheduling with and without valve point loading.

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LIST OF SYMBOLS AND ABBREVIATIONS

N	Number of thermal units
M	Number of hydro units
T	Overall period for scheduling
S	Reservoir storage
t_k	Duration of the k^{th} sub –interval
P_{dk}	Load demand during the k^{th} sub- interval
V_j	Available water for whole period
j	Index of hydro units
i	Index of thermal units
k	Index of time period
P_{ik}	Power output of the generating units in MW during the k^{th} interval
P_{max}	Maximum power of a generating unit in MW
P_{min}	Minimum power of a generating unit in MW
$Ploss_k$	Transmission losses during the k^{th} interval
a_i , b_i, c_i	Cost coefficients of the thermal units
d_i, e_i	Valve point coefficients
x_j, y_j z_j	Discharge coefficients of the hydro units
v_j	Water conversion factor
B_{ij} B_{io} and B_{oo}	loss –coefficients
q_{jk}	Rate of discharge from the j^{th} hydro unit in the interval k
λ_k	Incremental cost of power delivered in the system during the k^{th} interval
F_i	Thermal cost of the i^{th} unit
h	Effective head
X	Input vector
X_{max}	Maximum value of active power generation

X_{min}	Minimum value of active power generation
n	Number of input nodes
h	Number of hidden nodes
m	Number of output nodes
η	Momentum constant
α	Learning constant
p	Total no. of training patterns
t	Output target vector
z_j	Hidden unit j
δ_k	Error at the output unit y_k
δ_j	Error at the hidden unit z_j
v_{oj}	Bias on hidden unit j
w_{ok}	Bias on output unit k
y_k	Output unit k
ANN	Artificial neural network
EBP	Error back propagation

CHAPTER 1
INTRODUCTION

1.1 Overview

The electric power systems engineer is faced with the challenging task of planning and operating successfully one of the most complex systems of today's civilization. The basic requirement is to meet the demand for electric energy by the area served by the system at the lowest possible cost. Of equal importance is objective of minimizing the environmental impact of the operation.

It may be tempting to order the above objective on a priority list. However, these objectives interact, which makes it difficult for one to come up with a general clear-cut ordering. Not only does this vary with the system, but also with the times and socioeconomic factors. Economic dispatch ranks high among the major economy-security functions in power system operation. Conventional economic dispatch is a static optimization procedure to pre-selected generating units. This is a procedure for the distribution of total thermal generation requirements among alternatives sources for optimal system economy with due consideration of generating costs, transmission losses, and several recognized constraints imposed by the requirements of reliable service and equipment.

Modeling in the generation dispatch problem is critical to achieve optimal results. In the economic dispatch problem, the classical formulation presents deficiencies due to the simplicity of the models. Here, the power system is modeled through the power balance equation and generators are modeled with smooth quadratic cost functions and generator output side constraints limitations.

To improve power systems studies, new models are continuously being developed that result in a more efficient system operation. Cost functions that consider valve point loadings.

In this work short range scheduling of fixed head hydro plants is considered. The short term hydrothermal scheduling problem is concerned with allocating generation among hydro and thermal units over one day or one week, usually discretized in hourly intervals. The problem formulation must take into account many system operating constraints, including hydraulic, thermal and electrical aspects. The objective is to minimize the total operating cost represented by the fuel cost required for the system's thermal generation over the optimization interval.

1.2 Literature Review

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. However with insignificant marginal cost of hydro electric power, the problem of minimizing the operational cost of a hydrothermal system essentially reduces to minimizing the fuel cost for thermal units constrained by the generating limits, available water, and the energy balance condition in a given period of time. The performance of each hydro plant is represented by Glimn-Kirchmayer's model [l-2].

In recent years, many approaches have been suggested to solve the hydrothermal scheduling problem. The proposed approaches include, dynamic programming [3], functional analysis technique [4] method of local variations [5], principle of progressive optimality [6], general mathematical programming technique [7]. Generally these methods have slow convergence characteristics.

Another variable technique is the Newton-Raphson method [9-11]. Formulation of the scheduling problem in Newton-Raphson method for solving a set of nonlinear coordination equations leads to a large matrix expression. Problems with Newton's method when applied to fixed head problems include the computation of the inverse of a large matrix, the ill-conditioning of the Jacobian matrix and the divergence caused by starting values. M. Farid Zaghlool and F.C. Troot (1988), has proposed some efficient methods for optimal scheduling of fixed head hydro plants [11]. The electric network model used is the active power balance equation with Kron's loss formula to express the power transmission losses. For the optimal scheduling of fixed head hydro plants the method proposed by Abdul Halim and Khalid 1991 [12], linearizes the coordination equations *so* that the Lagrangian of the water availability constraint is determined separately from the unit generations. The existence of the water availability constraint Lagrange multiplier enables the Lagrange multiplier for the power balance constraint to be determined and hence leads to the computation of the generation of thermal and hydro units. The same method called Approximate Newton Raphson method is presented in [14].

To improve power systems studies, new models are continuously being developed that result in a more efficient system operation. Cost functions that consider valve point loadings [15-16] and prohibited operating zones [17] as well as constraints that provide a more accurate representation of the system such as: emissions line flow [18-20]. These improved models generally increase the level of complexity of the optimization problem due to the nonlinearity associated with them but they are cost effective.

Recent advances in computation and the search for better results of complex optimization problems have formented the developments of the techniques using Artificial Neural Networks. Artificial Neural Networks (ANN) are gaining popularity in various fields of engineering including electrical power systems due to their high computational rates and robustness. One of the ANN models extensively used for power system applications is the multilayer perceptron model based on back propagation algorithm [21-25].

1.3 Objectives

The topic of the work is" Optimal Scheduling of Short Range Fixed Head Hydro-Thermal Systems". This covers the short-range hydro thermal scheduling of fixed head plants using Approximate Newton Raphson Method with and without considering the effect of valve loading and their comparison. Further the formulation is also implemented using Error Back Propagation Method.

Specific objectives are:

1. To analyze and solve the optimal generation dispatch problem using the Approximate Newton Raphson Method and Error Back Propagation Method.
2. Comparison of result obtained from conventional and non-conventional techniques with and without valve point loading.
3. To test these techniques on different problems and coding is done in MATLAB 6.5.

1.4 Organization of Thesis

- An introduction to the optimal operation of hydro thermal systems is presented in Chapter 1 along with the overview and objectives of thesis.
- Chapter 2 provides a review of the hydro-thermal coordination, performance model of thermal and hydro plants and available literature.
- Chapter 3 presents an overview of the short range fixed head hydrothermal scheduling, problem formulation and the flowchart of the Approximate Newton Raphson Method.
- In Chapter 4 present the overview of short range hydrothermal scheduling with valve loading.
- In Chapter 5 the error back propagation method is discussed along with its algorithm.
- Chapter 6 presents the results and discussions.
- Chapter 7 presents conclusions and recommendations for future work.

CHAPTER 2
HYDRO-THERMAL COORDINATION

2.1 Introduction

In the present set-up of large systems with hydro and thermal power stations, the energy efficient generation scheduling is well considered in power sector in order to reduce the production cost and for the optimum utilization of all energy sources in the most economical manner. The system coordination of the operation of a system of hydro-electric generation plants is usually more complex than the scheduling of an all thermal generation system because the hydro-electric plants may very well coupled both electrically (i.e. they all serve the same load) and hydraulically (i.e. the water outflow from one plant may be a very significant portion of the inflow to one or more other, downstream plants).

The idea of integrated operation of the hydro-electric plants is for optimum utilization of all energy sources in economical manner. The operating cost of the thermal plants is very high, though their capital cost is low. On the other hand, the operating cost of hydro plants is low but their capital cost is high. So, it has become more economical as well as convenient to have both thermal and hydro plants in the same grid. The hydroelectric plants can be started quickly and it has higher reliability and greater speed of response. Hence hydro plants can take up fluctuating loads. In contrast to the hydro plants, the starting of thermal plants is slow and their speed of response is slow as well. Normally the thermal plant is preferred as a base load plant whereas hydro plant is run as peak plant.

In the hydro thermal coordination, it is essential to use the total quantity of water available from the hydro system to the fullest extent. In the hydro system, fixed charges continue regardless of the amount of power generated, as there is no fuel cost associated with hydropower. Therefore minimum overall cost is achieved by maximum exploitation of hydro resources i.e. water available over a time horizon. The hydrothermal coordination problem is the one which deals with how to run all the generation units during the particular period of time to meet the forecasted demand and other operating constraints, especially how the hydro units can be utilized at the maximum level to reduce the total generation fuel cost by minimizing the thermal generator operation. Most of the hydroelectric plants are multipurpose. In such cases, it is necessary to meet certain obligations other than the power generation. These may include a maximum fore way elevation, not to be exceeded because of danger of flooding, and minimum plant discharge and spillage to meet irrigational and navigational commitments. Other distinctions among hydro power systems are the number of hydro stations, their locations and operating characteristics. The problem is different in cases when the hydro plants are located on same steam or on different streams. The operation of downstream plant depends on the immediate upstream plant. But downstream plant influences the immediate upstream plant by its effect on tail water elevation and effective head.

2.2 Classification of Hydro Plants

2.2.1Classification on the Basis of Type

Hydro power plants, on the basis of their type can be classified into:

a) Pumped storage plants
b) Conventional plants

(a) Pumped Storage Plants

Pumped storage hydro plants are designed to save fuel cost by serving the peak load (a high fuel-cost load) with hydro energy and then pumping the water back up into the reservoir at light load periods (a lower cost load). These plants may involve separate pumps and turbines or more recently, reversible pump turbines. A pumped storage plants is associated with upper and lower reservoirs .During light load periods, water is pumped from the lower to the upper reservoir using the available energy from other sources as surplus energy. During peak load the water stored in the upper reservoir is released to generate power to save fuel costs of thermal plants. The pumped storage plants are operated until the added pumping cost exceeds the savings in thermal costs due to the peak sharing operation. Pumped storage plants may be operated on daily or weekly cycle. When operated on weekly cycle, pumped storage plants will start the week with a full reservoir. The plant will then be scheduled over a weekly period to act as a generator during high load hours and to refill the reservoir partially or completely during off- peak periods.

(b)Conventional Plants

Conventional plants are classified as run -of- river plants and storage plants.

1. Run -off- River Plants

Run -of- river plants have little storage capacity and use water as it becomes available. The water not utilized is spilled.

2. Storage Plants

Storage plants are associated with reservoirs which have significant storage capacity. During periods of low power requirements, water can be stored and then released when the demand is high.

2.2.2 Classification According to Quantity of Water Available

On the basis of quantity of water available Hydro plants can be classified as:

(a) Run-off- River Plants without Pondage

These plants do not store water; the plant uses water as it comes. The plant can use water as and when available. Since these plants depend for their generating capacity primarily on the rate of flow of water, during rainy season high flow rate may mean some quantity of water to go as waste while during low run-off periods, due to low flow rates the generating capacity will be low.

(b) Run-off -River Plants With Pondage

In these plants pondage permits storage of water during off peak periods and use of this water during peak periods. Depending on the size of pondage provided it may be possible to cope with hour to hour fluctuations. This type of plant can be used on parts of the load curve as required, and is more useful than a plant with out storage or pondage. When providing pondage tail race conditions should be such that floods do not raise tail-race water level, thus reducing the head on the plant and impairing its effectiveness. This type of plant is comparatively more reliable and its generating capacity is less dependent on available rate of flow of water.

(c) Reservoir Plants

A reservoir plant is that which has a reservoir of such size as to permit carrying over storage from wet season to the next dry season. Water is stored behind the dam and is available to the plant with control as required. Such a plant has better capacity and can be used efficiently through out the year. Its firm capacity can be increased and can be used either as a base load plant or as a peak load plant as required. It can also be used on any portion of the load curve as required.

2.2.3 Classification According to Availability of Water Head

On the basis of water head hydro plants are categorized as :

(a) Low-Head (less than 30 meters) Hydro Electric Plants

"Low head" hydro-electric plants are power plants which generally utilize heads of only a few meters or less. Power plants of this type may utilize a low dam or weir to channel water, or no dam and simply use the "run of the river". Run of the river generating stations cannot store water, thus their electric output varies with seasonal flows of water in a river. A large volume of water must pass through a low head hydro plant's turbines in order to produce a useful amount of power. Hydro-electric facilities with a capacity of less than about 25 MW are generally referred to as "small hydro", although hydro-electrical technology is basically the same regardless of generating capacity.

(b) Medium-Head (30 meters - 100 meters) Hydro Electric Plants

These plants consist of a large dam in a mountainous area which creates a huge reservoir. An open channel brings water from main reservoir to the forebay from where penstock carries water to turbines.

(c) High-Head Hydro Electric Plants

"High head" power plants are the most common and generally utilize a dam to store water at an increased elevation. The use of a dam to impound water also provides the capability of storing water during rainy periods and releasing it during dry periods. This results in the consistent and reliable production of electricity, able to meet the demand. Heads for this type of power plant may be greater than 100 m. Most large hydro-electric facilities are of the high head variety. High head plants with storage are very valuable to electric utilities because they can be quickly adjusted to meet the electrical demand on a distribution system.

2.2.4 Classification According to Nature of Load

(a) Base Load Plants

A base load power plant is one that provides a steady flow of power regardless of total power demand by the grid. These plants run at all times through the year except in the case of repairs or scheduled maintenance. Power plants are designated base load based on their low cost generation, efficiency and safety at set outputs. Base load power plants do not change production to match power consumption demands since it is always cheaper to run them rather than running high cost combined cycle plants or combustion turbines. Typically these plants are large enough to provide a majority of the power used by a grid, making them slow to fire up and cool down. Thus, they are more effective when used continuously to cover the power base load required by the grid. Each base load power plant on a grid is allotted a specific amount of the base load power demand to handle. The base load power is determined by the load duration curve of the system. For a typical power system, rule of thumb states that the base load power is usually 35-40% of the maximum load during the year. Load factor of such plants is high. Fluctuations, peaks or spikes in customer power demand are handled by smaller and more responsive types of power plants.

(b) Peak Load Plants

Power plants for electricity generation which, due to their operational and economic properties, are used to cover the peak load. Gas turbines and storage and pumped storage power plants are used as peak load power plants. The efficiency of such plants is around 60 -70%.

2.2.5 Classification on The Basis of Location

On the basis of their location, hydro plants are classified into three different categories:

(a) Hydro plants on different streams
(b) Hydro plants on same stream

(c) Multi-chain hydro plant

(a) Hydro Plants on Different Streams

The hydro plants are located on different streams and are independent of each other are shown in fig.2.1.

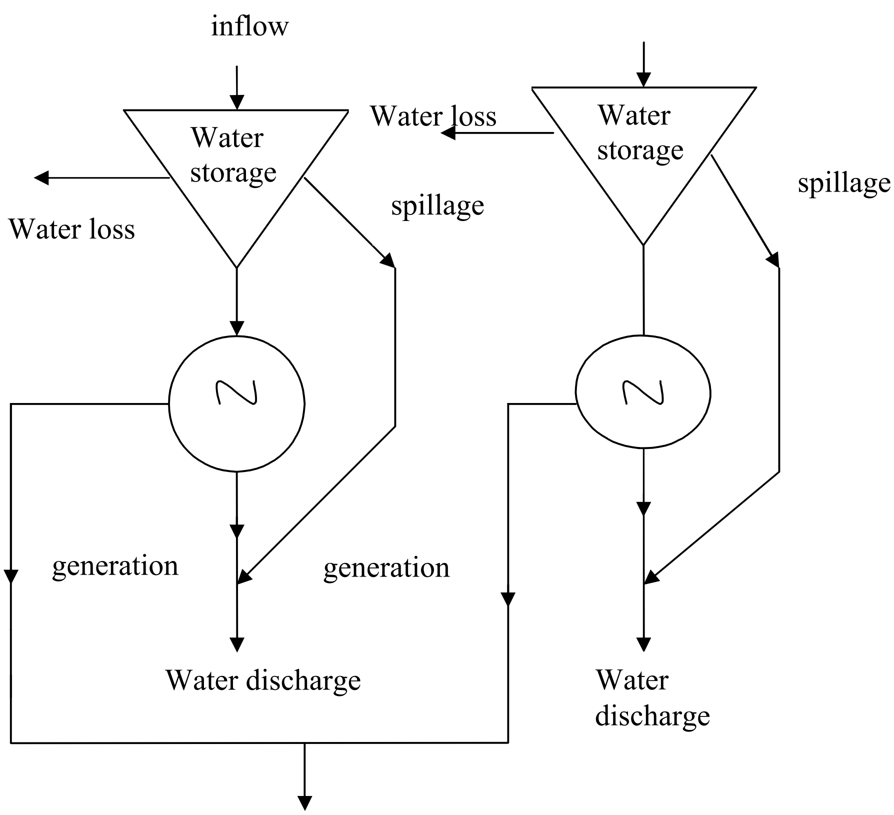

Figure 2.1 Hydro Plants on Different Streams

(b) Hydro Plants on Same Streams

When hydro plants are located on the same stream , the downstream plant depends on the immediate upstream plant. The arrangement is shown in figure 2.2. The downstream plant influences the immediate upstream plant by its effect on tail water elevation and effective head.

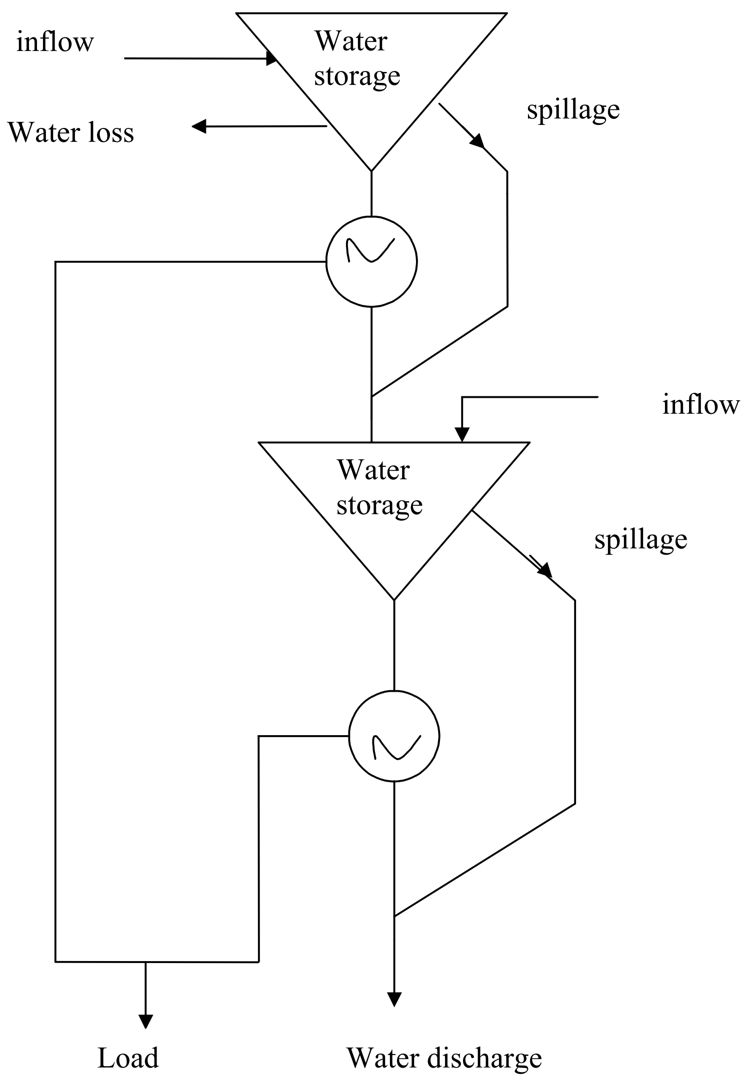

Figure 2.2 Hydro plants on same streams

(c) Multi-Chain Hydro Plants

These hydro plants are located on different streams as well as on same stream. The arrangement is shown in fig 2.3.

