SHORT RANGE FIXED HEAD HYDRO THERMAL SCHEDULING USING PSO

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

Master of Engineering

in

Power Systems & Electric Drives

By:

Surender Singh

(Regn. No. 800841016)

Under the supervision of:

Mr. Nitin Narang

(Asst.Prof.)

EIED

Electrical & Instrumentation Engineering Department

THAPAR UNIVERSITY

PATIALA – 147004

June 2010

Certificate

I hereby certify that the work which is being presented in the thesis entitled, **"Short Range Fixed Head Hydrothermal Scheduling Using PSO"**, 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 **Mr.Nitin Narang (Asst.Prof.)** and refers other researcher's works which are duly listed in the reference section.

The matter presented in this thesis has not been submitted for the award of any other degree of this or any other university.

Surender singh

(Surender singh)

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

NNarang

(Mr. Nitin Narang)

Electrical & Instrumentation Engineering Department

Thapar University

Patiala

Countersigned by

S. Ghosh 12/7/10

(Dr.Smarajit Ghosh)

Head

Electrical & Instrumentation Engineering Department

Thapar University (Patiala)

(Dr.R.K.SHARMA) 16.7.10

Dean (Academic Affairs)

Thapar University,

Patiala.

Acknowledgement

First of all, I wish to express my profound gratefulness and appreciation to **Mr. Nitin Narang (Asst.Prof.)** Department of Electrical And Instrumentation, Thapar University, Patiala, for his patient guidance and support throughout the report. He has been my mentor for help and without whose encouragement the learning would not have been realized.

Before I get into thick of things, I would like to add a few words to express my thanks to **Dr.Smarajit Ghosh,** Head of Electrical & Instrumentation Engineering Department, & all the faculty of EIED Department of Thapar University, Patiala, for their valuable and unstinted advice from time to time.

Thanks are due to my parents for their motivation and inspiration and providing me all time help which has made me to come on this platform.

In the last but not the least, multi million thanks to the Almighty God, who gave me the opportunity and strength to carry out this thesis work.

To conclude, my best regards and thanks are due to them to whom I have forgotten to mention who helped me directly or indirectly in the completion of this thesis successfully and also for the preparation of report.

Surender Shekhawat

Surender Singh

800841016

Abstract

Operation of a system having both hydro and thermal plants is quit more complex. As hydro-power plants have negligible operating cost, but hydro-power plant have higher capital cost in comparison to thermal-power plant and is required to operate under constraints of water available for hydro generation in a given period of time. Whereas the capital cost of thermal-power plant is less than the hydro-power plant, but its operating cost is high than the hydro-power plant as water is used as fuel in hydro-power plant and which is free of cost in comparison to fuel (coal) used in thermal-power plant. The problem of minimizing the operating cost of a hydrothermal system can be viewed as one of minimizing the fuel cost of thermal-power plants and under the constraints of water availability (storage and inflow) for hydro-generation over a given period of operation. Earlier, a wide variety of optimization techniques have been applied to solving the hydrothermal scheduling problems. Particle swarm optimization method is applied to solve short range hydrothermal scheduling. PSO is a stochastic random search technique that helps to avoid local minimum operating point, so best solution can be achieved with fulfillment of all the constraints.

Table of Content

List of Figure

List of Table

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

Plossk…………………………….....Transmission losses during the k^{th}interval

a_i,b_i,c_i……………………………… .Cost coefficients of the thermal units.

Xj,yjzj…………………………………………Discharge coefficients of the hydro units.

V_j……………………………………………….Water conversion factor.

Qjk………………………………………………Rate of discharge from the j^{th}hydro unit in the interval k

λk…………………………………………Incremental cost of power delivered in the system during the k^{th}interval

Fi…………………………………………………..Thermal cost of the i^{th}unit

h……………………………………………………..Effective head

Chapter 1
Introduction

1.1 Overview

A modern power system consists of a large number of thermal and hydro-plants connected at various load centers through a transmission network. An important objective in the operation of such a power system is to generate and transmit power to meet the system load demand at minimum fuel cost by an optimal mix of various types of plants. The study of the problem of optimum scheduling of power generation at various plants in a power system is of paramount importance, particularly where the hydro-sources are scares and high cost of thermal.

Generation has to be relied upon to meet the power demand. The hydro- resources being extremely limited, the worth of water is greatly increased. If optimum use is made of their limited resource in conjunction with the thermal sources, huge saving in fuel and the associated cost can be made.

All hydro-systems are basically different from each other in their characteristics. The reason of this difference are plenty- the chief points being their natural difference in their water areas, difference between release elements, control constraints, non-uniform water flow etc.

Sudden alteration in the volume of water flow due to natural constraints, occurrence of flood, draught and other – natural calamities also affect the hydro scheduling. Navigational requirement of agricultural water may also govern the hydro scheduling. Sometimes, water release may be dictated by treaties between the states and due to the fishing requirements. In certain sectors, however, the hydro- source is sufficiently large, particularly in rainy season as the inflows into the hydro reservoirs exhibits an annual cyclicity. Furthermore, there may be a seasonal variation in power demand on the system, and this too exhibits an annual cylices. The optimization interval of one year duration is thus a natural choice for long range optimal – generation scheduling studies. The solution to the scheduling problem in this case consists of determination of water quantities to be drawn from the reservoirs for hydro-generation in each sub-interval and the corresponding thermal generations to meet the load demand over each sub-interval utilizing the entire quantity of water available for power generation during the total interval. The long range scheduling (generally persisting from months to year) involves mainly the scheduling of water release. Long range scheduling also involves metrological and statistical analysis. The benefit of this scheduling is to save the cost of generation, in addition to meeting the agricultural and irrigational requirements. Long range scheduling involves optimization of the – operating policy in the context of major unknowns such as load, hydroelectric inflows, unit availability etc. The short range problem usually has an optimization interval of a day or a week. This period normally divided in to sub-intervals for scheduled purposes. Here, the load, water inflows and unit availabilities are assumes to be known. A set of starting conditions (i.e. reservoirs levels) being given, the optimal hourly schedule can be prepared that minimizes a desired objective while meeting system constraints successfully.

Cost optimization of hydro stations can be achieved by assuming the water heads constants and converting the incremental water (i.e. fuel) rate characteristics in to incremental fuel cost curves by multiplying it with cost of water per cubic meter and applying the conventional technique of minimizing the cost function [22].