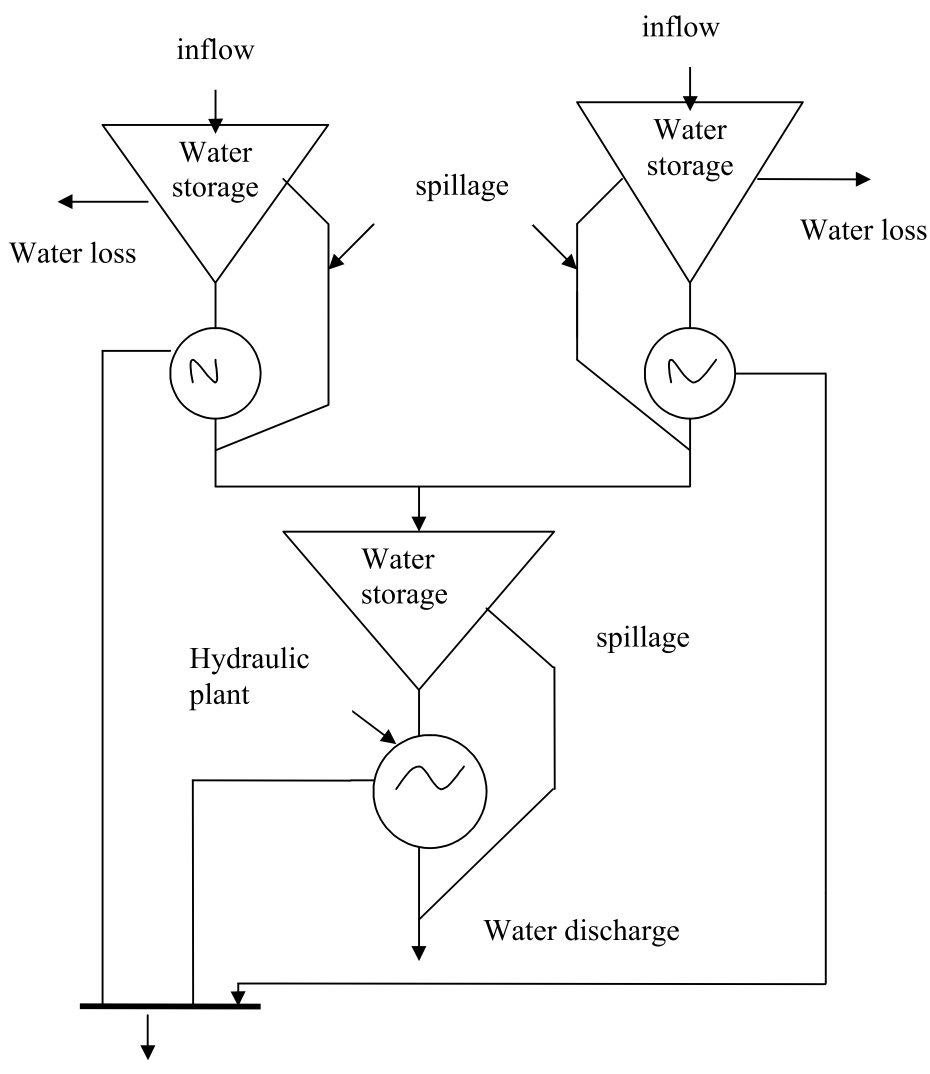

Figure 2.3 Multi -Chain Hydro Plants

2.3 Performance Models for Thermal System

2.3.1 Without Valve Point Loading

Each generator cost function establishes the relationship between the power injected to the system by the generator and the incurred costs to load the machine to that capacity. Typically, generators are modeled by smooth quadratic functions such as to simplify the optimization problem.

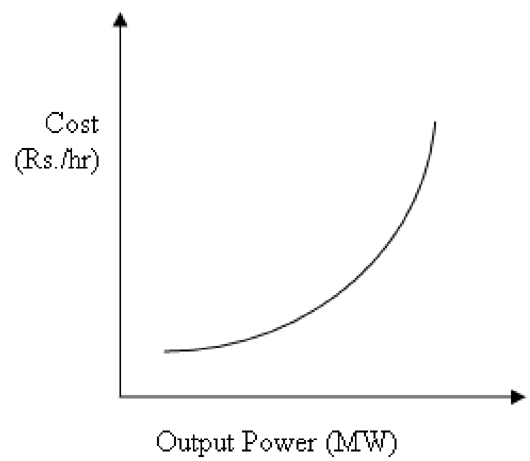

Fig 2.4 Fuel Cost for Thermal Units

$$F_i(P_{ik}) = a_i P_{ik}^2 + b_i P_{ik} + c_i$$

Where a_i, b_i, c_i are cost coefficients of the thermal plants and

P_{ik} =Power output of the generating units in MW during the kth interval.

2.3.2 With Valve Point Loading

Generators are commonly modeled using smooth quadratic functions (Fig2.5) to relate power output to production cost. This type of cost function simplifies greatly the economic dispatch problem and increases the number of techniques that can be applied to solve it. For some cases, quadratic representations do not model properly generators, requiring more accurate models to provide better results in the solution of the economic dispatch problem. More accurate models usually result in higher nonlinear, non-smooth and non-convex functions. Valve point loading is example of such type of cost function. Power plants commonly have multiple valves that are used to control the power output of the unit. When steam admission valves in thermal units are first opened, a sudden increase in losses is registered which results in ripples in the cost function (Fig. 2.5). This effect is known as a valve point loading. The cost function of thermal system with valve point loading is modeled as :

$$F_i = \sum_{i=1}^{N} a_i P_{ik}^2 + b_i P_{ik} + c_i + \left| d_i \sin[e_i (P_{\min} - P_{ik})] \right|$$

where a_i, b_i, c_i are the cost coefficients and d_i, e_i are valve point coefficients . N is the number of generating units.

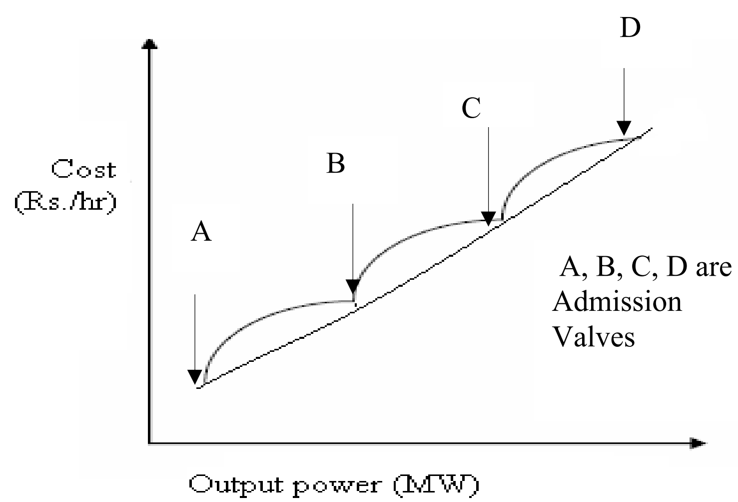

Fig 2.5 Fuel Cost function for a Thermal Generation Unit With Valve Point Loading

2.4 Hydro Plant Performance Model

A basic physically based relationship between the active power generated (in MW) by a hydro-unit and the rate of water discharge, q (in m3/sec), and the effective head, h (in meters), is described with the help of hydro plant performance models which are given below:

2.4.1 Glimn-Kirchmayer Model

This model [1] defines the rate of water discharge, q, as a separable function of P_{ik} and h of the form:

$$q = K\psi(h)\phi(P_{ik})$$

where h is effective head and P_{ik} is the output power . The parameter K is a constant of proportionality assumed to be unity, and the ψ and φ functions are quadratic and given by:

$$\psi(h) = \alpha h^2 + \beta h + \gamma$$

where α ,β and γ are the coefficients.

$$\phi(P_{ik}) = xP_{ik}^2 + yP_{ik} + z$$

where *x, y* and *z* are the cost coefficients.

2.4.2 Hildebrand's Model

In this model a discharge is in general polynomial form given by

$$q = \sum_{i=l_1}^{k_1} \sum_{i=l_2}^{k_2} C_{ij} P^i h^i$$

The lower limits l_1 and l_2 are zero while the upper exponents k_1 and k_2 are taken usually to be 2.

2.4.3 Hamilton-Lamont's Model

This model expresses discharge (q) as:

$$q = \psi(h)\ \phi(P_{ik})/h$$

The function ψ and ϕ are given by:

$$\psi(h) = \alpha h^2 + \beta h + \gamma \qquad \text{where } \alpha, \beta \text{ and } \gamma \text{ are coefficients.}$$

$$\phi(P_{ik}) = xP^3 + yP_{ik} + z \qquad \text{where } x, y \text{ and } z \text{ are coefficients.}$$

2.4.4 Arvanitidis-Rosing Model:

In this model, the output power is related to q and h and the efficiency related to the reservoir storage and as a result we have

$$P_{ik} = qh\left[\beta - e^{-\alpha S}\right]$$

where S is reservoir storage. With a vertical sided reservoir, we can express S as a function of the as

$$S = A\ [h - h0]$$

The reservoir area is denoted by A. As a result, the A-R model is given by:

$$P_{ik} = qh\left[\beta - e^{-\delta(h-h_o)}\right] \qquad \text{where } \delta = \alpha A .$$

The first three models express water discharge as a function of power output from the ith unit during time interval (k) and head of plant. The main reason for this is to confirm with the conventional requirements of economic scheduling methodology treating water discharge as an input and output power (P_{ik}) as an output in much the same manner adopted for the treatment for fuel cost for thermal units. Due to the difficulties in fitting one unit's data to the original form of the Glimn-Kirchmayer's model, a simple extension was devised in the course of this investigation in Hamilton-Lamont's Model where we assume that is a third order polynomial in output power instead of the usual quadratic form. A constant term h_o may be included in Arvantidis-Rosing's model to provide an offset to yield more satisfactory results for some hydro-plant types.

CHAPTER 3

SHORT RANGE FIXED- HEAD HYDRO THERMAL SCHEDULING

3.1 Introduction

The short term hydrothermal scheduling problem is concerned with allocating generation among hydro and thermal units over one day or one week, usually discretized in hourly intervals. The problem formulation must take into account many system operating constraints, including hydraulic, thermal and electrical aspects. Each specific formulation will depend on the characteristics of the particular system considered. The objective is to minimize the total operating cost represented by the fuel cost required for the system's thermal generation over the optimization interval. Each hydro plant is constrained by the amount of water available for draw down during the interval. A set of starting conditions is given and the optimal hourly schedule that minimizes a desired objective, while meeting hydraulic stream and electric system constraint is sought. Part of hydraulic constraint may involve meeting meeting "end point" conditions at the end of scheduling interval in order to confirm to a long range, water release schedule previously established.

The output of each hydro unit varies with the effective head and the rate of water discharge through the turbines. For large capacity reservoir, it is practical to assume that effective head is constant over the optimization interval.

The short range fixed head hydro thermal problem is defined as: Conisder an electric power system network having N thermal generating units and M hydro plants where M+N is the total no. of generating plants. The basic problem is to find the active power generation of each plant in the system as a function of time over a finite time period from 0 to T.

3.2 Problem Formulation

Given a power system consisting of N thermal units and M hydro units, the problem is to schedule the power generation of all units over t_k time sub -intervals in order to minimize the fuel cost. This schedule must meet given demand and pre-specified amount of water allocated at each hydro plant. The problem is solved by using approximate Newton Rapshon method.

3.2.1 Thermal Model

The objective function is to minimize the total operating cost (*C*) represented by the fuel cost of thermal generation over the optimization interval (T).

$$C = \sum_{k=1}^{T} \sum_{i=1}^{N} t_k F_i(P_{ik})$$

where the problem is to schedule the power generation of all units over t_k time sub - intervals in order to minimize the fuel cost which is given as :

$$F_i(P_{ik}) = a_i P_{ik}^2 + b_i P_{ik} + c_i \qquad (k = 1,2 \ldots T \; ; \; I = 1,2 \ldots N)$$

where a_i, b_i and c_i are cost coefficients of the i^th generating unit .

3.2.2 Hydro Model

In hydro system, there is no fuel cost incurred in the operation of hydro units. According to Glimn-krichmayer model, discharge is a function of power output and the head. For large capacity reservoir it is practical to assume that the effective head is constant over the optimization interval. Thus q_{jk} is the rate of discharge from the j^th unit in the interval k and is represented by the quadratic equation :

$$q_{jk} = x_j P_{j+N,k}^2 + y_j P_{j+N,k} + z_j$$

Where x_j, y_j and z_j discharge coefficients of the hydro units .

3.2.3 Constraints

(a) Load demand equality constraint

$$\sum_{i=1}^{N+M} P_{ik} = P_{dk} + Ploss_k$$

Where P_{dk} is the load demand during the kth sub- interval and $Ploss_k$ are the transmission losses during the kth interval.

(b) Minimum and maximum power generation limits from view point of economy and capacity of generating units.

$$P_{i\min} \le P_{ik} \le P_{i\max}$$

Where P_{ik} Power output of the generating units in MW during the k[th] interval, P_{max} is the maximum power of a generating unit in MW and P_{min} is the minimum power of a generating unit in MW.

3.2.4 Transmission Losses

The transmission losses during k[th] interval are given by the Kron's loss formula in terms of B- coefficients.

$$Ploss_k = \sum_{i=1}^{N+M} \sum_{j=1}^{N+M} P_{ik} B_{ij} P_{jk} + B_{io} P_{ik} + B_{oo}$$

The fixed head hydro thermal problem can be defined considering the optimization interval to meet the load demand in each interval. Each hydro plant is constrained by the amount of water available for draw –down in the interval. The problem is defined as:

$$\text{Minimize } C = \sum_{k=1}^{T} \sum_{i=1}^{N} t_k F_i(P_{ik}) \qquad (3.2.1)$$

Subjects to

$$\sum_{i=1}^{N+M} P_{ik} = P_{dk} + Ploss_k \qquad (k=1,2\ldots\ldots T,\ i=1,\ 2,\ldots\ldots N+M) \qquad (3.2.2)$$

$$\sum_{k=1}^{T} t_k q_{jk} = V_j \qquad (j=1,2\ldots\ldots M,\ K=1,2\ \ldots\ldots T) \qquad (3.2.3)$$

$$P_{i\min} \le P_{ik} \le P_{i\max} \qquad (i=1,2\ldots\ldots,N+M\ ;\ k=1,2,\ldots\ldots T) \qquad (3.2.4)$$

The simplest way to arrive at the required equations is to use the calculus of variations. Each constraint equation is associated with an unknown multiplier function known as a Lagrange multiplier. The augmented Lagrangian function L is:

$$L(P_{ik,} \lambda_k, v_j) = \sum_{k=1}^{T} [\ \sum_{i=1}^{N} t_k F_i(P_{ik}) + \sum_{j=1}^{M} v_j t_k q_{jk} + \lambda_k \left[P_{dk} + Ploss_k - \sum_{i=1}^{N+M} P_{ik} \right]\ ] - \sum_{j=1}^{M} v_j V_j \qquad (3.2.5)$$

where λ_k is the incremental cost of power delivered in the system and v_j is water conversion factor.

3.2.5 Coordination Equations

The set of coordination equations for a minimum cost operating condition is given by:

$$\frac{\partial L}{\partial P_{ik}} = 0 \Rightarrow t_k \frac{\partial F_i(P_{ik})}{\partial P_{ik}} + \lambda_k \left[\frac{\partial Ploss_k}{\partial P_{ik}} - 1 \right] \qquad (i = 1, 2, ...N; k = 1, 2, ...T) \qquad (3.2.5)$$

$$\frac{\partial L}{\partial P_{mk}} = 0 \Rightarrow v_j t_k \frac{\partial q_{jk}}{\partial P_{mk}} + \lambda_k \left[\frac{\partial Ploss_k}{\partial P_{ik}} - 1 \right] \qquad (j = 1, 2, ...N; m = j + N; k = 1, 2, ...T) \qquad (3.2.6)$$

$$\frac{\partial L}{\partial v_j} = 0 \Rightarrow \sum_{k=1}^{T} t_k q_{jk} = V_j \qquad (j=1,2\ldots\ldots\ldots M) \qquad (3.2.7)$$

$$\frac{\partial L}{\partial \lambda_k} = 0 \Rightarrow \sum_{i=1}^{N+M} P_{ik} = P_{dk} + Ploss_k \qquad (k=1,2\ldots\ldots\ldots T) \qquad (3.2.8)$$

These equations are non –linear. The Approximate Newton Raphson method is used to find P_{ik}, λ_k and v_j .

3.3 Approximate Newton Raphson Method

Conisder the hydro thermal system with N number of thermal units and M number of hydro units where M+N is the total no. of generating plants. The basic problem is to find the active power generation of each plant in the system as a function of time over a finite time period from 0 to T. initially the no. of subinterval T, cost -coefficients, $a_i, b_i\, c_i$,B-coefficients, discharge coefficients, x_i,y_i , z_i and pre-specified available water V_j are given and approximate Newton Raphson method is used to determine the P_{ik}, λ_k and v_j .

3.3.1 Initial Estimate

The convergence of Newton-type methods or solving nonlinear equations depends on the non-singularity of the Jacobian J at the solution, and the region in which quadratic convergence will occur decreases in size. Hence, the convergence of a Newton-type method will be unavoidably degraded if the Jacobian at the solution is very ill-conditioned. However, convergence occurs if the Jacobian at the solution differs in significantly from that at the initial solution. Thus, an initial estimate which meets these requirements is required to start the iterative process.