1.2 Literature Review

Hydrothermal scheduling is required in order to find the optimum allocation of hydro energy so that the annual operating cost of a mixed hydrothermal system is minimized. Over the last decade the hydrothermal scheduling problem has been the subject of considerable discussion in the power literature Quintana V.H and Chikhani A.Y, Lyra *et al.* [9,11]. The available methods differ in the system modeling assumptions and the solution. The annual hydrothermal scheduling problem involves the minimization of the annual operating cost of a power system subject to the several equality and inequality constraints imposed by the physical laws governing the system and by the equipment ratings. Different methods have been proposed for the solution of these problems in the past. Variational methods Drake *et al.* [2] uses the optimum operation of a hydrothermal system by using the pontryagins maximum principle. Dahlin E.B and DNC Shen [3] uses optimal solution to the hydro-steam dispatch problem for certain practical systems by using the general mathematical programming. Agarwal S.K and Nagrath I.J [6] use optimal scheduling of hydrothermal systems by the use of dynamic programming. Amado S.M and Rebeiro [14] uses about the short range generation scheduling of hydraulic multi reservoir multi area interconnected systems.W.W-G Yeh *et al*. [18] have been used to solve the problem in different formulations. Methods based on Lagrangian multiplier and gradient search techniques. Lyra *et al.* [8] for finding the most economical hydrothermal generation schedule under practical constraints have been well documented. Kirchmayer L.K [1] utilized calculus of variation for short range fixed head scheduling problem and proposed the well known coordination equations. Pereira M.V.F [13] gives an overview of optimal hydrothermal scheduling for the planning of electric systems so that the operating cost is reduced. Yeh *et al*. [24] this paper uses a novel hybrid chaotic genetic algorithm (HCGA) to solve the short-term generation scheduling of hydro system. The integration of chaotic sequence and genetic algorithm with a new self-adaptive error back-propagation mutation operator are developed, which can overcome premature and increase the convergence speed. Bond P.S and Carnerio A.A.F.M [17] this paper has presented an application of a deterministic algorithm with individualized representation of the hydro plants in the large scale Brazilian south-southeast interconnected hydro thermal system. Costas G. Baslis and Anastasios G. Bakirtzis [28] a mixed-integer programming approach for solving the yearly hydrothermal scheduling problem in a purely competitive electricity market has been presented. A major advantage of the proposed method is the straightforward coordination of medium and short-term decisions, such as monthly endpoint volume targets and hourly unit commitment, respectively, together with the simple and compact formulation of the problem. Suman *et al.* [26] in this paper, a novel method for the solution of the hydrothermal scheduling problem using hybrid evolutionary programming algorithm has been proposed. This algorithm is very much useful when addressing heavily constrained optimization problem in terms of solution accuracy and computation time. The first phase uses a novel evolutionary programming, while optimization by direct search and systematic reduction of the search region method is employed in the second phase. Luh *et al.* [21] an optimization-based algorithm has been presented for scheduling hydro units with cascaded reservoirs and discrete hydro constraints within the Lagrangian relaxation frame work. The algorithm can systematically deal with discontinuous operating regions and discrete operating states without discretization reservoir levels. Hamdan *et al*. [22] a comprehensive algorithm for HTC has been presented where an expert system is used as a postprocessor as well as a preprocessor to an efficient Lagrangian relaxation based HTC program. Important operating constraints (power balance, spinning reserve, capacity limits, ramp rate, limited generation for the first and last hour and hydro constraints) are considered. Nonlinear functions are used for thermal generation cost and water discharge rate. The hydro sub problem has not been solved independently. An efficient hydrothermal scheduling algorithm is used for solving the output levels of hydro units. Each thermal sub problem is solved independently using dynamic programming without discretizing generation levels .Sreeni *et al.*[27] has proposed a new PSO based algorithm for short term hydro thermal scheduling problems by taking the reservoir volume as the particle position. Software for real time hydro thermal scheduling applications has been developed using the proposed algorithm Lakshminarasimman. L and Subramanian.S. [25] has presented a novel approach based on modified differential evolution for solving the short-term hydrothermal scheduling problem. The differential evolution algorithm has been devised to efficiently handle the reservoir end-volume constraint. Hence the proposed technique does not require the use of penalty functions and explores the optimum solution at a lesser computational effort. It is evident from the comparison the proposed modified differential evolution based approach provides a competitive performance in terms of optimal solution as well as computation effort. Kit Wow Po and Yin Wa Wong. [19]. A simulated-annealing-based short-term hydrothermal scheduling algorithm for the determination of the optimum hydrothermal schedule has been developed. In the algorithm, an equivalent unit represents the thermal generator units. Reservoir volume constraints and the operation limits of the thermal and hydro units are included in the algorithm. Particle swarm optimization is a population based optimization method first proposed by Kennedy and Eberhart [20]. In order to find optimal or near optimal solution to the problem, PSO update the current generation of particle using the information about the best solution obtained by each particle and entire population.

1.3 Organization of Thesis

This thesis titled as “Short Range Fixed Head Hydrothermal Scheduling Particle Swarm Optimization” is divided into six chapters; the brief discussion is as follows

In chapter 1 a detailed introduction on hydrothermal scheduling is given. The brief literature review is done for hydrothermal scheduling and solution methodology.

In chapter 2 gives us the idea of different classification the hydrothermal scheduling problem and discusses the classical method.

The chapter 3 deals with the explanation of PSO technique and its algorithm.

In chapter 4 the formulation of algorithm to solve hydrothermal scheduling using PSO

In chapter 5, hydrothermal scheduling problem is discuss using PSO

In chapter 6, summarize the conclusions and scope for further work.

Chapter 2
Hydrothermal Scheduling

The operation planning of hydrothermal systems is called Hydrothermal Coordination problem. Hydrothermal coordination problem requires solving for the thermal unit commitments and generation dispatch as well as the hydro schedules. The objective is to minimize thermal production cost subject to meeting the forecasted demand and other operating constraints. Also the hydrothermal co-ordination problem determines the thermal unit commitments and generation dispatch, as well as the hydro schedules, to meet the forecasted demand and other operating constraints at minimum thermal production cost. The hydrothermal co-ordination problem is usually solved by decomposition of the original problem into long, medium and short term problems each one considering the appropriate aspects for its time step and horizon of study. It is also essential to take into consideration two basic aspects of the hydro system:

1. The available water quantity is stochastic in nature.
2. The decision for the energy allocated to hydro units is deterministic.

Different time horizons and base times are needed for the detailed examination of each one of the above operating practices. For example, for maintenance scheduling the time horizon is the year and the base time is the week or the two week period while for the economic dispatch the time horizon is the hour and the base time is the minute. It is thus obvious that the selection of the appropriate base time for the hydrothermal scheduling problem is crucial to the formulation and solution of the problem.

The objective of the hydrothermal scheduling problem is to determine the water releases from each reservoir of the hydro system at each stage such that the operation cost is minimized along the planning period. The operation cost includes fuel costs for the thermal units, import costs from neighboring systems and penalties for load shedding. The basic question in hydro thermal coordination is to find a trade-off between a relative gain associated with immediate hydro generation and the expectation of future benefits coming from storage [27].

2.1 Classification of hydropower plants

2.1.1: Classification on the basis of type

2.1.2: Classification on the basis of location

2.1.3: Classification According to Quantity of Water Available

2.1.4: Classification According to Availability of Water Head

2.1.5: Classification According to Nature of Load

2.2.1: Classification on the basis of type

Hydro power plants on the basis of their type can be classified into two ways, which is given as under-

- Pumped storage plants.
- Conventional plants.

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. It is associated with upper and lower reservoirs. During light load periods water is pumped from lower to the upper reservoirs using the available energy from other sources as surplus energy. During peak load the water stored in the upper reservoirs is released to generate power to save fuel cost of thermal plants. The pumped storage plant is operated until the added pumping cost exceeds the savings in thermal costs due to the peak sharing operation.

The schematic diagram of pumped storage power plant is shown as below

Where

J_i^k = water inflow into the main reservoir

P_i^k = water which is pumped back into the main reservoir by the use of pump during light load condition.

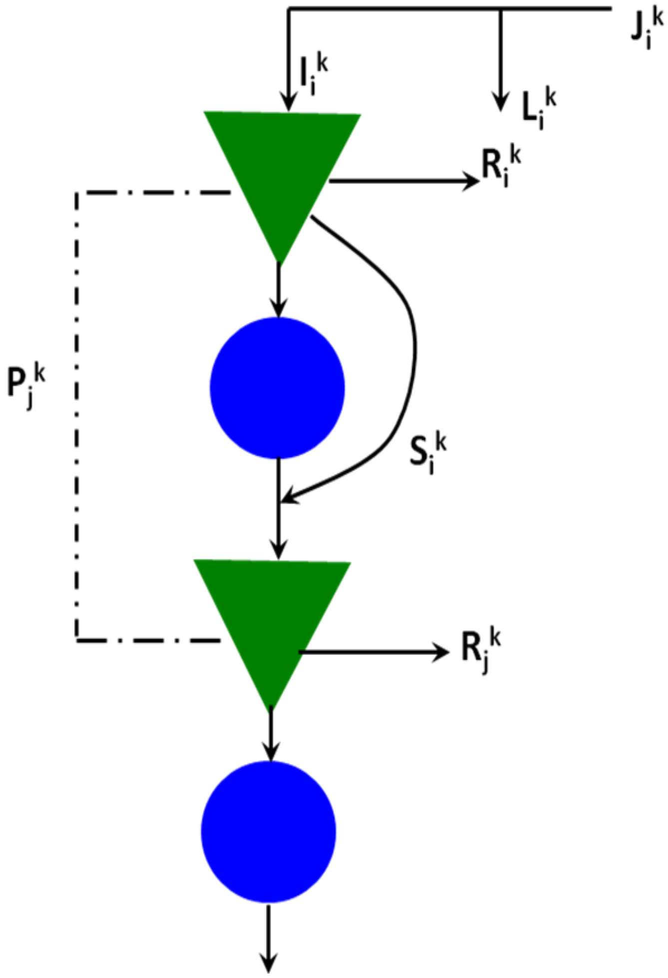


Figure 2.1: Pumped Storage power plant

Conventional plants: These are classified in to two different types, which is as under

- Run-of-river plants
- Storage plants

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

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.

2.1.2. Classification on the basis of location: on the basis of location it can be classified into three types as:

- Hydro plants on different streams.
- Hydro plants on the same stream.
- Multi-chain hydro plants

Hydro plants on different streams: The plants are located on different streams and are independent of each other. Both the hydro power plant are operated on the different stream hence their power generation is also different as their water inflow is different. Both the hydro power plant has different reservoir losses and spillage as they have different reservoir and inflow. Due to different inflow, the reservoir capacity is also different and hence different generation.