3.3.2 Equal-Share Vector

Power demand is equally distributed among thermal and hydro units during each interval. This is given by:

$$P_{ik}^{0} = \frac{P_{dk}}{N+M} \qquad \textit{(i=1,2,\ldots.N+M; k=1,2,\ldots\ldots.T)} \qquad (3.3.1)$$

Further it is assumed that there are no transmission losses.

$$\lambda_k = 2a_i P_{ik} + b_i \qquad \textit{(k=1,2\ldots\ldots T)} \qquad (3.3.2)$$

The water conversion factor can be obtained as:

$$v_j^0 (2x_j P_{mk}^0 + y_j) = \lambda_k^0$$

$$v_j^0 = \frac{\lambda_k^0}{(2x_j P_{mk}^0 + y_j)} \qquad (j = 1,2,\ldots\ldots N; m = j+N; k = 1,2,\ldots\ldots T) \qquad (3.3.3)$$

Assume that initial values of P_{ik}^0, λ_k^0 and v_j^0 are known. Small change in these can be obtained from the following equations to update the values of control variable in the next iteration.

$$P_{ik}^{new} = P_{ik}^0 + \Delta P_{ik} \qquad \textit{(i=1,2,\ldots.N+M; k=1,2,\ldots\ldots.T)}$$

$$\lambda_k^{new} = \lambda_k^0 + \Delta\lambda_k \qquad \textit{(k=1,2\ldots\ldots T)}$$

$$v_j^{new} = v_j^0 + \Delta v_j \qquad \textit{(j=1,2\ldots\ldots M)}$$

$$\left(t_k \frac{\partial^2 F_i}{\partial P_{ik}^2} + \lambda_k \frac{\partial^2 Ploss_k}{\partial P_{ik}^2} \right) \Delta P_{ik} + \lambda_k \sum_{\substack{j=1 \\ j \neq i}}^{N+M} \frac{\partial^2 Ploss_k}{\partial P_{ik} \partial P_{jk}} \Delta P_{jk} + \left(\frac{\partial Ploss_k}{\partial P_{ik}} - 1 \right) \Delta\lambda_k =$$

$$t_k \frac{\partial F_i(P_{ik})}{\partial P_{ik}} + \lambda_k \left[\frac{\partial Ploss_k}{\partial P_{ik}} - 1 \right] \qquad (3.3.4)$$

$$\left(v_j t_k \frac{\partial^2 q_{jk}}{\partial P_{mk}^2} + \lambda_k \frac{\partial^2 Ploss_k}{\partial P_{mk}^2} \right) \Delta P_{mk} + \lambda_k \sum_{\substack{l=1 \\ l \neq m}}^{N+M} \frac{\partial^2 Ploss_k}{\partial P_{mk} \partial P_{lk}} \Delta P_{lk} + \left(\frac{\partial Ploss_k}{\partial P_{mk}} - 1 \right) \Delta\lambda_k + \frac{\partial q_{jk}}{\partial P_{mk}} \Delta v_j$$

$$= -\left(v_j^0 t_k \frac{\partial q_{jk}}{\partial P_{mk}} + \lambda_k \left[\frac{\partial Ploss_k}{\partial P_{ik}} - 1 \right] \right) \qquad (3.3.5)$$

$$\sum_{j=1}^{N+M} \left[\frac{\partial Ploss_k}{\partial P_{ik}} - 1 \right] = -\left(\sum_{i=1}^{N+M} P_{ik} = P_{dk} + Ploss_k \right) \qquad (3.3.6)$$

$$\sum_{k=1}^{T} \left(\frac{\partial q_{jk}}{\partial P_{mk}} - 1 \right) \Delta P_{mk} = -\left(\sum_{k=1}^{T} q_{jk}^0 - V_j \right) \qquad (3.3.7)$$

Substituting the values of the derivatives in the equations no. (3.3.4) to (3.3.7) and neglecting the terms $\sum_{\substack{j=1 \\ j \neq i}}^{N+M} \frac{\partial^2 Ploss_k}{\partial P_{ik} \partial P_{jk}} \Delta P_{jk}$ and $\sum_{\substack{l=1 \\ l \neq m}}^{N+M} \frac{\partial^2 Ploss_k}{\partial P_{mk} \partial P_{lk}} \Delta P_{lk}$ the derivatives are evaluated about initial conditions, we get:

$$\left(2t_k a_i + 2\lambda_k^0 B_{ii}\right)\Delta P_{ik} + \left(K_{ik}^0 - 1\right)\Delta\lambda_k = -\left[t_k\left(2a_i P_{ik}^0 + b_i\right) + \lambda_k^0\left(K_{ik}^0 - 1\right)\right] \tag{3.3.8}$$

Where $K_{ik}^0 = \sum_{j=1}^{N+M} 2B_{ij}P_{jk}^0 + B_{i0}$

Rearranging the equation (3.3.8) ,we get:

$$\left(2t_k a_i + 2\lambda_k^0 B_{ii}\right)\Delta P_{ik} = \left[\lambda_k^{new}\left(1 - K_{ik}^0\right) - t_k(2a_i P_{ik}^0 + b_i)\right]$$

$$\Delta P_{ik} = \frac{(1 - K_{ik}^0)\lambda_k^{new} - \alpha_{ik}}{X_{ik}} \tag{3.3.9}$$

where $\alpha_{ik} = t_k(2a_i P_{ik}^0 + b_i)$ and $X_{ik} = 2(t_k a_i + \lambda_k^0 B_{ii})$

$$2(v_j^0 t_k x_j + \lambda_k^0 B_{mm})\Delta P_{mk} = -\left[t_k(2x_j P_{mk}^0 + y_j)v_j^{new} + \lambda_k^{new}(K_{mk}^0 - 1)\right]$$

$$\Delta P_{mk} = \frac{(1 - K_{mk}^0)\lambda_k^{new} - \beta_{jk}v_j^{new}}{Y_{jk}} \tag{3.3.10}$$

where $\beta_{jk} = t_k(2x_j P_{mk}^0 + y_j)$, $Y_{jk} = 2(v_j^0 t_k x_j + \lambda_k^0 B_{mm})$

Substuting the values of derivatives in equation (3.3.6) ,we get

$$\sum_{j=1}^{N+M}(1 - K_{mk}^0)\Delta P_{jk} = P_{dk} + Ploss_k^0 - \sum_{i=1}^{N+M} P_{ik}^0 \tag{3.3.11}$$

Substituting equation (3.3.9) and equation (3.3.10) in the equation (3.3.11), we get,

$$C_k \lambda_k^{new} - \sum_{j=1}^{M} D_{jk} v_j^{new} = F_k \tag{3.3.12}$$

where $C_k = \sum_{i=1}^{N} \frac{(1 - K_{ik}^0)^2}{X_{ik}} + \sum_{j=1}^{M} \frac{(1 - K_{mk}^0)^2}{Y_{jk}}$

$$D_{jk} = \frac{(1 - K_{mk}^0)\beta_{jk}}{Y_{jk}}$$

$$F_k = (P_{dk} + Ploss_k^0 - \sum_{i=1}^{N+M} P_{ik}^0 + \sum_{i=1}^{N} \frac{(1 - K_{mk}^0)\alpha_{ik}}{X_{ik}}$$

Equation (3.3.17) can be modified as :

$$\sum_{k=1}^{T} t_k (2x_j P_{mk}^0 + y_j)\Delta P_{mk} = -\left(t_k q_{jk}^0 - V_j\right)$$

Substituting the value of ΔP_{mk} in the above equation , we get:

$$\sum_{k=1}^{T} D_{jk}\lambda_k^{new} - H_j v_j^{new} = O_j \qquad (3.3.13)$$

where $H_j = \sum_{K=1}^{T} \frac{\beta_{jk}\beta_{jk}}{Y_{jk}}$ (3.3.14)

$$O_j = V_j - \sum_{k=1}^{T} t_k q_{jk}^0 \qquad (3.3.15)$$

The new value of incremental cost (λ_k^{new}) is calculated from equation (3.3.12)

$$\lambda_k^{new} = \frac{F_k}{C_k} + \sum_{j=1}^{M} \frac{D_{jk}}{C_k} v_j^{new} \qquad (3.3.16)$$

Substituting the value of λ_k^{new} in the equation (3.3.13),we get

$$\sum_{l=1}^{M}\left(\sum_{k=1}^{T} \frac{D_{jk}D_{lk}}{C_k} v_l^{new}\right) - H_j v_j^{new} = O_j - \sum_{k=1}^{T} \frac{D_{jk}F_k}{C_k} \qquad (3.3.17)$$

Equation (3.6.17) can be written in matrix form

$$\left[Q_{jl}\right]_{M\times M}\left[v_j\right]_{M\times l} = \left[R_j\right]_{M\times l} \qquad (3.3.18)$$

where $\left[Q_{jj}\right] = \left(\sum_{k=1}^{T} \frac{D_{jk}D_{jk}}{C_k}\right) - H_j$

$$\left[Q_{jl}\right] = \left(\sum_{k=1}^{T} \frac{D_{jk}D_{lk}}{C_k}\right)$$

$$\left[R_j\right] = O_j - \sum_{k=1}^{T} \frac{D_{jk}F_k}{C_k}$$

v_j^{new} is calculated by solving a matrix of $M \times M$ and λ_k^{new} is calculated from the equation(3.3.18).when the value v_j^{new} and λ_k^{new} is known then ΔP_{ik} and ΔP_{mk} can be calculated from the equation(3.3.9) and (3.3.10) respectively.

3.4 Flowchart for Approximate Newton Raphson Method

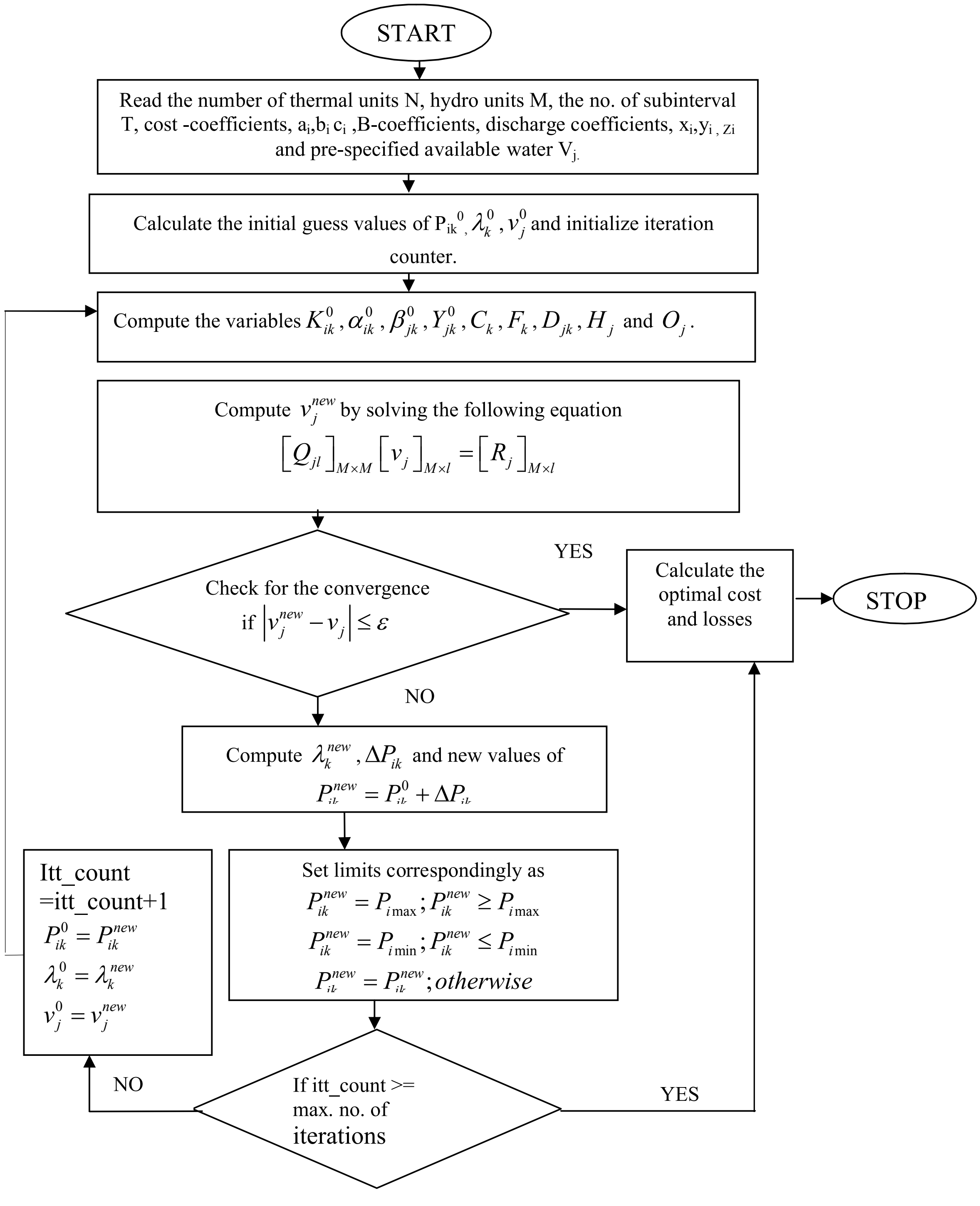

Fig 3.4 Flowchart For the Approximate Newton Raphson Method

CHAPTER 4

HYDRO THERMAL SCHEDULING WITH VALVE POINT LOADING

4.1 Introduction

Generators are commonly modeled using smooth quadratic functions to relate power output to production cost. This type of cost function simplifies greatly the economic dispatch problem and increases the number of techniques that can be applied to solve it. For some cases, quadratic representations do not model properly generators, requiring more accurate models to provide better results in the solution of the economic dispatch.

4.2 Valve Point Loading

Power plants commonly have multiple valves that are used to control the power output of the unit. When steam admission valves in thermal units are first opened, a sudden increase in losses is registered which results in ripples in the cost function. This effect is known as a valve point loading.

4.3 Hydro Thermal Scheduling With Valve Point Loading

4.3.1 Thermal Model

Valve Point Loadings economic dispatch minimizes the system cost based on the valve point loading cost function that considers valve transitions. Valve point loadings is usually modeled by adding a sinusoidal term to the basic quadratic cost function. The objective function is to minimize the total operating cost represented by the fuel cost of thermal generation over the optimization interval (T). Fuel cost of the thermal plants is modified as:

$$F_i = \sum_{i=1}^{N} a_i P_{ik}^2 + b_i P_{ik} + c_i + \left| d_i \sin[e_i (P_{\min} - P_{ik})] \right| \qquad (4.3.1)$$

where a_i, b_i and c_i are the cost coefficients and d_i , e_i are the valve point cost coefficients.

These superimposed sine components represent the rippling effects produced by the steam admission valve opening.

4.3.2 Hydro Model

In hydro system, there is no fuel cost incurred in the operation of hydro units. According to Glimn-krichmayer model, discharge is a function of power output and the head. For large capacity reservoir it is practical to assume that the effective head is constant over the optimization interval. Thus q_{jk} is the rate of discharge from the jth unit in the interval k and is represented by the quadratic equation:

$$q_{jk} = x_j P_{j+N,k}^2 + y_j P_{j+N,k} + z_j \qquad (4.3.2)$$

Where x_j, y_j and z_j discharge coefficients of the hydro units .

4.3.3 Constraints

(a) Load demand equality constraint:

$$\sum_{i=1}^{N+M} P_{ik} = P_{dk} + Ploss_k \qquad (4.3.3)$$

where P_{dk} is the load demand during the kth sub- interval and $Ploss_k$ are the transmission losses during the kth interval .

(b) Minimum and maximum power generation limits

$$P_{i\min} \leq P_{ik} \leq P_{i\max} \qquad (4.3.4)$$

where P_{ik} is Power output of the generating units in MW during the kth interval, P_{max} is the maximum power of a generating unit in MW and P_{min} is the minimum power of a generating unit in MW.

4.3.4 Transmission Losses

The transmission losses during kth interval is given by the Kron's loss formula in terms of B- coefficients .

$$Ploss_k = \sum_{i=1}^{N+M} \sum_{j=1}^{N+M} P_{ik} B_{ij} P_{jk} + B_{io} P_{ik} + B_{oo} \qquad (4.3.5)$$

The fixed head hydro thermal problem can be defined considering the optimization interval to meet the load demand in each interval. Each hydro plant is constrained by the amount of water available for draw-down in the interval. The problem is defined as:

$$\text{Minimize } C = \sum_{k=1}^{T}\sum_{i=1}^{N} t_k F_i(P_{ik}) \qquad (4.3.6)$$

Subjects to

$$\sum_{i=1}^{N+M} P_{ik} = P_{dk} + Ploss_k \qquad (k=1,2\ldots\ldots T,\ i=1,\ 2,\ldots\ldots N+M) \qquad (4.3.7)$$

$$\sum_{k=1}^{T} t_k q_{jk} = V_j \qquad (j=1,2\ldots\ldots M,\ K=1,2\ \ldots\ldots T) \qquad (4.3.8)$$

$$P_{i\min} \le P_{ik} \le P_{i\max} \qquad (i=1,2\ldots\ldots,N+M\ ;\ k=1,2,\ldots..T) \qquad (4.3.9)$$

The simplest way to arrive at the required equations is to use the calculus of variations. Each constraint equation is associated with an unknown multiplier function known as a Lagrange multiplier. The augmented Lagrangian function L is :

$$L(P_{ik,}\lambda_k, v_j) = \sum_{k=1}^{T}\ \sum_{i=1}^{N} t_k F_i(P_{ik}) + \sum_{j=1}^{M} v_j t_k q_{jk} + \lambda_k \left[P_{dk} + Ploss_k - \sum_{i=1}^{N+M} P_{ik} \right]] - \sum_{j=1}^{M} v_j V_j \qquad (4.3.10)$$

where λ_k is the incremental cost of power delivered in the system and v_j is water conversion factor.

4.3.5. Coordination Equations

The set of coordination equations for a minimum cost operating condition is given by:

$$\frac{\partial L}{\partial P_{ik}} = 0 \Rightarrow t_k \frac{\partial F_i(P_{ik})}{\partial P_{ik}} + \lambda_k \left[\frac{\partial Ploss_k}{\partial P_{ik}} - 1 \right] \qquad (i=1,2,\ldots\ldots.N;k=1,2,\ldots\ldots T) \qquad (4.3.11)$$

$$\frac{\partial L}{\partial P_{mk}} = 0 \Rightarrow v_j t_k \frac{\partial q_{jk}}{\partial P_{mk}} + \lambda_k \left[\frac{\partial Ploss_k}{\partial P_{ik}} - 1 \right] (j=1,2,\ldots\ldots.N; m=j+N; k=1,2,\ldots\ldots T) \qquad (4.3.12)$$

$$\frac{\partial L}{\partial v_j} = 0 \Rightarrow \sum_{k=1}^{T} t_k q_{jk} = V_j \qquad (j=1,2\ldots\ldots M) \qquad (4.3.13)$$

$$\frac{\partial L}{\partial \lambda_k} = 0 \Rightarrow \sum_{i=1}^{N+M} P_{ik} = P_{dk} + Ploss_k \qquad (k=1,2\ldots\ldots T) \qquad (4.3.14)$$

These equations are non –linear. The Approximate Newton Raphson method is used to find P_{ik}, λ_k and v_j .

4.4 Approximate Newton Raphson Method

Conisder the hydro thermal system with N number of thermal units and M number of hydro units where M+N is the total no. of generating plants. The basic problem is to find the active power generation of each plant in the system as a function of time over a finite time period from 0 to T. initially the no. of subinterval T, cost –coefficients (a_i, b_i & c_i) and d_i, e_i are valve point coefficients and B-coefficients, discharge coefficients, x_i, y_i, z_i and pre-specified available water V_j are given and approximate Newton Raphson Method is used to determine the P_{ik}, λ_k and v_j .

4.4.1 Equal-Share Vector

Power demand is equally distributed among thermal and hydro units during each interval. This is given by:

$$P_{ik}^0 = \frac{P_{dk}}{N+M} \qquad (i=1,2,\ldots\ldots N+M;\ k=1,2,\ldots\ldots\ldots T) \qquad (4.4.1)$$

Further it is assumed that there are no transmission losses.

$$\lambda_k = 2a_i P_{ik} + b_i - \left| d_i e_i \cos[e_i(P_{\min} - P_{ik})] \right| \qquad (k=1,2\ldots\ldots T) \qquad (4.4.2)$$

The water conversion factor can be obtained as:

$$v_j^0(2x_j P_{mk}^0 + y_j) = \lambda_k^0$$
$$v_j^0 = \frac{\lambda_k^0}{(2x_j P_{mk}^0 + y_j)} \qquad (j = 1,2,\ldots\ldots N; m = j+N; k = 1,2,\ldots\ldots T) \qquad (4.4.3)$$

Assume that initial values of P_{ik}^0, λ_k^0 and v_j^0 are known. Small change in these can be obtained from the following equations to update the values of control variable in the next iteration.

$$P_{ik}^{new} = P_{ik}^0 + \Delta P_{ik} \qquad (i=1,2,\ldots\ldots N+M;\ k=1,2,\ldots\ldots\ldots T)$$

$$\lambda_k^{new} = \lambda_k^0 + \Delta\lambda_k \qquad (k=1,2\ldots\ldots\ldots T)$$

$$v_j^{new} = v_j^0 + \Delta v_j \qquad (j=1,2\ldots\ldots\ldots M)$$

$$\left(t_k \frac{\partial^2 F_i}{\partial P_{ik}^2} + \lambda_k \frac{\partial^2 Ploss_k}{\partial P_{ik}^2}\right)\Delta P_{ik} + \lambda_k \sum_{\substack{j=1 \\ j\neq i}}^{N+M} \frac{\partial^2 Ploss_k}{\partial P_{ik}\partial P_{jk}}\Delta P_{jk} + \left(\frac{\partial Ploss_k}{\partial P_{ik}} - 1\right)\Delta\lambda_k =$$

$$t_k \frac{\partial F_i(P_{ik})}{\partial P_{ik}} + \lambda_k \left[\frac{\partial Ploss_k}{\partial P_{ik}} - 1\right] \tag{4.4.4}$$

$$\left(v_j t_k \frac{\partial^2 q_{jk}}{\partial P_{mk}^2} + \lambda_k \frac{\partial^2 Ploss_k}{\partial P_{mk}^2}\right)\Delta P_{mk} + \lambda_k \sum_{\substack{l=1 \\ l\neq m}}^{N+M} \frac{\partial^2 Ploss_k}{\partial P_{mk}\partial P_{lk}}\Delta P_{lk} + \left(\frac{\partial Ploss_k}{\partial P_{mk}} - 1\right)\Delta\lambda_k + \frac{\partial q_{jk}}{\partial P_{mk}}\Delta v_j$$

$$= -\left(v_j^0 t_k \frac{\partial q_{jk}}{\partial P_{mk}} + \lambda_k \left[\frac{\partial Ploss_k}{\partial P_{ik}} - 1\right]\right) \tag{4.4.5}$$

$$\sum_{j=1}^{N+M} \left[\frac{\partial Ploss_k}{\partial P_{ik}} - 1\right] = -\left(\sum_{i=1}^{N+M} P_{ik} = P_{dk} + Ploss_k\right) \tag{4.4.6}$$

$$\sum_{k=1}^{T} \left(\frac{\partial q_{jk}}{\partial P_{mk}} - 1\right)\Delta P_{mk} = -\left(\sum_{k=1}^{T} q_{jk}^0 - V_j\right) \tag{4.4.7}$$

Substituting the values of the derivatives in the equations (4.4.4) to (4.4.7) and neglecting the terms $\sum_{\substack{j=1 \\ j\neq i}}^{N+M} \frac{\partial^2 Ploss_k}{\partial P_{ik}\partial P_{jk}}\Delta P_{jk}$ and $\sum_{\substack{l=1 \\ l\neq m}}^{N+M} \frac{\partial^2 Ploss_k}{\partial P_{mk}\partial P_{lk}}\Delta P_{lk}$ the derivatives are evaluated about initial conditions, we get:

$$\begin{aligned}&\left(t_k(2a_i + d_i e_i^2(\sin[e_i(P_{\min} - P_{ik})]) + 2\lambda_k^0 B_{ii})\right)\Delta P_{ik} + \left(K_{ik}^0 - 1\right)\Delta\lambda_k = \\ &-\left[t_k\left(2a_i P_{ik}^0 + b_i - d_i e_i(\cos[e_i(P_{\min} - P_{ik})])\right) + \lambda_k^0\left(K_{ik}^0 - 1\right)\right]\end{aligned} \tag{4.4.8}$$

Where $K_{ik}^0 = \sum_{j=1}^{N+M} 2B_{ij}P_{jk}^0 + B_{i0}$

Rearranging the equation (4.4.8) ,we get:

$$\left(2t_k a_i + d_i e_i^2 \sin[e_i(P_{\min} - P_{ik})] + 2\lambda_k^0 B_{ii}\right)\Delta P_{ik} = \left[\lambda_k^{new}\left(1 - K_{ik}^0\right) - t_k(2a_i P_{ik}^0 + b_i) - d_i e_i(\cos[e_i(P_{\min} - P_{ik})])\right]$$

$$\Delta P_{ik} = \frac{(1-K_{ik}^0)\lambda_k^{new} - \alpha_{ik}}{X_{ik}} \quad (4.4.9)$$

Where

$$\alpha_{ik} = t_k(2a_i P_{ik}^0 + b_i - \left| d_i e_i \cos[e_i(P_{\min} - P_{ik})] \right|)$$

$$X_{ik} = 2t_k a_i + \left| d_i e_i^2 \sin[e_i(P_{\min} - P_{ik})] \right| + 2\lambda_k^0 B_{ii}$$

$$2(v_j^0 t_k x_j + \lambda_k^0 B_{mm})\Delta P_{mk} = -\left[t_k(2x_j P_{mk}^0 + y_j)v_j^{new} + \lambda_k^{new}(K_{mk}^0 - 1) \right]$$

$$\Delta P_{mk} = \frac{(1-K_{mk}^0)\lambda_k^{new} - \beta_{jk} v_j^{new}}{Y_{jk}} \quad (4.4.10)$$

Where $\beta_{jk} = t_k(2x_j P_{mk}^0 + y_j)$, $Y_{jk} = 2(v_j^0 t_k x_j + \lambda_k^0 B_{mm})$

Substuting the values of derivatives in equation (4.4.6),we get

$$\sum_{j=1}^{N+M} (1-K_{mk}^0)\Delta P_{jk} = P_{dk} + Ploss_k^0 - \sum_{i=1}^{N+M} P_{ik}^0$$

Substituting equation (4.4.8) and equation (4.4.9) in the equation (4.4.10), we get ,

$$C_k \lambda_k^{new} - \sum_{j=1}^{M} D_{jk} v_j^{new} = F_k \quad (4.4.11)$$

Where $C_k = \sum_{i=1}^{N} \frac{(1-K_{ik}^0)^2}{X_{ik}} + \sum_{j=1}^{M} \frac{(1-K_{mk}^0)^2}{Y_{jk}}$

$$D_{jk} = \frac{(1-K_{mk}^0)\beta_{jk}}{Y_{jk}}$$

$$F_k = (P_{dk} + Ploss_k^0 - \sum_{i=1}^{N+M} P_{ik}^0 + \sum_{i=1}^{N} \frac{(1-K_{mk}^0)\alpha_{ik}}{X_{ik}}$$

Equation (4.4.7) can be modified as:

$$\sum_{k=1}^{T} t_k(2x_j P_{mk}^0 + y_j)\Delta P_{mk} = -\left(t_k q_{jk}^0 - V_j \right)$$

Substituting the value of ΔP_{mk} in the above equation, we get:

$$\sum_{k=1}^{T} D_{jk}\lambda_k^{new} - H_j v_j^{new} = O_j \tag{4.4.12}$$

Where $H_j = \sum_{K=1}^{T} \frac{\beta_{jk}\beta_{jk}}{Y_{jk}}$ (4.4.13)

$$O_j = V_j - \sum_{k=1}^{T} t_k q_{jk}^0 \tag{4.4.14}$$

The new value of incremental cost (λ_k^{new}) is calculated from equation (4.4.11)

$$\lambda_k^{new} = \frac{F_k}{C_k} + \sum_{j=1}^{M} \frac{D_{jk}}{C_k} v_j^{new} \tag{4.4.15}$$

Substituting the value of λ_k^{new} in the equation (4.4.15), we get

$$\sum_{l=1}^{M} \left(\sum_{k=1}^{T} \frac{D_{jk}D_{lk}}{C_k} v_l^{new} \right) - H_j v_j^{new} = O_j - \sum_{k=1}^{T} \frac{D_{jk}F_k}{C_k} \tag{4.4.16}$$

Equation (4.4.16) can be written in matrix form

$$\left[Q_{jl}\right]_{M\times M} \left[v_j\right]_{M\times l} = \left[R_j\right]_{M\times l} \tag{4.4.17}$$

Where $\left[Q_{jj}\right] = \left(\sum_{k=1}^{T} \frac{D_{jk}D_{jk}}{C_k} \right) - H_j$

$$\left[Q_{jl}\right] = \left(\sum_{k=1}^{T} \frac{D_{jk}D_{lk}}{C_k} \right)$$

$$\left[R_j\right] = O_j - \sum_{k=1}^{T} \frac{D_{jk}F_k}{C_k}$$

v_j^{new} is calculated by solving a matrix of $M \times M$ and λ_k^{new} is calculated from the equation (4.4.17).when the value v_j^{new} and λ_k^{new} is known then ΔP_{ik} and ΔP_{mk} can be calculated from the equation(4.4.8.) and (4.4.9.) respectively.

CHAPTER 5
ERROR BACK PROPAGATION METHOD

5.1 Introduction

Artificial Neural Networks (ANN) are gaining popularity in various fields of engineering including electrical power systems due to their high computational rates and robustness. In this paper an Artificial Neural Network [ANN] based method is proposed. ANN can be defined as a class of mathematical algorithms designed to solve a specific problem. Basically ANNs are parallel computational models comprised of densely interconnected adaptive processing units. An extremely important and human characteristic of ANNs is their adaptive nature, where learning by experience replaces programming in solving problems .A neural network is a computational structure inspired by the study of biological neural processing. There are many different types of neural networks, from relatively simple to very complex, just as there are many theories on how biological neural processing works. One of the ANN models extensively used for power system applications is the multilayer perceptron model based on back propagation algorithm

5.2 Backpropagation

The Backpropagation training algorithm for training feed-forward networks was developed by Paul Werbos, and later by Parker, and Rummelhart and McClelland. This type of network configuration is the most common in use, due to its ease of training. It is estimated that over 80% of all neural network projects in development use backpropagation. In backpropagation, there are two phases in its learning cycle, one to propagate the input pattern through the network and the other to adapt the output, by changing the weights in the network. It is the error signals that are backpropagated in the network operation to the hidden layers. The portion of the error signal that a hidden-layer neuron receives in this process is an estimate of the contribution of a particular neuron to the output error. Adjusting on this basis the weights of the connections, the squared error, or some other metric, is reduced in each cycle and finally minimized, if possible. The feedforward backpropagation network is a very popular model in neural networks. It does not have feedback connections, but errors are backpropagated during training. Least mean squared error is used. Many applications can be formulated for using a feedforward backpropagation network, and the methodology has been a model for most multilayer neural networks. Errors in the output determine measures of hidden layer output errors, which are used as a basis for adjustment of connection weights between the input and hidden layers. Adjusting the two sets of weights between the pairs of layers and recalculating the outputs is an iterative process that is carried on until the errors fall below a tolerance level. Learning rate parameters scale the adjustments to weights. A momentum parameter can also be used in scaling the adjustments from a previous iteration and adding to the adjustments in the current iteration.

5.2.1 Mapping

The feedforward backpropagation network maps the input vectors to output vectors. Pairs of input and output vectors are chosen to train the network first. Once training is completed, the weights are set and the network can be used to find outputs for new inputs. The dimension of the input vector determines the number of neurons in the input layer, and the number of neurons in the output layer is determined by the dimension of the outputs. If there are k neurons in the input layer and m neurons in the output layer, then this network can make a mapping from k-dimensional space to an m-dimensional space. Of course, what that mapping is depends on what pair of patterns or vectors are used as example to train the network, which determine the network weights. Once trained, the network gives the image of a new input vector under the mapping. Knowing mapping, the feedforward backpropagation network to be trained for implies the dimensions of the input space and the output space, so that you can determine the numbers of neurons to have in the input and output layers.

5.2.2 Layout

The architecture of a feedforward backpropagation network is shown in Figure 5.1. While there can be many hidden layers, we will illustrate this network with only one hidden layer. Also, the number of neurons in the input layer and that in the output layer are determined by the dimensions of the input and output patterns, respectively.

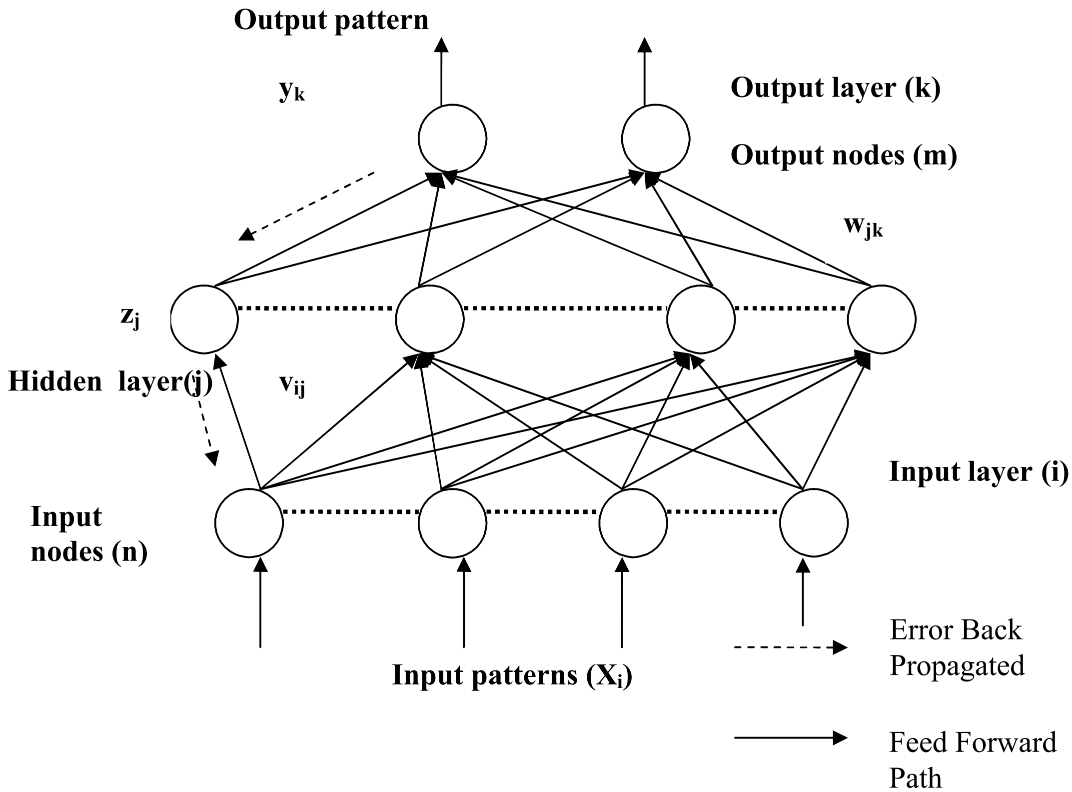

FIG 5.1 A 3 Layered Perceptron Model of ANN

5.2.3 Training

The feed-forward back propagation network undergoes supervised training, with a finite number of pattern pairs consisting of an input pattern and a desired or target output pattern. An input pattern is presented at the input layer. The neurons here pass the pattern activations to the next layer neurons, which are in a hidden layer. The outputs of the hidden layer neurons are obtained by using perhaps a bias, and also a threshold function with the activations determined by the weights and the inputs. These hidden layer outputs become inputs to the output neurons, which process the inputs using an optional bias and a threshold function. The final output of the network is determined by the activations from the output layer. The computed pattern and the input pattern are compared, a function of this error for each component of the pattern is determined, and adjustment to weights of connections between the hidden layer and the output layer is computed. A similar computation, still based on the error in the output, is made for the connection weights between the input and hidden layers. The procedure is repeated with each pattern pair assigned for training the network. Each pass through all the training patterns is called a *cycle* or an *epoch.* The process is then repeated as many cycles as needed until the error is within a prescribed tolerance.

5.3 Issues Related to the ANN Model

5.3.1 Issues Related to the Representation of ANN Model

i) Type of ANN model

ii) Number of hidden layers and nodes.

5.3.2 Issues Related to Training of the ANN

i) Convergence Difficulties

A selective update technique has been suggested to overcome slow convergence when a valley is encountered.

ii) Normalization of Variables

If any of the variables, say output vector assumes value close to unity (l) or zero (0), it causes difficulty in training as the values unity or zero are practically never realized by the activation or threshold function. A way to overcome this difficulty is to normalize the variables (X_i to remain between some suitable range (say 0.1 to 0.9). If X_{min} and X_{max} are the possible minimum and maximum limiting values of variables, its normlized values can be written as :

$$X_i = \frac{(X_i - X_{\min}) \times 0.8}{X_{\max} - X_{\min}} + 0.1$$

while testing the ANN, the variables are reconverted to their actual values.

iii) Number of training sets

The accuracy of ANN model depends on the number of input patterns for which it has been trained in a given range. The number of patterns for a given problem can be established through experimentation. As the system size and complexity increases, number of training sets required may become prohibitively large.

iv) Initial Weights for Training

In literature no systematic procedure is available on choice of initial weights assigned to the interconnections between two nodes. Choice of random initial weights, far away from the optimum point, may result into increased number of iterations for convergence of training algorithm, thus increasing substantially the training time. Hence, the motivation was to explore some basis for selecting the values of initial weights observing the trend of the weight patterns.