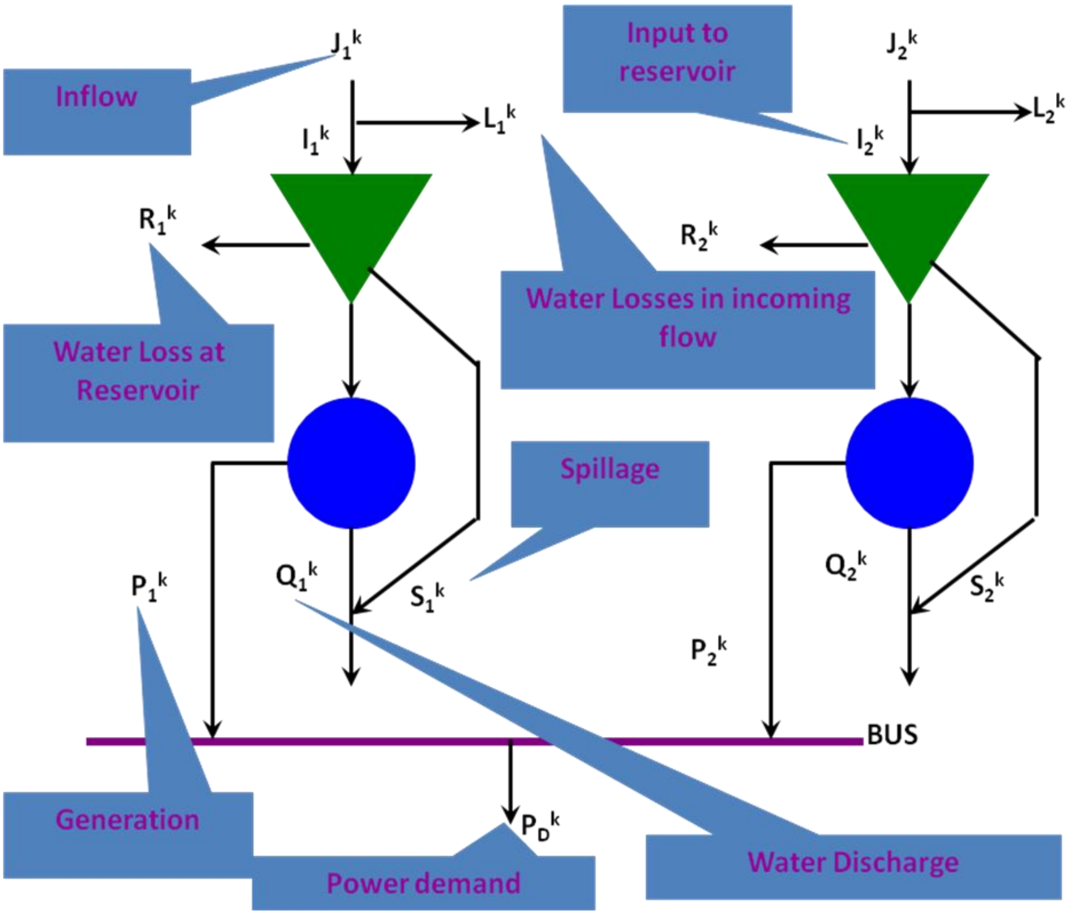


Figure 2.2: Hydro plants on different stream.

Hydro plants on the same stream:

When hydro plants are located on the same stream, the downstream plant depends on the immediate upstream plant. The down stream power plant will depend upon the water discharge and spillage of upper power plant as that water discharge and spillage will act as a inflow to the lower power plant. The inflow to the lower power plant will depend upon the delay time. As delay time is defined as the time which elapsed from the time when input to the upper power plant and reaches up to the lower power plant.

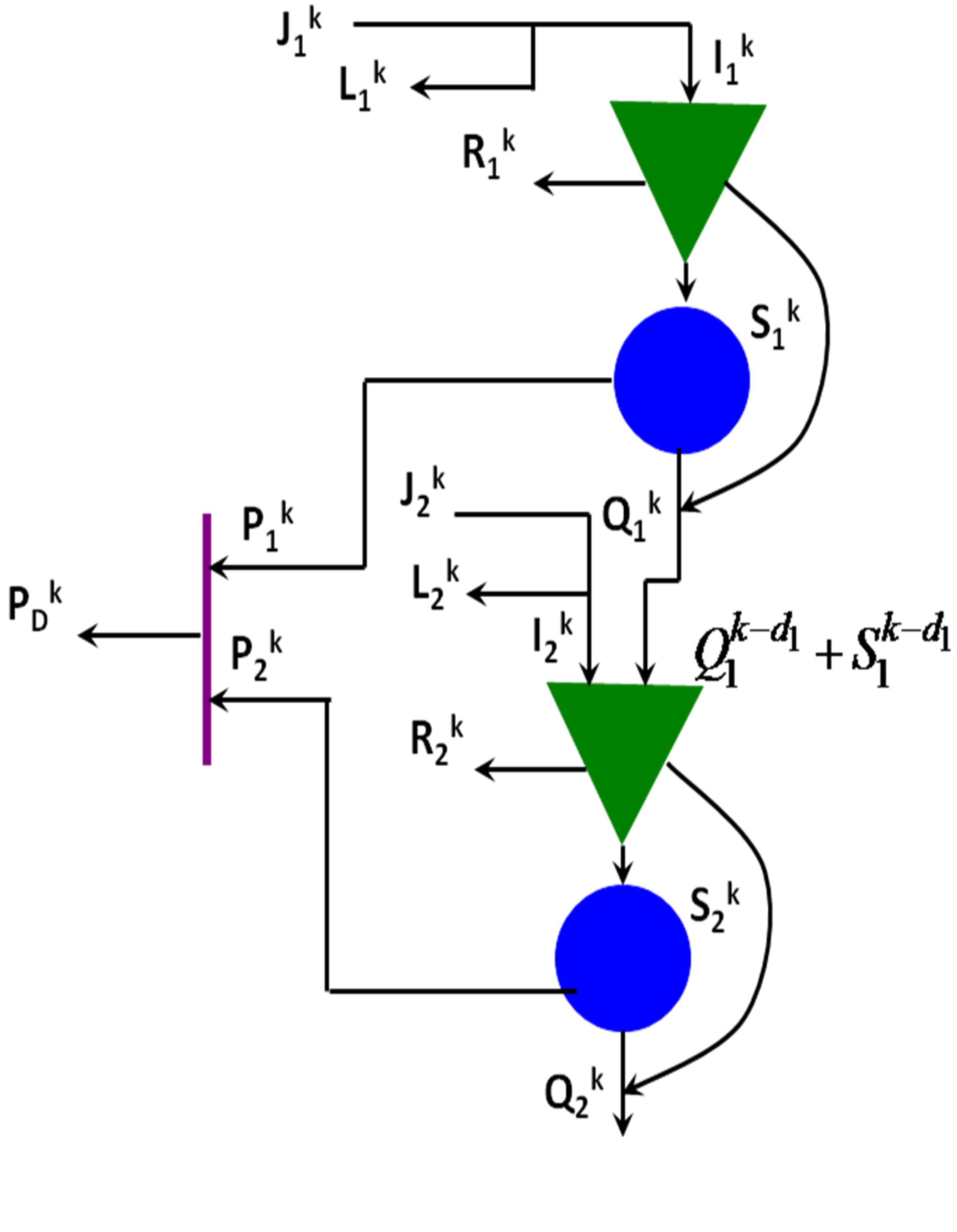


Figure 2.3: Hydro plants on the same

Multi-chain hydro plants:

These hydro plants are located on different streams as well as same stream. From the below figure we see that the upper power plant on the different stream and the lower power plant has a input from both the upper power plant. Upper power plant are not depend upon each other as they has different stream, but lower will depend upon the both upper water discharge and spillage which act as input to the lower power plant.

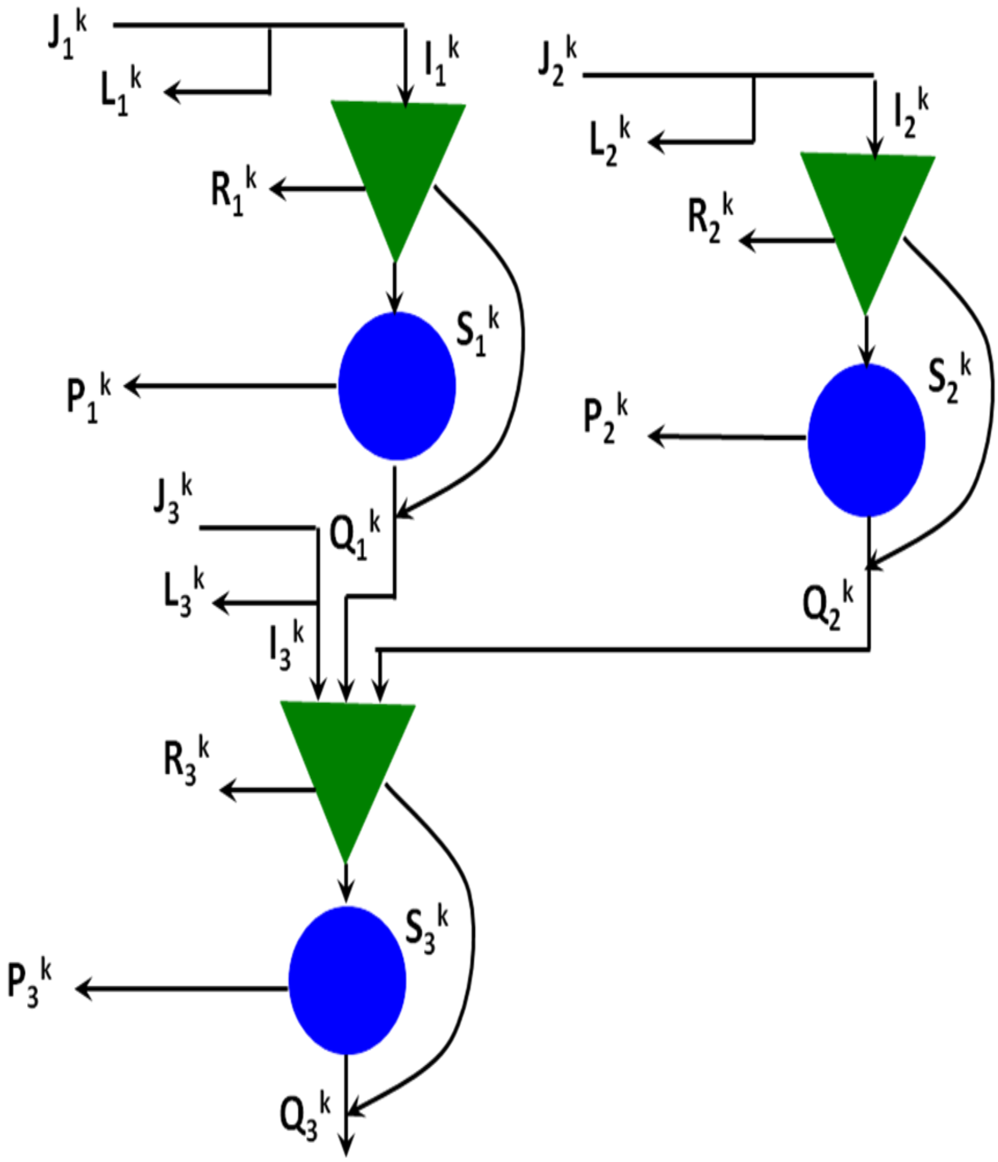


Figure 2.4:Multi-chain hydro plants

2.1.3. Classification According to Quantity of Water Available

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

- Run-off- River Plants without Poundage.
- Run-off- River Plants with Poundage.
- Reservoir Plants

Run-off- River Plants without Poundage

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.

Run-off- River Plants with Poundage:

In these plants poundage permits storage of water during off peak periods and use of this water during peak periods. Depending on the size of poundage 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 without storage or poundage. When providing poundage 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.

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 throughout 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 [22, 27].

2.1.4. Classification According to Availability of Water Head

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

Low-Head 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. The height of the dam in case of low head hydro electric plants is less than 30 meters.

Medium-Head 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 fore bay from where penstock carries water to turbines. The height of the dam in case of low head hydro electric plants is between 30 meters and 100meters.

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.

2.1.5. Classification According to Nature of Load

- Base load plants
- Peak load plants

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.

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% [22].

2.2. Classification of Hydrothermal Scheduling Problem

2.2.1. Long range problem

2.2.2. Short range problem

2.2.1. Long Range Problem

Long range problem includes the yearly cyclic nature of reservoir water inflows and seasonal load demand and correspondingly a scheduling period of one year is used. The solution of the long range problem considers the dynamics of head variations through the water flow continuity equation. The coordination of the operation of hydroelectric plants involves, of course, the scheduling of water releases. The long-range hydro-scheduling problem involves the long-range forecasting of water availability and the scheduling of reservoir water releases (i.e., "drawdown") for an interval of time that depends on the reservoir capacities. Typical long-range scheduling go anywhere from 1 week to 1 year or several years. For hydro schemes with a capacity of impounding water over several seasons, the long-range problem involves meteorological and statistical analysis. Nearer-term water inflow forecasts might be based on snow melt expectations and near-term weather forecasts. For the long-term drawdown schedule, a basic policy selection must be made. Should the water be used under the assumption that it will be replaced at a rate based on the statistically expected (i.e., mean value) rate, or should the water be released using a "worst-case" prediction. In the first instance, it may well be possible to save a great deal of electric energy production expense by displacing thermal generation with hydro-generation. If, on the other hand, a worst-case policy was selected, the hydro plants would be run so as to minimize the risk of violating any of the hydrological constraints (e.g., running reservoirs too low, not having enough water to navigate a river). Conceivably, such a schedule would hold back water until it became quite likely that even worst-case rainfall (runoff, etc.) would still give ample water to meet the constraints. Usually, long-term hydrothermal scheduling is used for breaking down the long-term problem into a number of midterm (e.g., monthly) problems. Long-term produces a near optimal cost estimation while the mid-term case can use a more detailed cost representation (short-term cases use the most detailed cost formulation). The purpose of the long-term scheduling is to provide a good feasible solution that is close to the long-term cost minimization of the whole system. The problem is usually very difficult to solve due to its size, the time span (up to several years) and the randomness of the water inflows over the long term Long-range scheduling involves optimizing a policy in the context of unknowns such as load, hydraulic inflows, and unit availabilities (steam and hydro). These unknowns are treated statistically, and long-range scheduling involves optimization of statistical variables.

2.2.2. Short Range Problem

The load demand on the power system exhibits cyclic variation over a day or a week and the scheduling interval is either a day or a week. As the scheduling interval of short range problem is small, the solution of the short-range problem can assume the head to be fairly constant. [22]The amount of water to be utilized for the short-range scheduling problem is known from the solution of the long-range scheduling problem. Short-range hydro-scheduling (1 day to1week) involves the hour-by-hour scheduling of all generation on a system to achieve minimum production cost for the given time period. In such a scheduling problem, the load, hydraulic inflows, and unit availabilities are assumed known. A set of starting conditions (e.g. reservoir levels) is given, and the optimal hourly schedule that minimizes a desired objective, while meeting hydraulic steam, and electric system constraints, is sought. Part of the hydraulic constraints may involve meeting "end-point" conditions at the end of the scheduling interval in order to conform to a long-range; water-release schedule previously established. The short term hydrothermal scheduling problem is classified in to two groups.

- Fixed head hydrothermal scheduling
- Variable head hydrothermal scheduling

Fixed head hydrothermal scheduling

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

Thermal model

Minimize $$J = \sum_{k=1}^{T} \sum_{i=1}^{N} t_k \, F_i\left(P_{ik} \right) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2.1)$$

Where

$F_i(Pik)$ is the cost function of thermal unit in the interval k and is defined by

$$F_i(P_{ik}) = a_i P_{ik}^2 + b_i P_{ik} + c_i \quad \text{Rs/h}$$

Where $a_{i,}$ bi, c_i are the cost coefficient

P_{ik} is the output of hydro and thermal unit durning the k^{th} interval

Equality and Inequality Constraints

(i)Load demand equality constraints:

$$\sum_{i=1}^{N+M} P_{ik} = P_{Dk} + P_{Lk} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2.2)$$

Where

P_{Dk} is the load demand during the sub-interval

P_{LK} is the transmission losses during the sub-interval (ii)Limits are imposed as:

$$P_i^{\min} \le P_{ik} \le P_i^{\max} \quad \text{...} (2.3)$$

P_i^{max} is the upper limit of i^{th} generartor output

P_i^{min} is the lower limit of i^{th} generartor output

Hydro model

In a hydro system there is no fuel cost incurred in the operation of hydro units.