(v) Choice of Learning Constant (α)

For multi-layer perceptron model using back propagation algorithm (BPA) for training, the function must be differentiable. It is worth exploring the effect of selecting a different value of α on accuracy of test results for a specific problem. The value of α can be taken as between 0.5 to 0.9.

5.4 Merits and Demerits of Back Propagation

Merits

1. This method can be applied any network and does not require any special mention of the features of the function to be learnt.
2. The computing time is reduced if the weights chosen are small at the beginning.
3. The batch update of weight exists, which provides a smoothing effect on the weight correction terms.

Demerits

1. The number of learning steps may be large and also the learning phase has intensive calculations.
2. The selection of number of hidden nodes in the network may be a problem .if the number of hidden neurons is small, then the function to be learnt may not be possibly represented as the capacity is small. If the numbers of hidden neurons are increased, the number of independent variable of the error function also increases and the computing time also increases rapidly.
3. The network may get trapped in local minima even though there is much deeper minimum nearby.

5.5 Back Propagation Algorithm for Hydro Thermal Scheduling

1. Read the input value (X_i), where X_i is the initial values of power generation which is calculated from equal share vector method as described in conventional method, target values *(T)*,where *T* is the output power vector obtained from conventional method, momentum constant (η), learning rate coefficient *(a)*, maximum number of iterations *(itrmax)*, neurons in hidden layer *(h)*, input nodes (n), output nodes(m), maximum value of input (X_{max}) which is the maximum value of active power generation, minimum value of input X_{min} is the minimum value of active power generation, bias on the hidden unit (V_{oj}), w_{ok} (bias on the output unit k) and tolerance *(ε)*.
2. Normalize the input vector

$$X_i = \frac{(X_i - X_{\min}) \times 0.8}{(X_{\max} - X_{\min})} + 0.1 \tag{5.5.1}$$

   Where X_i is the matrix of initial values of power generation.
3. Generate the random weights (w) and bias vector(v) of small values.
4. Set I =*1* and set mse (mean of squared error) = 0.0.
5. Each hidden unit (z_j,j= 1,2….,h) sums its weighted input signals.

$$z_{inj} = v_{oj} + \sum_{i=1}^{n} x_i v_{ij} \tag{5.5.2}$$

6. Applying activation function $Z_j = \dfrac{1}{1+e^{-\lambda z_{inj}}}$ and sends signal to all units in layer above i.e. output units. The value of λ is taken as 1.
7. Each output unit (y_k, k =1, 2,…...m) sums its weighted input signals as :

$$y_{ink} = w_{ok} + \sum_{j=1}^{h} z_j w_{jk} \tag{5.5.3}$$

   where w_{ok} is bias on output unit k.
8. Applies its activation function to calculate the output of the network .

$$Y_k = \frac{1}{1+e^{-\lambda y_{ink}}} \tag{5.5.4}$$

9. Each output unit (y_k, k=1, 2…….m) receives a target pattern corresponding to

an input pattern , error information term is calculated as

$$\delta_k = (t_k - y_k)Y_k \tag{5.5.5}$$

10. Each hidden unit (z_j, j=1,2……..h) sums its delta inputs from units in the layer above.

$$\delta_{inj} = \sum_{k=1}^{m} \delta_j w_{jk} \tag{5.5.6}$$

The error information term is calculated as

$$\delta_j = \delta_{inj} Z_j$$

Error is calculated as (e_k) = (t_k- y_k)

11. Calculate the sum of square of errors (sse)= e_k* e_k and mse (mean of squared error)

$$\text{mse=sse/2} \tag{5.5.7}$$

12. Each output unit (y_k , k=1,2… m) update its bias and weights (j=1,……h) and the weight correction term is given as:

$$\Delta w_{jk} = \alpha \delta_k z_j \tag{5.5.8}$$

the bias correction factor is given as:

$$\Delta w_{ok} = \alpha \delta_k \tag{5.5.9}$$

update the weights of output unit

$$w_{jk}(new) = \Delta w_{jk} + w_{ok}(old) \tag{5.5.10}$$

13. Each hidden unit (z_j , j=1,2… p) update its bias and weights (i=0,……n) and the weight correction term is given as:

$$\Delta v_{ij} = \alpha \delta_j X_i + \eta v_{ij}(old) \tag{5.5.11}$$

the bias correction factor is given as:

$$\Delta v_{ok} = \alpha \delta_j$$

Therefore $v_{ij}(new) = \Delta v_{ij} + v_{ij}(old)$

14. If I<itrmax go to step 4.
15. Check for tolerance, if ms$e$ > ε then go to step 4.
16. Stop.

CHAPTER 6

RESULTS AND DISSCUSSION

Introduction:

The approximate Newton Raphson Method is implemented on test system with and without considering the effect of valve loadings. The error back propagation method is also implemented on same test system and the results of these three algorithms are compared.

6.1 Case Study 1

Hydro Thermal Scheduling Without Valve loading Using Approximate Newton Raphson Method

Test System

This is a system having one thermal plant and one hydro plant. The fuel cost of the thermal plant and the hydro plant discharge characteristics are given below :

$F_1=0.001991P_1^2+9.606P_1+373.7$ Rs./hr

$Q_2= 0.0007749P_2^2+0.009079P_2+61.53$ M cubic ft per hr.

Data for Thermal Plant

Cost of the ith unit	a_i	b_i	c_i
1.	0.001991	9.606	373.7

Data for Hydro Plant

Discharge coefficients	x_j	y_j	z_j
2.	0.0007749	0.009079	61.53

Generator Real Power Limits

Generator	**Min. Active Power Generation (MW)**	**Max. Active Power Generation (MW)**
1 (Thermal unit)	170	500
2 (Hydro unit)	200	300

The volume of water available for a dispatch period of one day is:

V = 2559.6 M cubic ft .

The loss formula coefficients are:

B_{11}=0.00005, B_{12}= 0.00001, and B_{22}=0.00015 per MW

The load demands during different interval is shown below in the graph between the load demand and time interval is shown in fig 6.1.

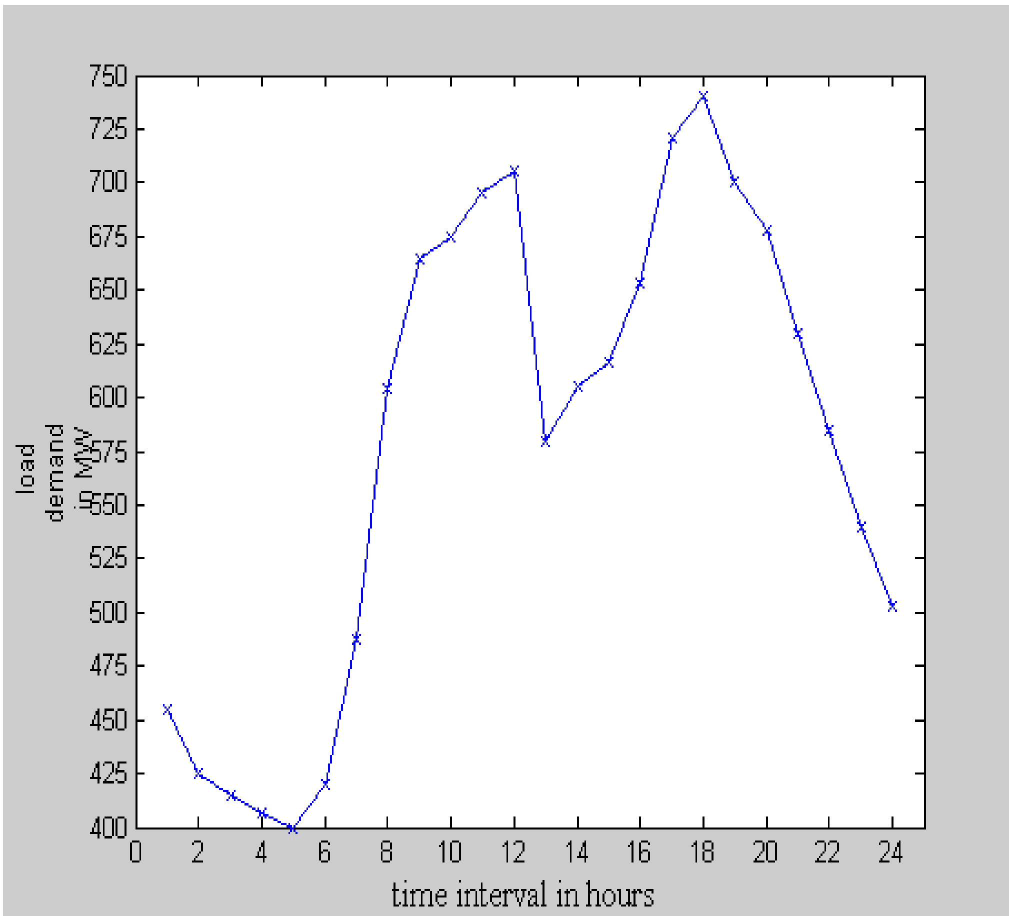

Fig 6.1 Load Demand Over a Day

Results

The hourly power demand for the dispatch period and the corresponding values of power output is given in table 6.1. and the fuel cost , water discharge and incremental cost are given in table 6.2.

Table 6.1 Thermal, Hydro generation and Losses Corresponding to Load Demand Over a Day Without Valve Point Loading

Time interval (Hrs.)	Load Demand (P_{DK}) ((MW)	Output Power of thermal unit (P_{ik}) (MW)	Output Power of hydro unit (P_{jk}) (MW)	Losses $Ploss_k$ (MW)
1	455	233.750219	229.316059	7.8879
2	425	206.630684	225.904598	7.6549
3	415	197.592150	224.766047	7.5780
4	407	190.361793	223.854708	7.5166
5	400	184.035571	223.056926	7.4632
6	420	202.111336	225.335409	7.6164
7	487	262.684272	232.947911	8.1397
8	604	368.532998	246.162635	9.0894
9	665	423.756303	253.010588	9.6022
10	675	432.811778	254.130366	9.6873
11	695	450.924835	256.367482	9.8586
12	705	459.982420	257.484810	9.9448
13	580	346.812847	243.460362	8.8909
14	605	369.438090	246.275133	9.0977
15	616	379.394560	247.512095	9.1893
16	653	412.890656	251.665789	9.5004
17	721	474.476028	259.270814	10.0832
18	740	491.689547	261.388917	10.2486
19	700	455.453539	256.926249	9.9017
20	678	435.528557	254.466142	9.7130
21	630	392.067641	249.085038	9.3065
22	585	351.337552	244.023702	8.9321
23	540	310.621346	238.946788	8.5643
24	503	277.153855	234.7611	8.2669

Table 6.2 Fuel Cost, Incremental Cost and Water Discharge Corresponding to Load Demand Over a Day Without Valve Point Loading

Time Interval (k) (Hrs.)	Load Demand (P_{DK}) (MW)	Fuel Cost (F_k) (Rs./hr)	Incremental cost (λ_k) (Rs/MWh)	Water discharge (q_{jk}) (M cubic ft. per hr.)
1	455	2727.9	10.839	104.36
2	425	2443.6	10.695	103.13
3	415	2349.5	10.648	102.72
4	407	2274.5	10.609	102.39
5	400	2209	10.576	102.11
6	420	2396.5	10.671	102.92
7	487	3034.4	10.994	105.69
8	604	4184.2	11.565	110.72
9	665	4801.8	11.867	113.43
10	675	4904.3	11.916	113.88
11	695	5110.1	12.016	114.79
12	705	5213.6	12.066	115.24
13	580	3944.7	11.446	109.67
14	605	4194.3	11.569	110.76
15	616	4304.7	11.624	111.25
16	653	4679.4	11.807	112.89
17	721	5379.7	12.147	115.97
18	740	5578.2	12.242	116.85
19	700	5161.8	12.041	115.01
20	678	4935.1	11.931	114.02
21	630	4446	11.693	111.87
22	585	3994.4	11.471	109.89
23	540	3549.6	11.251	107.94
24	503	3189	11.071	106.37

Other Results:

Total fuel cost is 95006.179193 Rs. and the total discharge is 2633.890601 M cubic per and v_j is 27.547.

The thermal power generation over a day is shown in fig. 6.2.

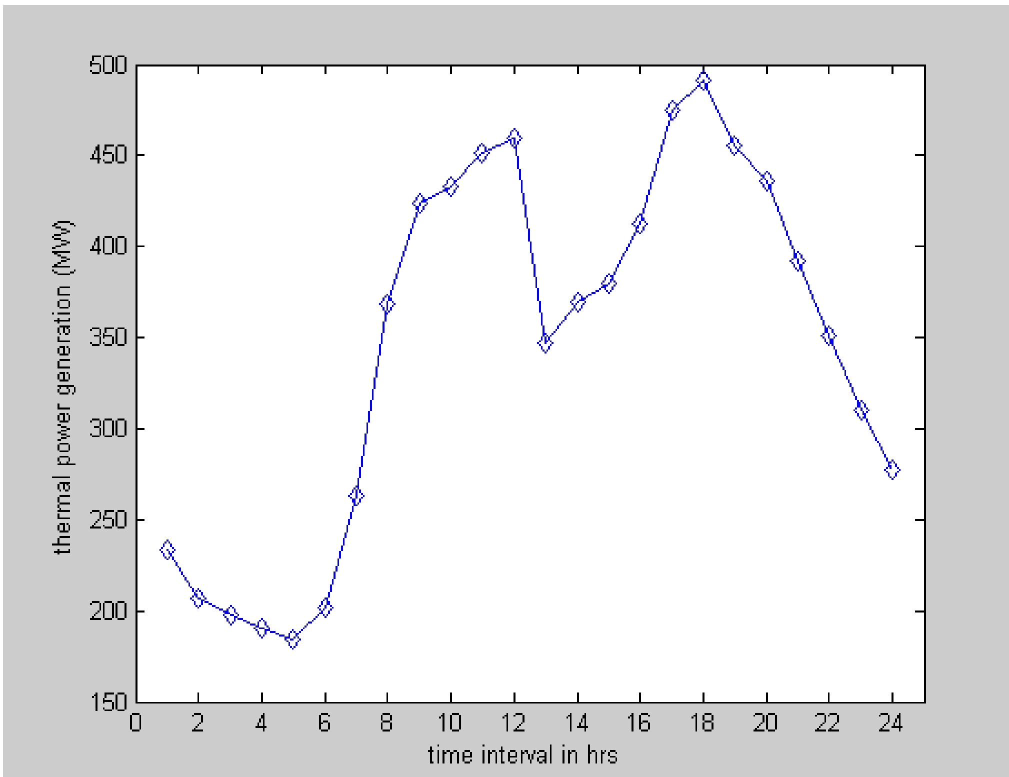

Fig 6.2 Thermal Power Generation Over a day Without Valve Point Loading

The hydro power generation over a day and the combined graph between load demand, thermal generation and hydro generation over a day is shown in fig 6.3 and 6.4 respectively.

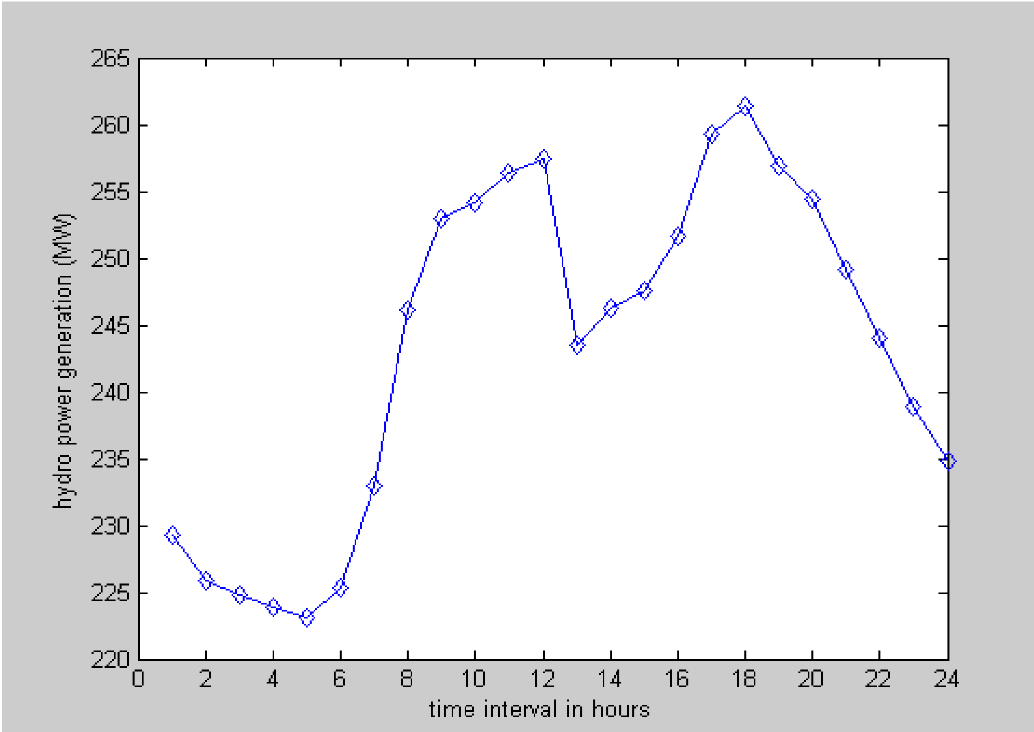

Fig 6.3 Hydro Power Generation over a Day Without Valve Point Loading

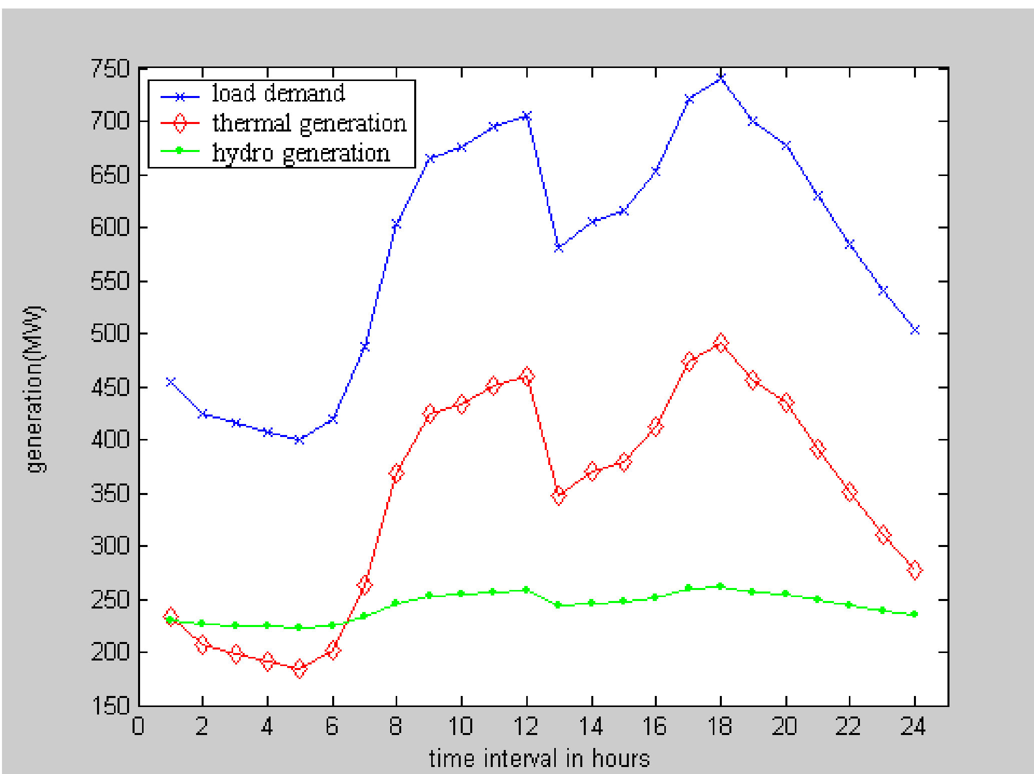

Fig 6.4 Load demand, Thermal Generation, Hydro Generation Over a Day Without Valve Point Loading