According to Glimn-Kirchmayer model discharge is

$$q_{jk} = K_j \phi(P_{mk}) \psi(h_{jk}) \quad m^3/h \ldots\ldots\ldots\ldots\ldots\ldots\ldots (2.4)$$

Where

ψ and Φ are two independent functions of head and hydro generation.

$K_j =$ constant proportionality.

$$q_{jk} = K_j' \varphi(P_{mk}) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(2.5)$$

For a large capacity reservoir, it is practical to assume that the effective head is constant over the optimization interval. Hence the discharge equation is rewritten as:

$$K_j' = K_j \Phi(P_{mk}) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2.6)$$

$$\Psi(h_j(t)) = s*h_j^2 + d*h_j + m$$

$$\Phi(P_m) = n*P_m^2 + o*P_m + y$$

$$\sum_{k=1}^{T} t_k \, q_{jk} = V_j \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.........(2.7)$$

P_{dk} is the demand during the k^{th} interval

q_{jk} is the rate of discharge from the j^{th} hydro-unit in interval k and is defined-

$$q_{jk} = x_j P_{j+N}^2 + y_j P_{j+N} + z_j \quad m^3/h$$

Where x_j, y_j, z_j are discharge coefficient.

V_j is the pre-specified volume of water available for unit j for whole of the period.

N is the number of thermal unit

M is the number of hydro unit.

T is the overall period of scheduling.

Transmission Losses

A common approach to model transmission losses in the system is to use Kron's approximated loss formula in terms of B-coefficients.

$$P_{Lk} = \sum_{i=1}^{N+M} \sum_{j=1}^{N+M} P_{ik} B_{ij} P_{jk} + \sum_{i=1}^{N+M} B_{io} P_{ik} + B_{oo} \quad \ldots\ldots\ldots\ldots\ldots\ldots(2.8)$$

Where

B_{oo},B_{io} and B_{ij} are B-coefficients.

The fixed head hydrothermal scheduling can be defined considering the operating cost over the optimization interval to meet the load demand in each interval. Each hydro plant is constraints by the amount of water available for draw-down in the interval.

The problem is defined as

Minimize

$$J = \sum_{k=1}^{T} \sum_{i=1}^{N} t_k \; F_i\left(P_{ik} \right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2.9)$$

Subject to

$$\sum_{i=1}^{N+M} P_{ik} = P_{Dk} + P_{Lk} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2.10)$$

Classical Method

The optimality condition is described by tacking the partial derivatives of augmented objective function w.r.t. Decision variables.

$$T_k * \partial F_i / \partial P_{ik} - \lambda_k = 0 = -\Delta_p^k \quad (i=1,2,..N;\ k=1,2,.T) \ldots\ldots\ldots\ldots\ldots(2.11)$$

$$v_j * t_k * \partial q_{ik} / \partial P_{mk} - \lambda_k = 0 = -\Delta_m^k \quad (j=1,2,..M;\ m=N+j;\ k=1,2,.T) \ldots\ldots\ldots(2.12)$$

$$\sum_{i=1}^{N+M} P_{ik} = P_{Dk} + P_{Lk} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2.13)$$

$$\sum_{k=1}^{T} t_k \; q_{jk} = V_j \quad (j=1,2,3,\ldots\ldots M) \ldots\ldots\ldots\ldots\ldots(2.14)$$

Inherently these equations are non-linear. The Newton-Raphson method has been applied to find P_{ik}(i=1,2,……N+M),λ_k for all T interval, v_j the water conversion factor is modified to satisfy the available of water constraints.

$$T_k * \partial F_i^2 / \partial P_{ik}^2 = 0 = -\Delta_{pp}^k \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2.15)$$

$$v_j * t_k * \partial q_{ik}^2 / \partial P_{mk}^2 = 0 = -\Delta_{mm}^k \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots(2.16)$$

$$-\Delta_{\lambda\lambda}^k = 0 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2.17)$$

$$- \Delta p_{\lambda} = 1 \quad \text{..(2.18)}$$

$$- \Delta_{m\lambda}^{k} = 6 \quad \text{..(2.19)}$$

$$\sum_{i=1}^{N+M} P_{ik} = P_{Dk} + P_{Lk} = - \Delta_{\lambda}^{k} \quad \text{......................................(2.20)}$$

Variable head hydrothermal scheduling

The head of reservoir is variable if the hydro plant are having reservoir of small capacity.

Thermal model

Minimization $$J = \sum_{k=1}^{T} \sum_{i=1}^{N} t_k \, F_i(P_{ik}) \quad \text{..........................(2.21)}$$

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

Where

a_i, bi, c_i are the cost coefficient

P_{ik} is the output of hydro and thermal unit durning the k^{th} interval

Hydro model

In a hydro system there is no fuel cost incurred in the operation of hydro units.

According to Glimn-Kirchmayer model discharge is

$$q_{jk} = K_j \, \phi(P_{mk}) \psi(h_{jk})$$

Where

ψ and Φ are two independent functions of head and hydro generation.

K_j = constant proportionality.

$$\Psi(h_j(t)) = s * h_j^2 + d * h_j + m$$

$$\Phi(P_m) = n * P_m^2 + o * P_m + y$$

Reservoir constraints

$$h_j(t) = h_j(0) + \frac{1}{S_j} \int_0^t (I_j(t) - q_j(t)) dt \quad \text{..........................(2.22)}$$

h(0)=initial hydraulic head

I(t)=natural inflow

q(t)=rate of water discharge

s=surface area of reservoir

$$\sum_{k=1}^{T} t_k \, q_{jk} = V_j \quad (j=1,2,3,\ldots\ldots\ldots..M)\ldots\ldots\ldots\ldots\ldots\ldots..(2.23)$$

$$P_i^{\min} \le P_{ik} \le P_i^{\max} \qquad (i=1,2,\ldots\ldots\ldots.N)$$

P_{dk} is the demand during the k^{th} interval

P_i^{min} is the lower limit of i^{th} generartor output

P_i^{max} is the upper limit of i^{th} generartor output

q_{jk} is the rate of discharge from the j^{th} hydro-unit in interval k and is defined-

$$q_{jk} = x_j \, P_{j+N}^2 + y_j \, P_{j+N} + z_j \;\; m^3/h$$

Where

x_j, y_j, z_j are discharge coefficient.

V_j is the pre-specified volume of water available for unit j for whole of the period.

N is the number of thermal unit

M is the number of hydro unit.

T is the overall period of scheduling.

2.3. Initial Guess

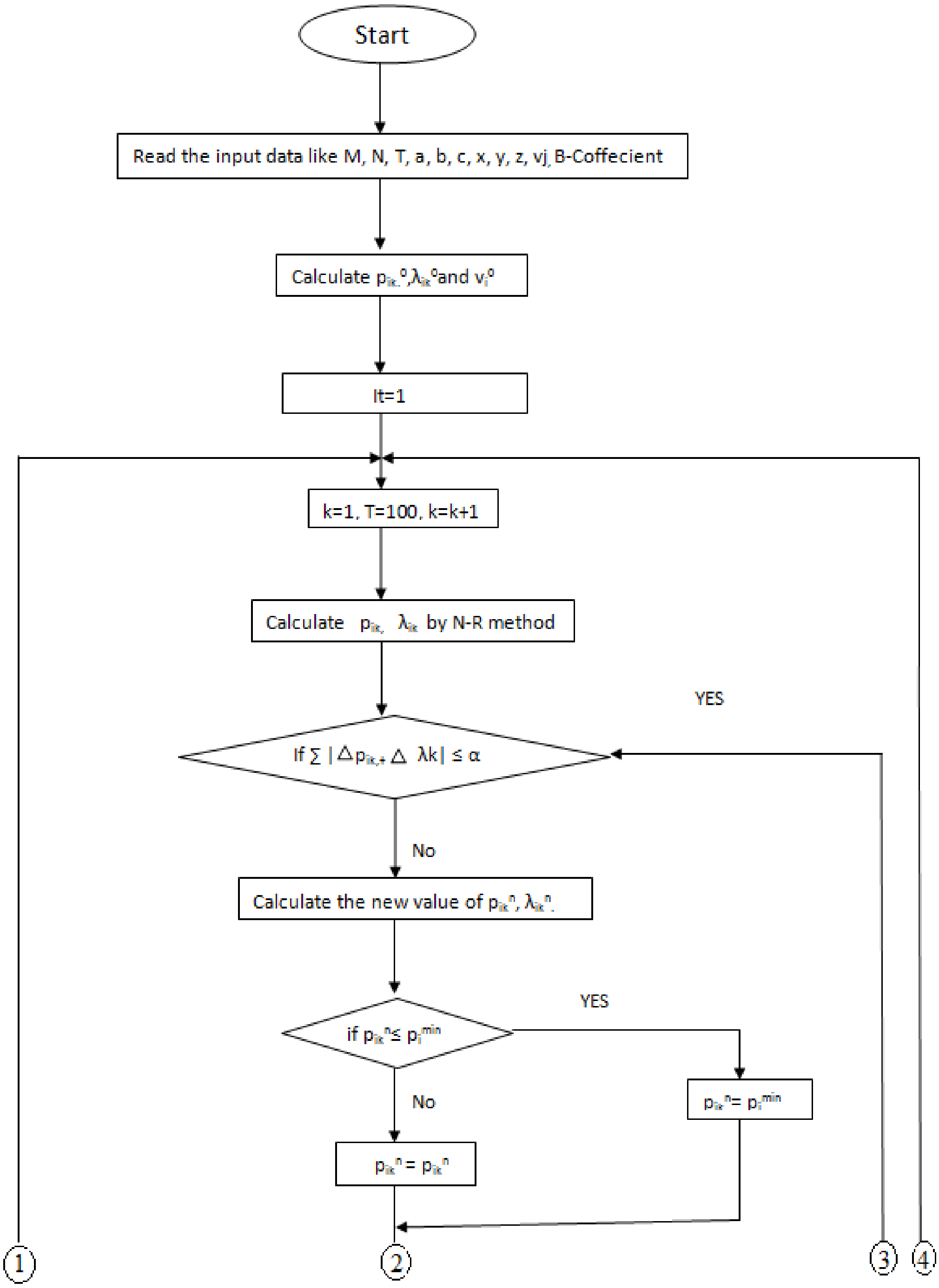
It is assumed that the hydro generator requires more water for a long time period or higher load demand. Thus the whole available amount of water allocated in each time interval, considering time interval and load demand.

2.3.1. Algorithm for Classical Method

1. Read all the input data.
2. Calculate the initial guess value of P_{ik}, λ_k, Vj.
3. Consider V_j as calculated in step 2.
4. Start the iteration counter r = 1.
5. Start the hourly count k = 1.
6. Consider Pik and λ_k.
7. Now compute new values for , P_{ik}, λ_k P_{jk} for given values of k.
8. Calculate total volume utilized.
9. Check for convergence.
10. If convergence is not achieved update volume and go to step 4 and increase the iteration counter and repeat.
11. Print the generation, utilized volume of water and cost.

2.3.2 Flowchart of classical method

The flowchart of classical method is explained as below:



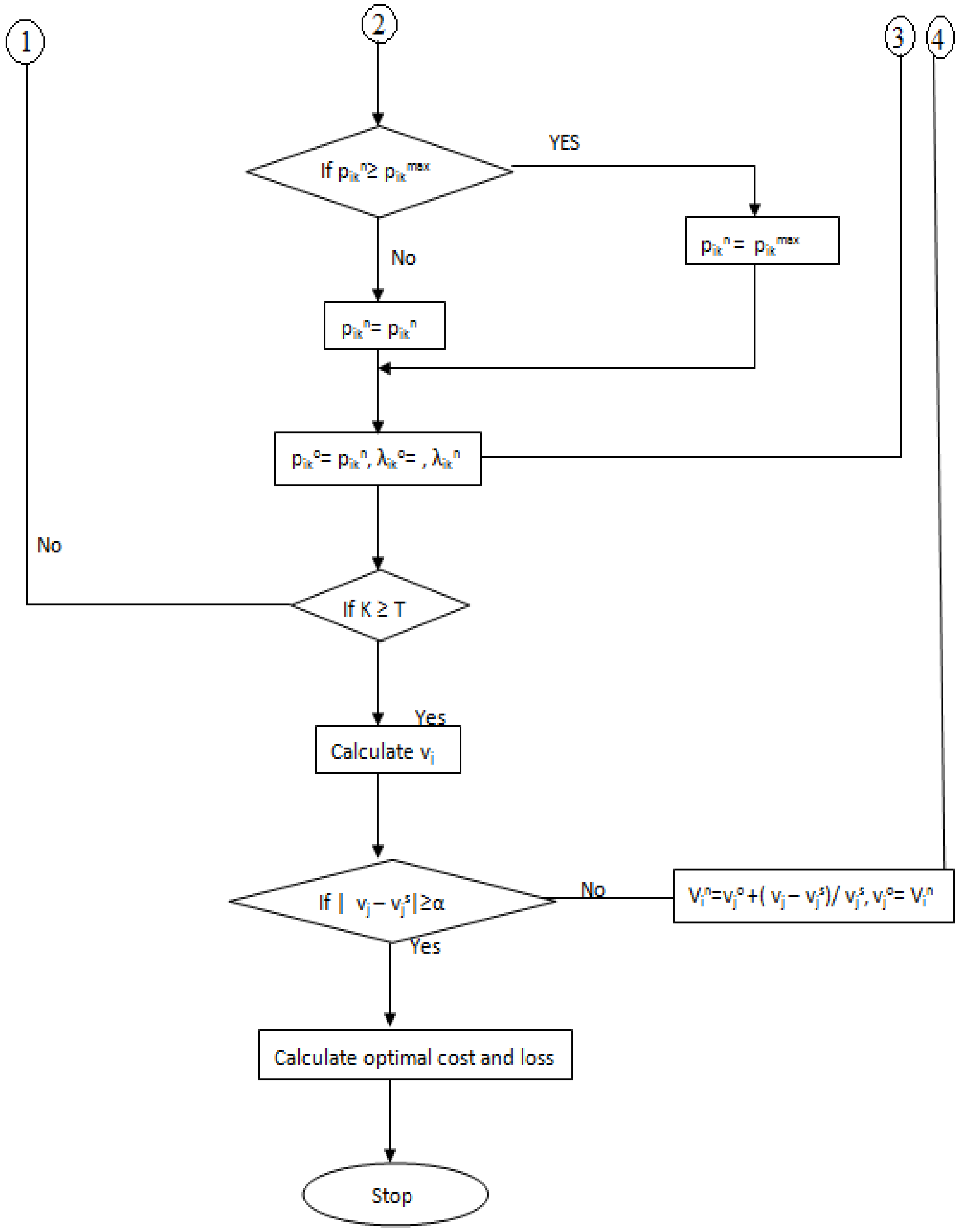


Figure: 2.5 Flow Chart of classical method

Chapter 3
Particle Swarm Optimization (PSO)

The optimization of nonlinear functions using particle swarm methodology is described. Implementations of two paradigms are discussed and compared, including a recently developed locally oriented paradigm. Benchmark testing of both paradigms is described, and applications,

Including neural network training and robot task learning, are proposed. Relationships between particles swarm optimization and both artificial life and evolutionary computation are reviewed. Particle swarm optimization is a stochastic, population-based search and optimization algorithm for problem solving. It is a kind of swarm intelligence that is based on social psychological principles and provides insights into social neighbor, as well as contributing to engineering applications. James Kennedy and Russell C. Eberhart [20] first described the particle swarm optimization algorithm in 1995. The techniques have evolved greatly since then, and the original version of the algorithm is barely used at present. Social influence and social learning enable a person to maintain cognitive consistency. People solve problems by talking with other people about them, and as they interacts their beliefs, attitudes, and neighbor changes, the changes could typically be depicted as the individuals moving toward one another in a socio-cognitive space. The particle swarm simulates a kind of social optimization. A problem is given, and some way to evaluate a proposed solution to it exists in the form of a fitness function.

A communication structure or social network is also defined, assigning neighbours for each individual to interact with a population of individuals defined as random guesses as the problem solutions is initialized. These individuals are candidate solutions and are also known as the particles, hence the name particle swarm. An iterative process to improve these candidate solutions is set in motion. The particles iteratively evaluate the fitness of the candidate solutions and remember the location where they had their best success. The individual’s best solution is called the particle best or the local best. Each particle makes this information available to their neighbours. They are also able to see where their neighbours have had success. Movements through the search space are guided by these successes, with the population usually converging, by the end of a trial, on a problem solution better than that of non-swarm approach using the same

methods. The particle swarm optimization (PSO) algorithm is a population-based search algorithm inspired by the social behaviour of birds within a flock [13]. The initial intent of the particle swarm concept was to graphically simulate the graceful and unpredictable choreography of a bird flock, the aim of discovering patterns that govern the ability of birds to fly synchronously, and to suddenly change direction with a regrouping in an optimal formation. From this initial objective, the concept evolved into a simple and efficient optimization algorithm. In PSO, individuals, referred to as particles, are "flown" through hyper dimensional search space.
Changes to the position of particles within the search space are based on the social-psychological tendency of individuals to emulate the success of other individuals. The changes to a particle within the swarm are therefore influenced by the experience, or knowledge, of its neighbours. The search behaviour of a particle is thus affected by that of other particles within the swarm therefore PSO is the kind of symbiotic cooperative algorithm. The consequence of modelling this social behaviour is that the search process is such that particles stochastically return toward previously successful regions in the search space. The operation of the PSO is based on the neighbourhood principle as social network structure.