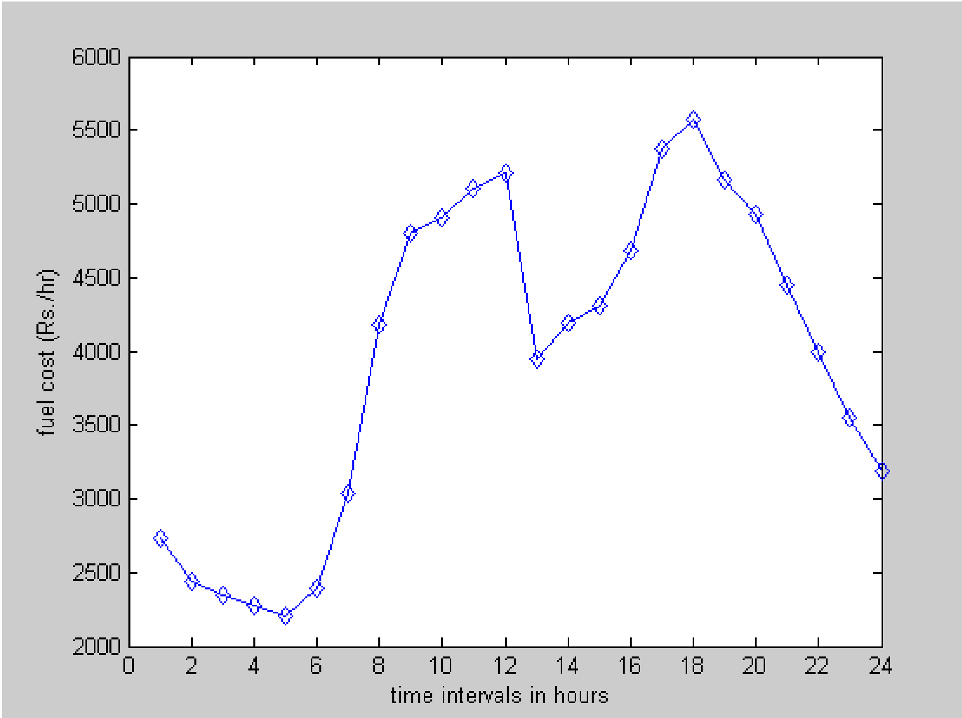

Fig 6.5 Fuel Cost Over a Day Without Valve Point Loading

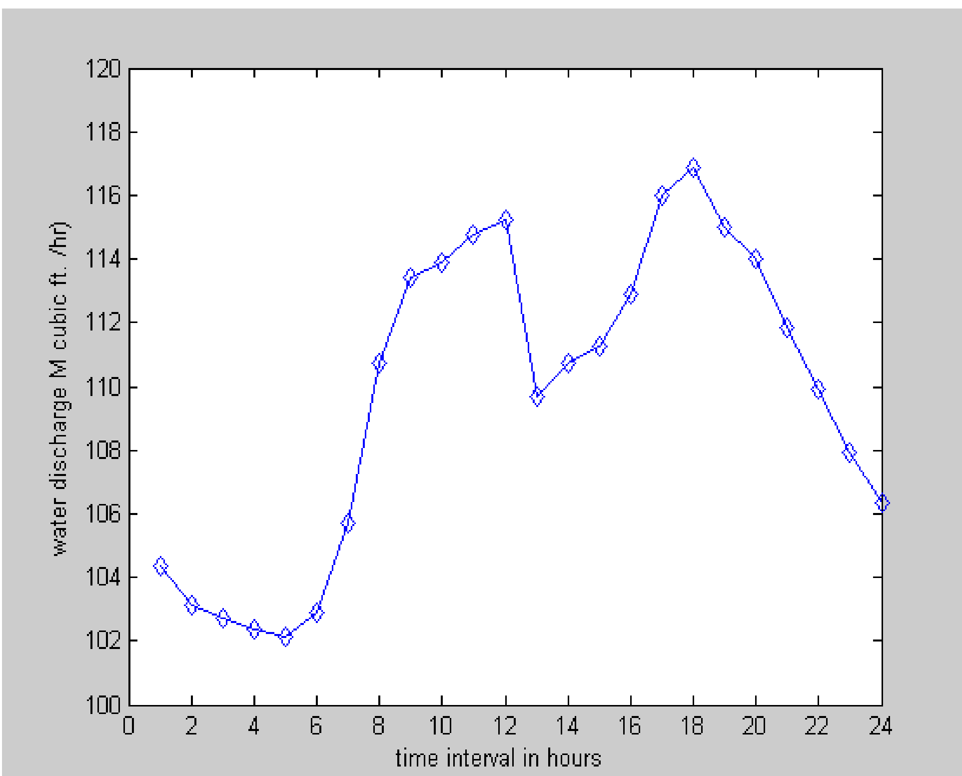

Fig 6.6 Water Discharge Over a Day Without Valve Point Loading

6.2 Case Study 2

Hydro thermal scheduling With Valve Point Loading Using Approximate Newton Raphson Method

This is a system having one thermal plant and one hydro plant. The fuel cost of the thermal plant and the hydro plant discharge characteristics are given below :

$$F_1 = 0.001991P_1^2 + 9.606P_1 + 373.7 + \left|300 * \sin(0.04\left(P_{min} - P(i,k)\right)\right|$$

$Q_2 = 0.0007749P_2^2 + 0.009079P_2 + 61.53$ M cubic per hr.

Data for thermal plant

Cost of the i^{th} unit	a_i	b_i	c_i	d_i	e_i
1.	0.001991	9.606	373.7	300	0.04

Data for hydro plant

Discharge coefficients	x_j	y_j	z_j
2.	0.0007749	0.009079	61.53

Generator real power limits

Generator	**Min. Active Power Generation (MW)**	**Max. Active Power Generation (MW)**
1 (Thermal unit)	170	500
2 (Hydro unit)	200	300

The volume of water available for a dispatch period of one day is:

V = 2559.6 M cubic ft per hr.

The loss formula coefficients are:

B_{11}=0.00005, B_{12}= 0.00001, and B_{22}=0.00015 per MW

Results

The load demand during different time interval is same as in case study 6.1. The hourly power demand for the dispatch period and the corresponding values of power output of thermal and hydro unit are given in table 6.3.

Table 6.3 Thermal, Hydro generation and Losses Corresponding to Load Demand Over a Day without Valve Point Loading

Time Interval (k) (Hrs.)	Load Demand ($P_{DK)}$ (MW)	Output Power of thermal unit (MW	Output Power of hydro unit (MW)	$Ploss_k$ (losses in MW)
1	455	218.9221	244.8718	8.9943
2	425	193.1839	239.9646	8.6374
3	415	186.9651	235.8655	8.3449
4	407	186.4079	227.9807	7.7963
5	400	185.6513	221.3722	7.3508
6	420	188.4821	239.5783	8.6097
7	487	247.3707	249.0702	9.3054
8	604	289.6236	330.3480	16.369
9	665	330.9558	352.7172	18.661
10	675	332.9551	361.5434	19.607
11	695	337.2605	378.9199	21.537
12	705	339.1724	387.8948	22.569
13	580	268.8538	326.4035	15.981
14	605	290.4378	330.5671	16.391
15	616	299.2305	333.1542	16.649
16	653	331.2903	339.2164	17.26
17	721	341.5018	403.0827	24.371
18	740	349.1317	415.9129	25.948
19	700	338.2488	383.3701	22.046
20	678	333.6105	364.1351	19.889
21	630	310.1557	336.7359	17.009
22	585	273.4287	326.9608	16.036
23	540	260.4286	292.1063	12.799
24	503	258.9493	253.9615	9.6745

Table 6.4 Fuel Cost, Incremental Cost and Water Discharge Corresponding to Load Demand Over a Day Without Valve Point Loading

Time Interval (k) (Hrs.)	Load Demand (P_{DK}) (MW)	Fuel Cost (F_k) (Rs/hr.)	Incremental cost (λ_k) (Rs/MWh)	Water discharge (q_{jk}) (M cubic ft per hr.)
1	455	2850	-0.60336	110.22
2	425	2543.7	-0.3664	108.33
3	415	2427.6	-0.32917	106.78
4	407	2416.6	-0.38657	103.88
5	400	2401.5	-0.42847	101.51
6	420	2457.1	-0.31559	108.18
7	487	2885.8	-0.81761	111.86
8	604	3622	-0.7303	149.09
9	665	3817.3	-0.99437	161.14
10	675	3862.6	-0.96297	166.1
11	695	3958.7	-0.88396	176.23
12	705	4000.4	-0.82886	181.65
13	580	3318	-0.51233	147.05
14	605	3629.9	-0.73785	149.21
15	616	3695.6	-0.81476	150.56
16	653	3824.9	-1.0601	153.78
17	721	4050	-0.71019	191.09
18	740	4201.8	-0.68085	199.35
19	700	3980.3	-0.85799	178.9
20	678	3877.4	-0.95309	167.58
21	630	3732.5	-0.89957	152.45
22	585	3400.8	-0.56456	147.34
23	540	3147.8	-0.7017	130.3
24	503	3116	-0.88358	113.81

The thermal power generation and hydro power generation over a day is shown in figure 6.5 and 6.6 respectively.

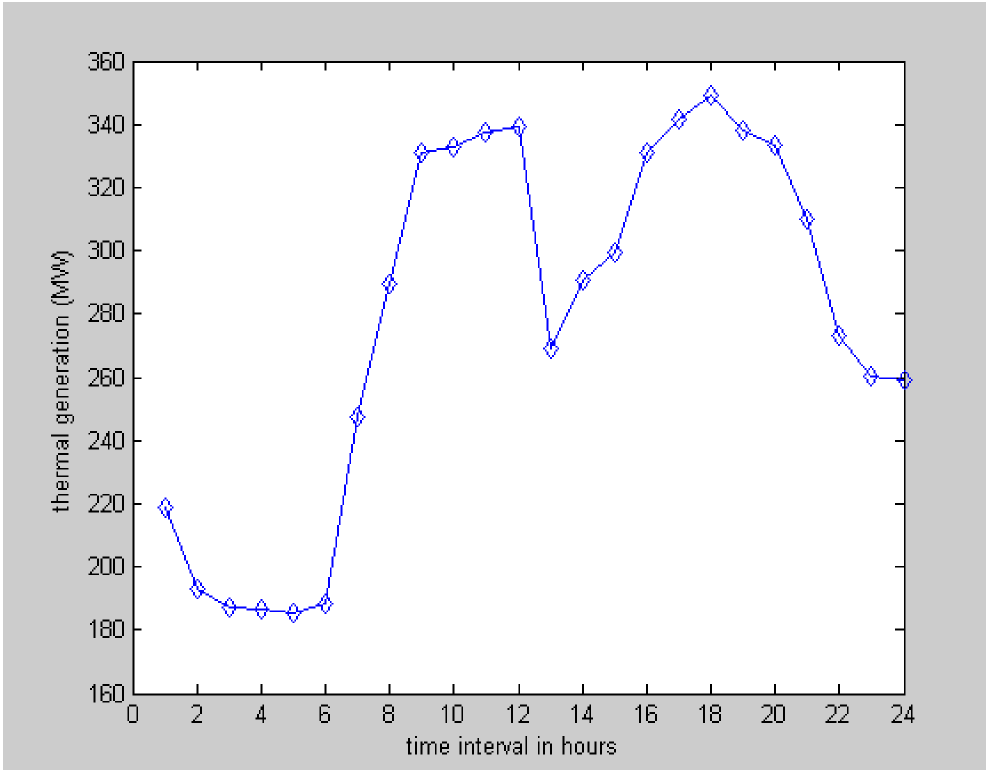

Fig 6.7 Thermal Power Generation Over a Day With Valve Point Loading

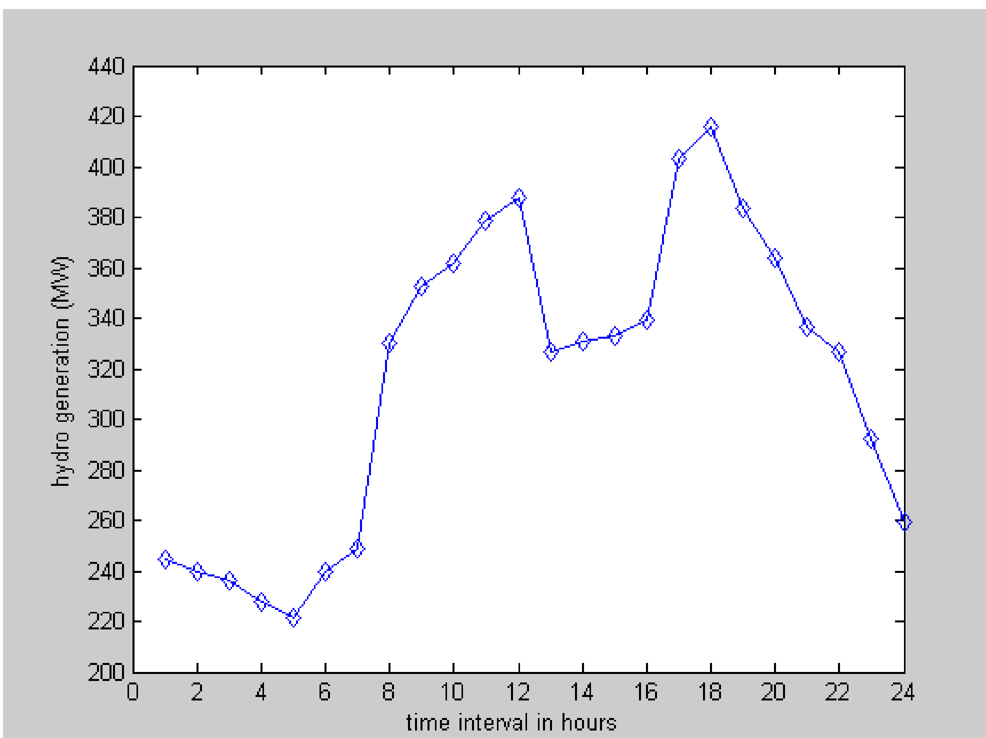

Fig 6.8 Hydro Power Generation Over a Day with Valve Point Loading

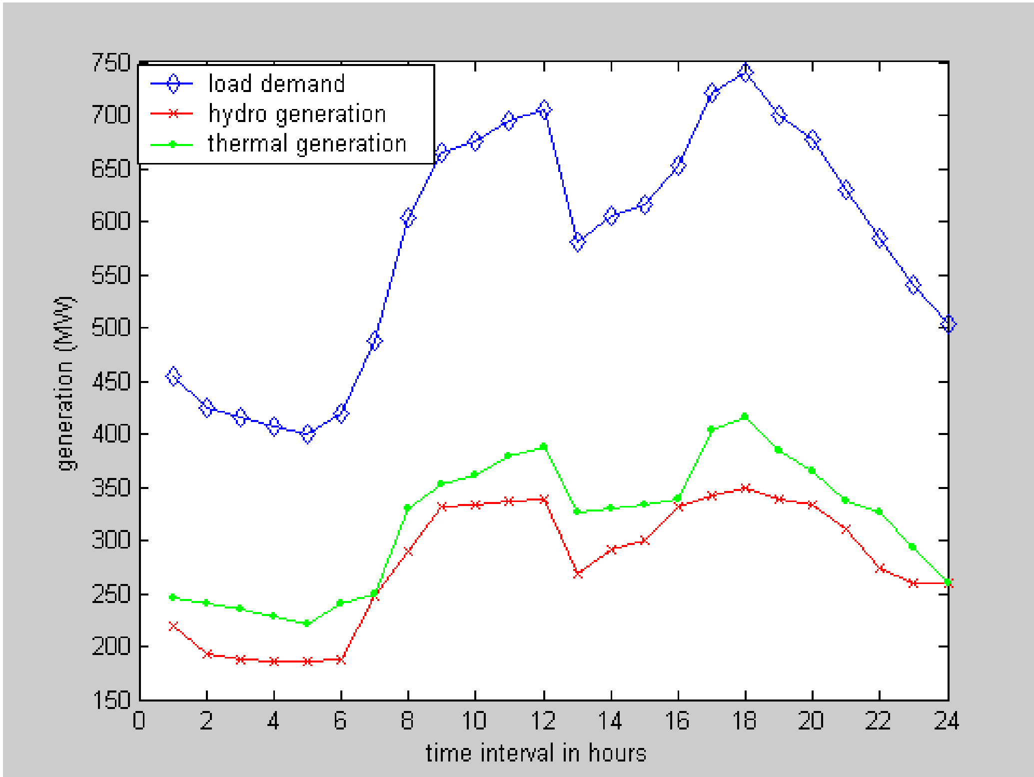

Fig 6.9 Load Demand , Thermal Generation and Hydro Generation Over a Day With Valve Point Loading