3.1 Flocks, Swarm and Particle

A number of scientists have created computer simulations of various interpretations of the movement of organisms in a bird flock or fish school. Notably, Reynolds and Heppner and Grenander presented simulations of bird flocking. It became obvious during the development of the particle swarm concept that the neighbour of the population of agents is more like a swarm than a flock. The term swam has a basis in the literature. In particular, the authors use the term in accordance with a paper by Millonas , who developed his models for applications in artificial life, and arliculated five basic principles of swarm intelligence[11, 14].
First is the proximity principle: the population should be able to carry out simple space and time computations.
Second is the quality principle: the population should be able to respond to quality factors in the environment.
Third is the principle of diverse response: the population should not commit its activities along excessively narrow.

Fourth is the principle of stability: the population should not change its mode of neighbour every time the environment changes.

Fifth is the principle of ability: the population must be able to change the behaviour mode when it's worth the computational price. Note that principles four and five are the opposite sides of the same coin. Particle swarm optimization concept and paradigm presented in this paper seem to adhere to all five principles. Basic to the paradigm are n-dimensional space calculations carried out over a series of time steps. The population is responding to the quality factors local best. Further, liccvcs discusses particle systems consisting of clouds of primitive particles as models of diffuse objects such as clouds, fire and smoke. Thus the label the authors have chosen to represent the optimization concept is particle swarm.

3.2 The Particle Swarm Optimization Concept

Particle swarm optimization is similar to a genetic algorithm in that the system is initialized with a population of random solutions. It is unlike a genetic algorithm, however, in that each potential solution is also assigned a randomized velocity, and the potential solutions, called particles, are then "flown" through hyperspace. Each particle keeps track of its coordinates in hyperspace, which are associated with the best solution (fitness) it has achieved so far. (The value of that fitness is also stored.) This value is called pbest (local best). Another "best" value is also tracked. The "global" version of the particle swarm optimizer keeps track of the overall best value, and its location, obtained thus far by any particle in the population; this is called gbest. The particle swarm optimization concept consists of, at each time step, changing the velocity (accelerating) each particle toward its pbest (local best) and gbest (global version). Acceleration is weighted by a random term, with separate random numbers being generated for acceleration toward pbest and gbest. This paper introduces a "local" version of the optimizer in which, in addition to pbest, each particle keeps track of tlie best solution, called Zbest, and attained within a local topological neighbourhood of particles. Both the global and local versions are described in more detail below [9].

Acceleration constant is also specified, but in the experience of the authors, is not usually varied among applications. This paper introduces a new form of the particle swarm optimizer, examines how changes in the paradigm affect the number of iterations required to meet an error criterion, and the frequency with which models cycle interminably around a non global optimum. Three versions were tested: the "GBEST" model, in which every agent has information about the group's best evaluation, and two variations of the "LBEST" version, one with a neighbourhood of six, and one with a neighbourhood of two. It appears that the original GBEST version performs best in terms of median number of iterations to convergence, while the LBEST version with a neighbourhood of two is most resistant to local minima.

In terms of median number of iterations to convergence, while the LBEST version with a neighbourhood of two is most resistant to local minima.

Particle swarm optimization is an extremely simple algorithm that seems to be effective for optimizing a wide range of functions. We view it as a mid-level form of a life or biologically derived algorithm, occupying the space in nature between evolutionary search, which requires eons, and neural processing, which occurs on the order of milliseconds. Social optimization occurs in the time frame of ordinary experience – in fact, it *is* ordinary experience. In addition to its ties with A-life, particle swarm optimization has obvious ties with evolutionary computation. Conceptually, it seems to lie somewhere between genetic algorithms and evolutionary programming. It is highly dependent on stochastic processes, like evolutionary programming. The adjustment toward pbest and gbest by the particle swarm optimizer is conceptually similar to the crossover operation utilized by genetic algorithms. It uses the concept of fitness, as do all evolutionary computation paradigms. The concept of particle swarm optimization is flying potential solutions through hyperspace, accelerating toward "better" solutions. Other evolutionary computation schemes operate directly on potential solutions, which are represented as locations in hyperspace. Much of the success of particle swarms seems to lie in the agents' tendency to hurtle past their target. Holland's chapter on the "optimum allocation of trials" reveals the delicate balance between consecutive testing of known regions versus risky exploration of the unknown. It appears that the current version of the paradigm allocates trials nearly optimally [17].

The stochastic factors allow thorough search of spaces between regions that have been found to be relatively good, and the momentum effect caused by modifying the extant velocities rather than replacing them results in over shooting, or exploration of unknown regions of the problem domain. Much further research remains to be conducted on this simple new concept and paradigm. The goals in developing it have been to keep it simple and robust, and it seems to have succeeded at that. The algorithm is written in a very few lines of code, and requires only specification of the problem and a few parameters in order to solve it.

3.3 Particle Swarm Optimization Variables

A swarm consists of a set of particles, where each particle represents a potential solution. Particles are then flown through the hyperspace, where the position of each particle is changed according to its own experience and that of its neighbors. Let $x_i(t)$ denotes the position of particle p_i in search space, at time step t. The position of p_i is then changed by adding a velocity $v_i(t)$ to the current position. The velocity vector drives the optimization process and reflects the socially exchanged information. Three different phases are differing in the extent of the social information exchange, which is detailed below. Form the basis of initial PSO algorithm. The phases are global best, local best.

3.3.1 Individual Best

The local best reflects the circle neighborhood structure. Particles are influenced by the best position within their neighborhood, as well as their own past experience. Individual best is also called as local best. While local best is slower in convergence than global best, local best results in much better solution and searches a larger part of the search space. The farther away a particle is from its previously found best solution, the larger the change in velocity to return the individual toward its best solution. The upper limit of the random value positions is a system parameter specified by the user. The larger the upper limit of positions, the more the trajectory of the particles oscillates. Smaller the value of positions ensures smooth trajectories.

3.3.2 Global Best

The global best, gbest, of PSO reflects the star neighborhood structure. The social knowledge used to drive the movement of particles includes the position of the best particle from the entire swarm. In addition, each particle uses its history of experiences in terms of its own best solution thus far. The further away a particle is from the global best position and its own best solution, the larger the change in velocity to move the particle back toward the best solutions.

3.3.3 Inertia weight

Improved performance can be achieved through application of an inertia weight applied to the previous velocity:

$$V_{id}^{k+1} = WV_{id}^{k} + c_1 r_1 \left(Pd_{id}^{k} - X_{id}^{k} \right) + c_2 r_2 \left(gb^{k} - X_{id}^{k} \right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.1)$$

Where W is the inertia weight. The inertia weight controls the influence of previous velocities on the new velocity. Large inertia weights cause larger exploration of the search space, while smaller inertia weights focus the search on a smaller region. Typically, PSO is started with a large inertia weight, which is decreased over time.

According to the discussion in above sections, the following procedure can be used for implementing the PSO algorithm.

3.3.4 Convergence

The algorithms above continue until convergence has been reached. Usually, a PSO algorithm is executed for a fixed number of iterations, or fitness function evaluations. Alternatively, a PSO algorithm can be terminated if the velocity changes are close to zero for all the particles, in which case there will be no further changes in particle positions [21].

3.4 Basic algorithm of PSO

The following steps are used by the PSO technique

1. Initialize the parameters such as the size of population, lower limit, upper limit, inertia weight, random velocity and position of each particle and acceleration constant etc.
2. Calculate the fitness of each individual population using the fitness function or cost function
3. Compute local best and global best fitness, corresponding note down their positions.
4. Modify the individual's velocity vid of each individual pi and weight for each population

W= Wmax -(Wmax - Wmin)*it/iteraation

$$V_{id}^{k+1} = WV_{id}^{k} + c_1 r_1 \left(Pd_{id}^{k} - X_{id}^{k} \right) + c_2 r_2 \left(gb^{k} - X_{id}^{k} \right) \ldots\ldots\ldots\ldots (3.2)$$

5. Modify the individual's position pi as

pi(t)= pi(t - 1)+ vi(t)……………………………………………………………(3.3)

6. Calculate the fitness of each individual in the population using the fitness function. After that compares these fitness values with each other.