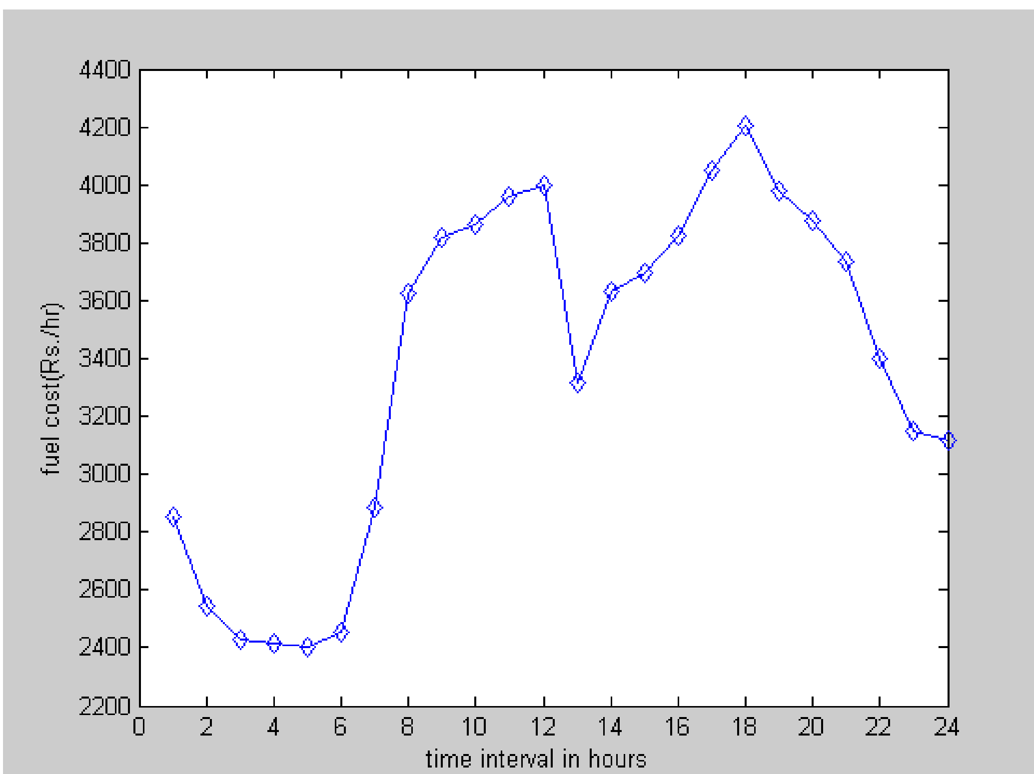

Fig 6.10 Fuel Cost Over a Day With Valve Point Loading

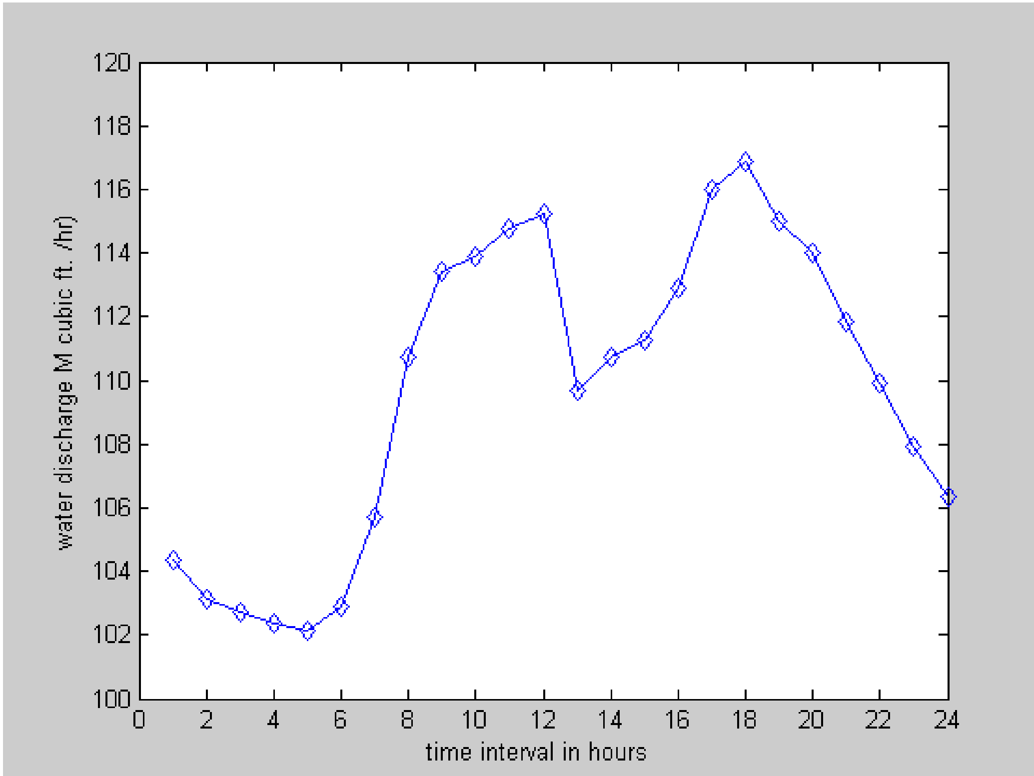

Fig 6.11 Water Discharge Over a Day With Valve Point Loading

Other Results:

Total fuel cost is 81218.431279 Rs and the total discharge is 3466.4 M cubic ft. per hr and $V_{j\ is}$ -2.1011.

Case study 3:

Hydro thermal scheduling using error back propagation method without valve point loading

Data for Thermal Plant

Cost of the ith unit	a_i	b_i	c_i
1.	0.001991	9.606	373.7

Data for Hydro Plant

Discharge coefficients	x_j	y_j	z_j
2.	0.0007749	0.009079	61.53

Generator Real Power Limits

Generator	**Min. Active Power Generation (MW)**	**Max. Active Power Generation (MW)**
1 (Thermal unit)	170	500
2 (Hydro unit)	200	300

The volume of water available for a dispatch period of one day is:
V = 2559.6 M cubic f t.
The loss formula coefficients are:
B_{11}=0.00005, B_{12}= 0.00001, and B_{22}=0.00015 per MW

Results

The hourly load demand for the dispatch period and the corresponding values of training patterns in different time interval are shown in table 6.5 and the thermal generation, hydro generation and error in thermal and hydro generation is shown in table 6.6 . The values of input vector calculated from equal share vector method from conventional method .The hourly demand and the corresponding values of fuel cost and water discharge and losses are shown in table 6.7.

η = 0.9, alpha= 0.7, epochs (iterations)=35 .

Table 6.5 Input Vector and its Normalized Values Corresponding to Load Demand Without Valve Point Loading

Time Interval (k) (Hrs.)	Load Demand (P_{DK}) (MW)	Input vector X_i (MW)		Normalised Values of X_i	
1	455	227.5	227.5	0.23939	0.23939
2	425	212.5	212.5	0.20303	0.20303
3	415	207.5	207.5	0.19091	0.19091
4	407	203.5	203.5	0.18121	0.18121
5	400	200	200	0.17273	0.17273
6	420	210	210	0.19697	0.19697
7	487	243.5	243.5	0.27818	0.27818
8	604	302	302	0.42	0.42
9	665	332.5	332.5	0.49394	0.49394
10	675	337.5	337.5	0.50606	0.50606
11	695	347.5	347.5	0.5303	0.5303
12	705	352.5	352.5	0.54242	0.54242
13	580	290	290	0.39091	0.39091
14	605	302.5	302.5	0.42121	0.42121
15	616	308	308	0.43455	0.43455
16	653	326.5	326.5	0.47939	0.47939
17	721	360.5	360.5	0.56182	0.56182
18	740	370	370	0.58485	0.58485
19	700	350	350	0.53636	0.53636
20	678	339	339	0.5097	0.5097
21	630	315	315	0.45152	0.45152
22	585	292.5	292.5	0.39697	0.39697
23	540	270	270	0.34242	0.34242
24	503	251.5	251.5	0.3303	0.3303

Table 6.6 Thermal, Hydro Generation and Error Corresponding to Load Demand Over a Day Without Valve Point Loading Using Error Back Propagation

Time Interval (k) (Hrs.)	Load Demand ($P_{DK)}$ (MW)	Thermal Generation (MW)	Hydro Generation (MW)	Mean of squared error (mse) in thermal generation (MW)	Mean of squared error (mse) in hydro generation (MW)
1	455	233.7404	229.3005	0.0096	0.0195
2	425	206.6239	225.8812	0.0061	0.0188
3	415	197.5848	224.7514	0.0052	0.0000
4	407	190.3555	223.8315	0.0045	0.0185
5	400	184.0361	223.0417	0.0039	0.0183
6	420	202.1043	225.3213	0.0057	0.0187
7	487	262.6661	232.9298	0.0139	0.0202
8	604	368.4927	246.1370	0.0373	0.0230
9	665	423.7061	252.9855	0.0539	0.0245
10	675	432.7533	254.1053	0.0567	0.0247
11	695	450.8569	256.3448	0.0631	0.0252
12	705	459.9137	257.4545	0.0663	0.0255
13	580	346.7784	243.4376	0.0316	0.0224
14	605	369.4026	246.2570	0.0374	0.0230
15	616	379.3497	247.4867	0.0403	0.0233
16	653	412.8396	251.6458	0.0504	0.0242
17	721	474.4082	259.2441	0.0718	0.0259
18	740	491.6115	261.3636	0.0785	0.0264
19	700	455.3852	256.9046	0.0648	0.0254
20	678	435.4724	254.4452	0.0576	0.0248
21	630	392.0260	249.0664	0.0440	0.0236
22	585	351.3074	243.9975	0.0326	0.0225
23	540	310.5969	238.9285	0.0231	0.0215
24	503	277.1335	234.7394	0.0165	0.0206

Table 6.7 Fuel Cost, Water Discharge and Losses Corresponding to Load Demand Over a Day Without Valve Point Loading Using Error Back Propagation

Time Interval (k) (Hrs.)	Load Demand (P_{DK}) (MW)	Fuel Cost (F_k) (Rs/hr.)	Water discharge (q_{jk}) (M cubic ft. per hr.)	Losses $Ploss_k$ MW)
1	455	2727.7	104.36	8.0409
2	425	2443.5	103.12	7.5051
3	415	2349.4	102.71	7.3362
4	407	2274.4	102.39	7.1870
5	400	2208.9	102.10	7.0778
6	420	2396.4	102.92	7.4256
7	487	3034.2	105.69	8.5959
8	604	4183.7	110.71	10.6297
9	665	4801.1	113.42	11.6916
10	675	4903.4	113.87	11.8586
11	695	5109.2	114.78	12.2017
12	705	5212.6	115.23	12.3682
13	580	3944.2	109.66	10.2160
14	605	4193.7	110.76	10.6596
15	616	4304.1	111.24	10.8364
16	653	4678.6	112.89	11.4854
17	721	5378.8	115.96	12.6523
18	740	5577.1	116.84	12.9751
19	700	5160.9	115.01	12.2898
20	678	4934.3	114.01	11.9176
21	630	4445.4	111.86	11.0924
22	585	3994	109.88	10.3049
23	540	3549.3	107.94	9.5254
24	503	3188.7	106.36	8.8729

Other Results

The total fuel cost is 94996.143867 Rs./hr and total discharge is 2633.7metre cubic ft./hr.

The hourly demand and the corresponding values of fuel cost and water discharge and losses are shown in table 6.7.

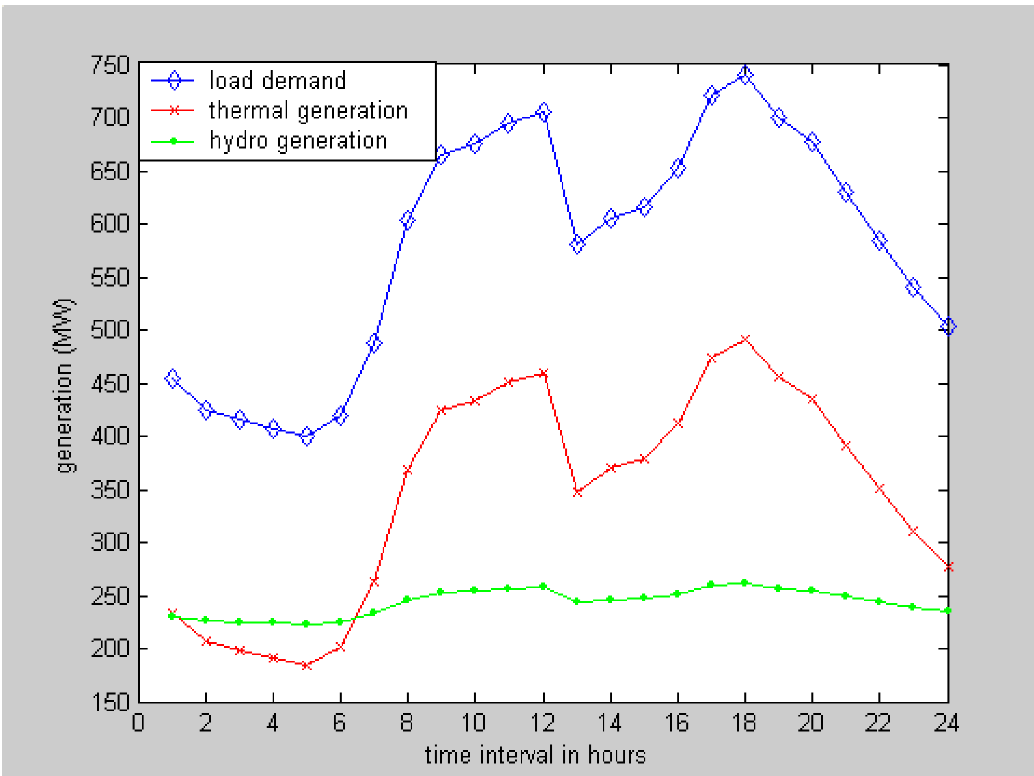

Fig 6.12 Load Demand, Thermal Generation, Hydro Generation Over a Day Without Valve Point Loading

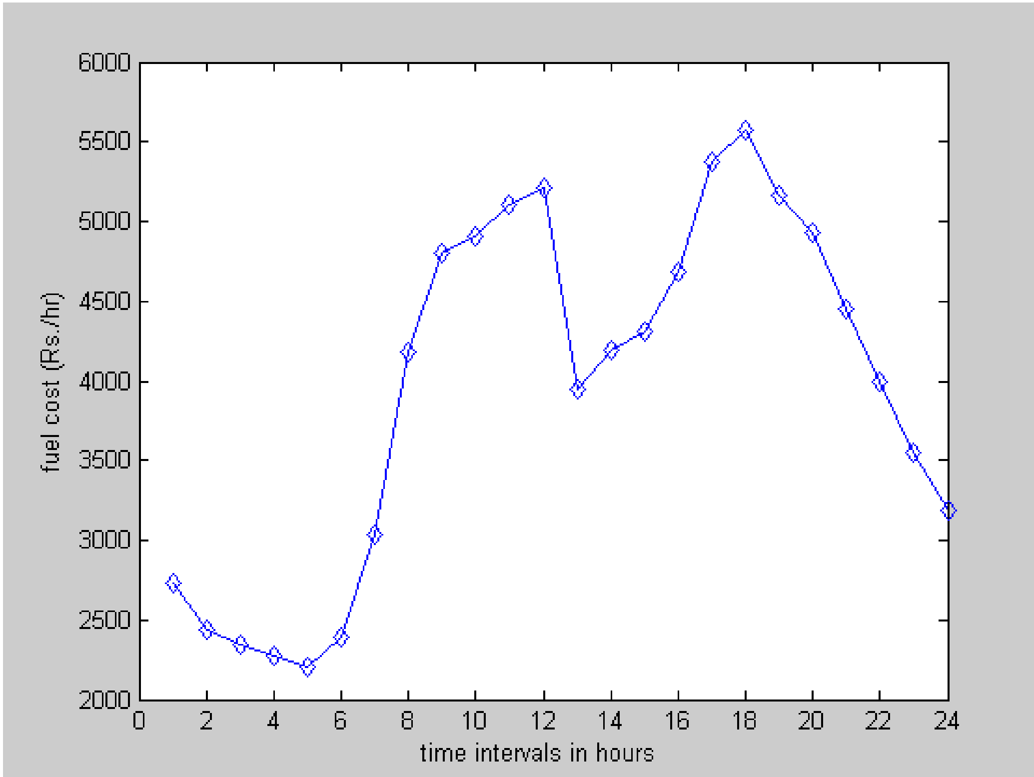

Fig 6.13 Fuel Cost Over a Day Without Valve Point Loading

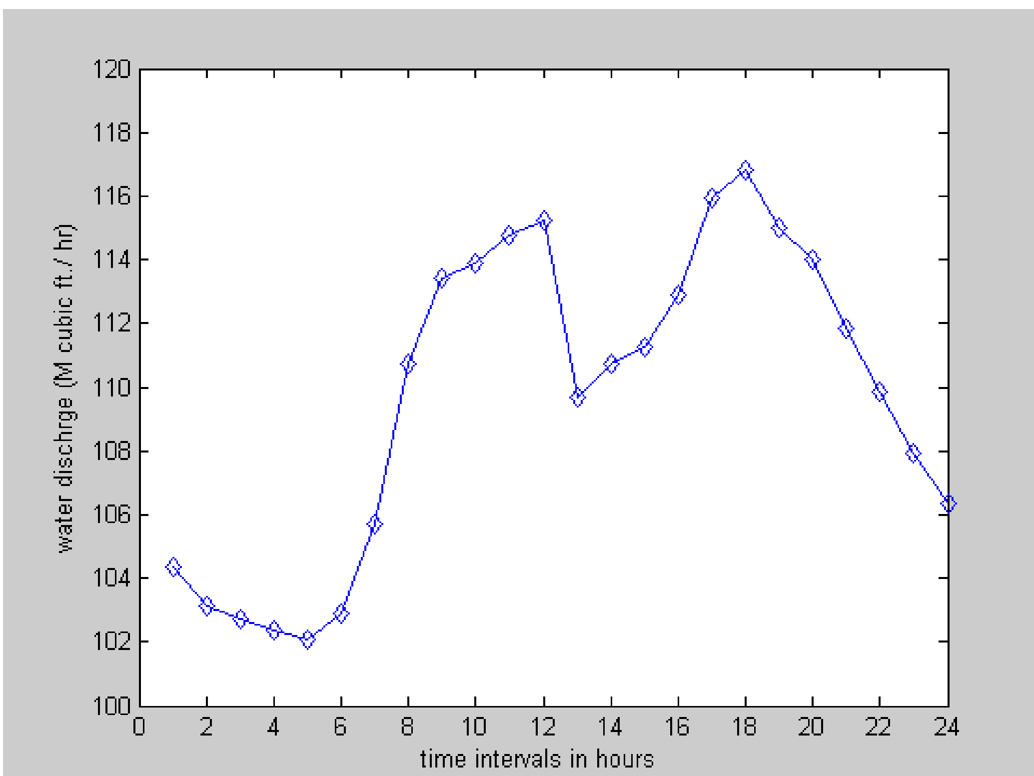

Fig 6.14 Water Discharge Over a Day Without Valve Point Loading

Case study 4:

Hydro Thermal Scheduling Using Error Back Propagation Method With Valve Point Loading

This is a system having one thermal plant and one hydro plant. The fuel cost of the thermal plant and the hydro plant discharge characteristics are given below :

$$F_1 = 0.001991P_1^2 + 9.606P_1 + 373.7 + \left|300 * \sin(0.04\left(P_{min} - P(i,k)\right)\right|$$

$Q_2 = 0.0007749P_2^2 + 0.009079P_2 + 61.53$ M cubic ft. per hr.

Data for Thermal Plant

Cost of the ith unit	a_i	b_i	c_i	d_i	e_i
1.	0.001991	9.606	373.7	300	0.04

Data for Hydro Plant

Discharge coefficients	x_j	y_j	z_j
2.	0.0007749	0.009079	61.53

Generator Real Power Limits

Generator	**Min. Active Power Generation (MW)**	**Max. Active Power Generation (MW)**
1 (Thermal unit)	170	500
2 (Hydro unit)	200	300

The volume of water available for a dispatch period of one day is:

V = 2559.6 M cubic f t .

The loss formula coefficients are:

B_{11}=0.00005 , B_{12}= 0.00001, and B_{22}=0.00015 per MW

Results

The value of learning constant α is taken as 0.7 and the value of momentum constant is taken as 0.9 and the results which are shown below are obtained in 35 epochs . The hourly load demand for the dispatch period and the corresponding values of training patterns in different time interval are shown in table 6.8 and the thermal generation, hydro generation and error in thermal and hydro generation is shown in table6.9

Table 6.8 Input Vector and its Normalized Values Corresponding to Load Demand With Valve Point Loading

Time Interval (k) (Hrs.)	Load Demand (P_{DK})(MW)	Input vector X_i (MW)		Normalised values of X_i	
1	455	227.5	227.5	0.23939	0.23939
2	425	212.5	212.5	0.20303	0.20303
3	415	207.5	207.5	0.19091	0.19091
4	407	203.5	203.5	0.18121	0.18121
5	400	200	200	0.17273	0.17273
6	420	210	210	0.19697	0.19697
7	487	243.5	243.5	0.27818	0.27818
8	604	302	302	0.42	0.42
9	665	332.5	332.5	0.49394	0.49394
10	675	337.5	337.5	0.50606	0.50606
11	695	347.5	347.5	0.5303	0.5303
12	705	352.5	352.5	0.54242	0.54242
13	580	290	290	0.39091	0.39091
14	605	302.5	302.5	0.42121	0.42121
15	616	308	308	0.43455	0.43455
16	653	326.5	326.5	0.47939	0.47939
17	721	360.5	360.5	0.56182	0.56182
18	740	370	370	0.58485	0.58485
19	700	350	350	0.53636	0.53636
20	678	339	339	0.5097	0.5097
21	630	315	315	0.45152	0.45152
22	585	292.5	292.5	0.39697	0.39697
23	540	270	270	0.34242	0.34242
24	503	251.5	251.5	0.3303	0.3303

Table 6.9 Thermal, Hydro Generation and Error Corresponding to Load Demand Over a Day With Valve Point Loading Using Error Back Propagation

Time Interval (k) (Hrs.)	Load Demand (P_{DK}) (MW)	Thermal generation P_{ik} (MW)	Hydro generation P_{jk} (MW)	Mean of squared error in thermal generation mse (MW)	Mean of squared error in hydro generation mse (MW)
1	455	218.9042	244.8646	0.0179	0.00720
2	425	193.1706	239.9581	.0133	0.0065
3	415	186.9527	235.8594	0.0124	0.0061
4	407	186.3956	227.9754	0.0123	0.0053
5	400	185.6392	221.3676	0.0121	0.0046
6	420	188.4695	239.5718	0.0126	0.0065
7	487	247.3471	249.0626	0.0236	0.0076
8	604	289.5898	330.3270	0.0338	0.0210
9	665	330.9104	352.1462	0.0454	0.0258
10	675	332.9092	361.5156	0.0459	0.0278
11	695	337.2132	378.8877	0.0473	0.0322
12	705	339.1246	387.8604	0.0478	0.0344
13	580	268.8252	326.3833	0.0286	0.0202
14	605	290.4039	330.5461	0.0339	0.0210
15	616	299.1942	333.1326	0.0363	0.0216
16	653	331.2448	339.1935	0.0455	0.0229
17	721	340.9696	403.0441	0.0484	0.0386
18	740	349.0807	415.8706	0.0510	0.0423
19	700	338.2012	383.6676	0.0476	0.0334
20	678	333.5644	364.1067	0.0461	0.0284
21	630	310.1164	336.3367	0.0393	0.0223
22	585	273.3991	326.9406	0.0296	0.0202
23	540	260.4020	292.0924	0.0266	0.0139
24	503	258.9230	253.9532	0.0263	0.0083

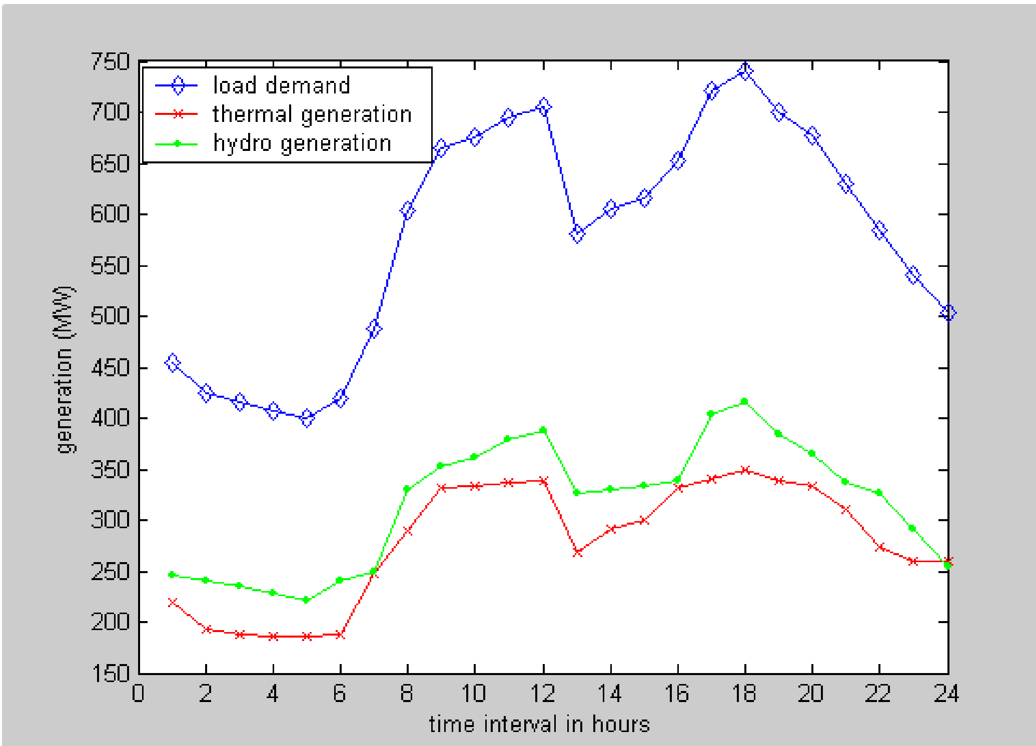

Fig 6.15 Load Demand, Thermal Generation , Hydro Generation Over a Day With Valve Point Loading Using Error Back Propagation

The hourly load demand, fuel cost, water discharge and the losses are shown in table 6.10.

Table 6.10 Fuel Cost, Water Discharge and Losses Corresponding to Load Demand Over a Day With Valve Point Loading Using Error Back Propagation

Time Interval (k) (Hrs.)	Load Demand (P_{DK}) (MW)	Fuel Cost (F_k) (Rs/hr.)	Water discharge (q_{jk}) (M cubic ft per hr.)	$Ploss_k$ (losses in MW)
1	455	2849.9	110.22	8.7688
2	425	2543.5	108.33	8.1287
3	415	2427.4	106.78	7.8121
4	407	2416.3	103.87	7.3710
5	400	2401.2	101.51	7.0068
6	420	2456.9	108.18	8.0413
7	487	2885.8	111.86	9.4097
8	604	3621.7	149.08	15.9168
9	665	3816.2	160.82	18.0566
10	675	3861.6	166.09	19.4248
11	695	3957.7	176.21	21.1009
12	705	3999.3	181.62	21.9850
13	580	3317.5	147.04	15.2085
14	605	3629.6	149.2	15.9500
15	616	3695.4	150.55	16.3268
16	653	3823.8	153.76	17.4383
17	721	4038.8	191.07	23.0137
18	740	4200.8	199.32	24.9513
19	700	3979.3	179.08	21.8688
20	678	3876.4	167.57	19.6711
21	630	3732.5	152.24	16.4531
22	585	3400.3	147.33	15.3397
23	540	3147.2	130.29	12.4944
24	503	3115.4	113.81	9.8762

The total fuel cost is 81195 Rs and total discharge is 3465.8 meter cubic ft.

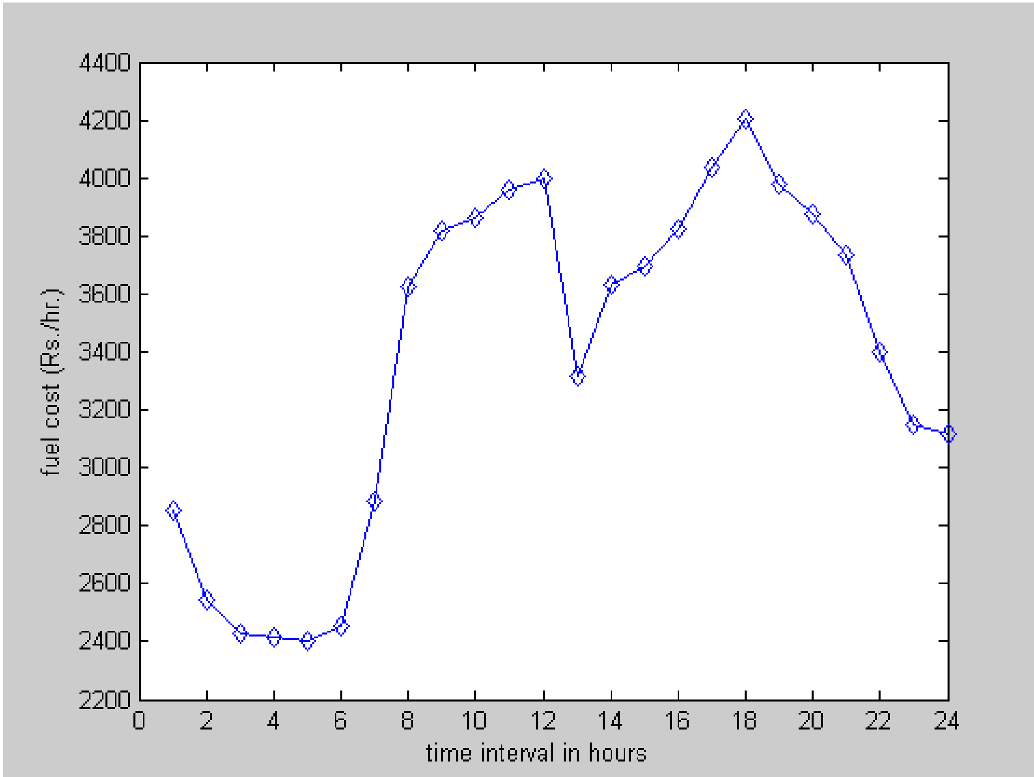

Fig 6.16 Fuel Cost Over a Day With Valve Point Loading Using Error Back Propagation

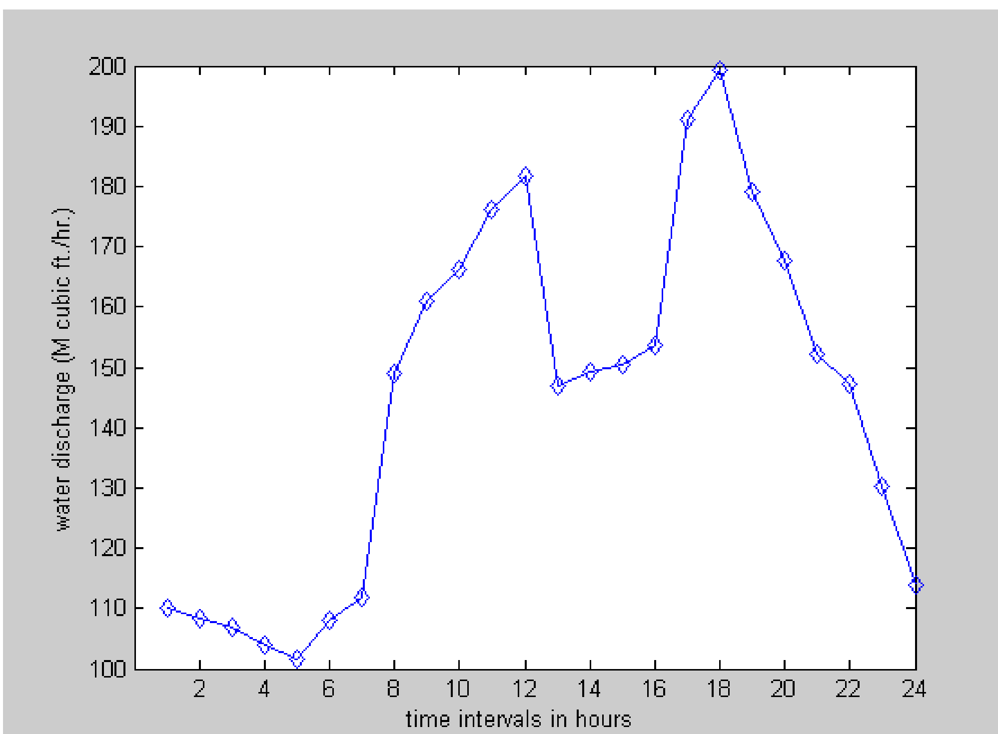

Fig 6.17 Water Discharge Over a Day With Valve Point Loading Using Error Back Propagation

6.5 Comparison of fuel cost

A graph of comparison between fuel cost obtained from the approximate Newton Raphson Method with and without valve loading and Error Back Propagation with and without valve loading point is shown below in fig 6.18.

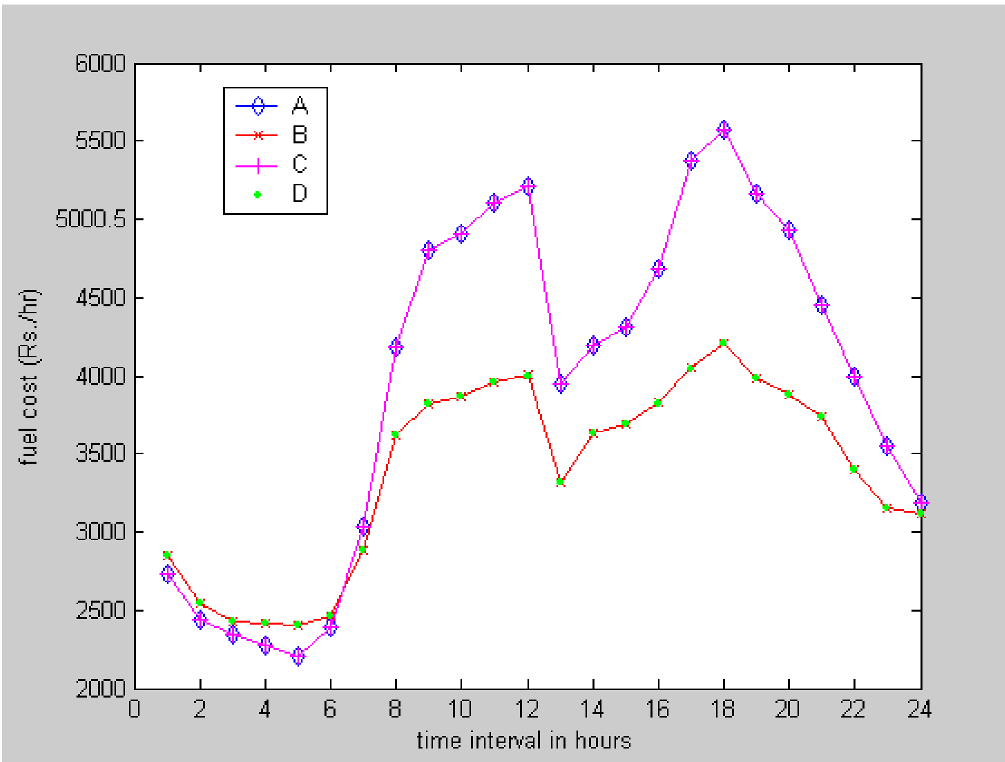

Fig 6.18 Comparison of Fuel Cost Over a Day

A- Fuel cost without valve loading using Approximate Newton Raphson Method

B-Fuel cost with valve loading using Approximate Newton Raphson Method

C-Fuel cost without valve loading using Error Back Propagation Method

D- Fuel cost with valve point loading using Error Back Propagation Method

Thus it can be seen in the above figure that using Approximate Newton Raphson Method and Error Back Propagation Method for both the cases of with and without valve point loading, we get very closer results.

CHAPTER 7
CONCLUSIONS AND FUTURE SCOPE

7.1 Conclusion

An Approximate Newton Raphson method for hydrothermal scheduling algorithm for dealing with nonlinear functions such as the water discharge characteristics, thermal cost and transmission loss is developed. It is then incorporated into the hydrothermal coordination program. The program has been tested on a practical utility system using the data of the generating units and system demands. Approximate Newton Raphson method is developed and demonstrated to solve the hydrothermal scheduling problem with quadratic thermal cost function together with and without valve point loading effect. The hydrothermal scheduling problem with quadratic thermal cost function is easier to solve as compared to the hydrothermal scheduling considering the effect of valve point loading while the hydrothermal scheduling without valve point loading does not give accurate result but hydro thermal scheduling with valve point effect give precise results and minimum cost .

ANN (artificial neural network) models are faster as compared to conventional method (Approximate Newton Raphson Method) and provide accurate result as close to the conventional methods. Here error back propagation method is used to solve the hydro thermal scheduling with and without valve point loading. EBP(Error Back Propagation Method) gives close result as to the approximate Newton Raphson method and convergence is faster .

7.2 Major Findings

Table 7.1

Method	Approximate Newton Raphson without valve point loading	Approximate Newton Raphson with valve point loading	Error back propagation Without valve point loading	Error back propagation With valve point loading
Thermal cost (Rs)	95006.179193	81218.431279	94996.143867	81195

Thus it can be concluded that the Approximate Newton Raphson method with valve point loading is able to achieve less cost as compared to the Approximate Newton Raphson method without valve loading .The EBP (Error Back Propagation Method) also gives closer results as compared with Approximate Newton Raphson method.

7.3 Future Scope

The work previously presented provides an understanding of new optimization techniques capable of solving complex power systems engineering problems. The economic dispatch problem was covered and the results demonstrate the capability of the algorithm to obtain the desired values. Some lines of future work should be:

- Hydro thermal scheduling using Approximate Newton Raphson method can also be used for the determination of thermal cost functions that consider fuel switching and prohibited operating zones as well as constraints that provide a more accurate representation of the system such as: emissions , line flow limits , ramp rate ,spinning reserve requirement and their results can be compared with the valve point loading effect which is discussed in this thesis. EBP is also used for the determination of all the above cases.
- Application of hybrid intelligent techniques can also be used for hydrothermal scheduling of fixed head and their results can be compared with the error back propagation method.

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