7. Minimum value of fitness will be the global best fitness.

8. If the number of iteration reaches the maximum then go to step 10. Otherwise go to step 3.

9. The individual that generates the latest is the optimal position of each particle with the minimum fitness.

3.5 Basic flowchart of PSO

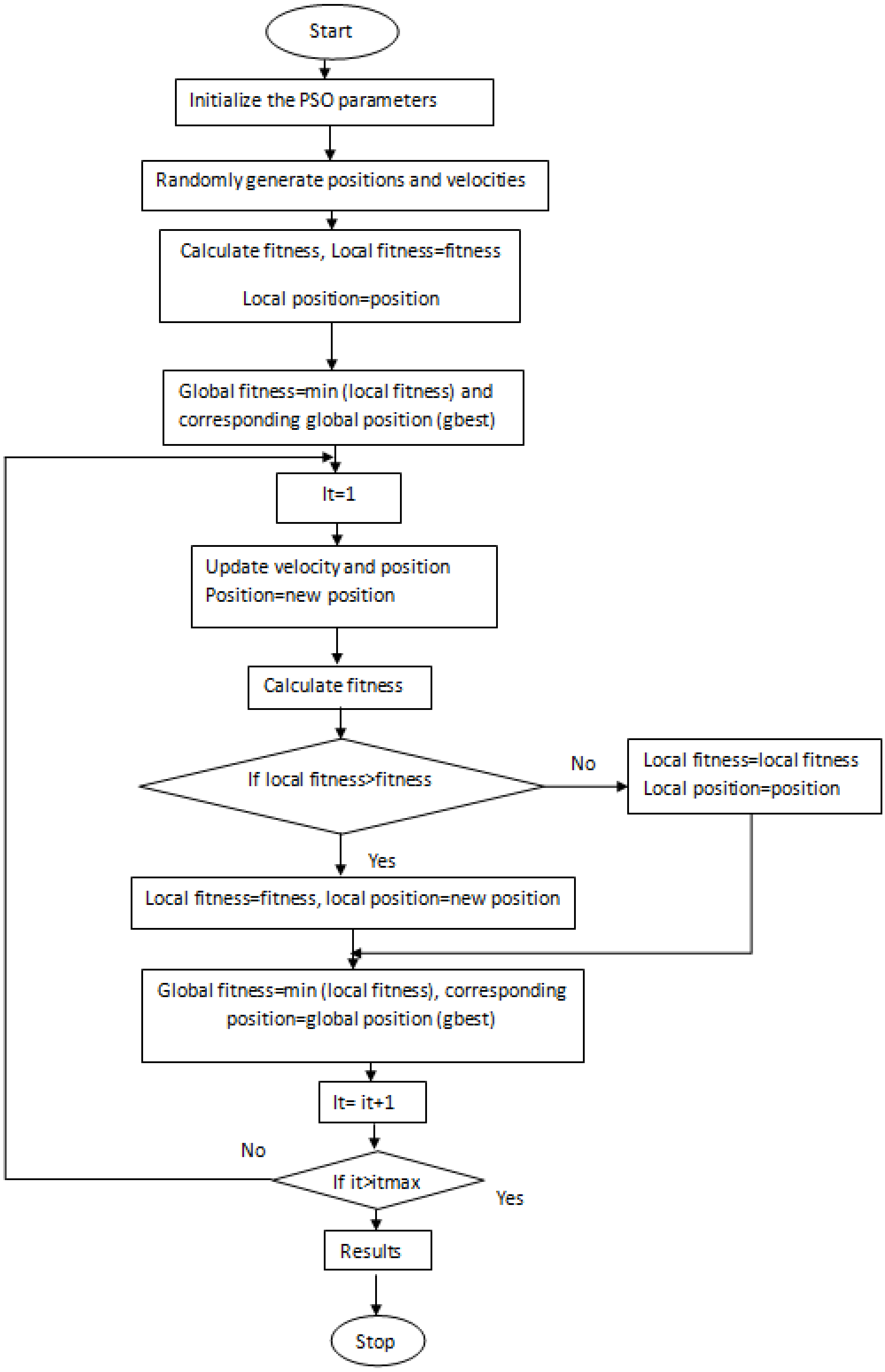


Figure 3.1: Flow -chart for basic PSO

Hydrothermal scheduling is a nonlinear mixed integer optimization problem to schedule the operation of the generating units at minimum operating cost while satisfying the demand and other equality and inequality constrains. The hydrothermal scheduling problem has to determine the on/off state of the generating units at each hour of the planning period and optimally generate the required generation. Hydrothermal scheduling is the most significant optimization task in the operation of the power systems. Solving the hydrothermal scheduling problem or large power systems is computationally expensive. The complexity of the hydrothermal scheduling problems grows exponentially to the number of generating units.

There are many methods to solve the hydrothermal scheduling but here we are choosing particle swarm optimization. The algorithm to solve hydrothermal scheduling problem is discuss in detail in this chapter. Here the generating units are behaving like dimension of the system, in PSO. The position or the value of the generating unit generated randomly between the upper and lower limit. After that, these values are updating till the optimization level reached.

Here the hydrothermal scheduling problem is solved by PSO (Particle Swarm Optimization). The formulation and algorithm is simple and required less parameter tuning and thus poised to overcome various shortcomings of traditional and other stochastic search and optimization technique.

4.1 Problem Formulation

The fixed head hydrothermal scheduling problem can be defined considering the operating cost over the optimization interval to meet the load in each interval. Each hydro-plant is constraints by the amount of water available for drawdown in the interval. The problem is defined as-

$$J = \sum_{k=1}^{T} \sum_{i=1}^{N} t_k \ F_i\left(P_{ik} \right) (k=1,2,\ldots\ldots T)\ldots\ldots\ldots\ldots\ldots\ldots\ldots(4.1)$$

Where

F_i (Pik) is the cost function of thermal unit in the interval k and is defined by

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

Where

a_i, b_i, c_i are the cost coefficient

N is the number of thermal unit

M is the number of hydro unit.

T is the overall period of scheduling.

4.1.1 Power balance constraint

Subject to

$$\sum_{i=1}^{N+M} P_{ik} = P_{Dk} \quad \text{...(4.2)}$$

Where

P_{ik} = P_{ik} is the output of hydro and thermal unit durning the k^{th} interval

P_{dk} = P_{dk} is the demand during the k^{th} interval

4.1.2 Generation limit constraint

$$P_i^{\min} \le P_{ik} \le P_i^{\max} \quad (i=1,2,\ldots\ldots\ldots N)\ldots\ldots\ldots\ldots\ldots\ldots(4.3)$$

P_i^{min} is the lower limit of i^{th} generartor output

P_i^{max} is the upper limit of i^{th} generartor output

4.1.3 Water discharge constraint

$$\sum_{k=1}^{T} t_k\, q_{jk} = V_j \qquad (j=1,2,3,\ldots\ldots M)\ldots\ldots(4.4)$$

q_{jk} is the rate of discharge from the j^{th} hydro-unit in interval k and is defined-

$$q_{jk} = x_j\, P_{j+N}^2 + y_j\, P_{j+N} + z_j \ \ m^3/h$$

Where

x_j, y_j, z_j are discharge coefficient.

V_j is the pre-specified volume of water available for unit j for whole of the period.

4.2 Particle Swarm Optimization for Solving Hydrothermal scheduling problem

The Particle swarm optimization (PSO) has been briefed in chapter 3. PSO is a population based searching algorithm. This approach simulates the simplified social system such as fish schooling and birds flocking. A population of potential solutions called particles initializes PSO. Each particle flies in the search space with a certain velocity. The particle's flight is influenced by cognitive and social information attained during its exploration. It has very few tunable parameters and the evolutionary process is very simple. It is capable of providing quality solutions to many complex power system problems. One such problem is the unit hydrothermal scheduling problem in the power system. PSO is used to minimize the total operating cost by scheduling those optimal combinations of the units, which satisfy the constraints, and gives the minimum cost corresponding to that combination. The algorithm for hydrothermal scheduling is detailed as follow:

4.2.1 Algorithm

The following steps are used by the PSO technique to solve the hydrothermal scheduling problem:

1. Initialize the parameters such as the size of population, lower limit, upper limit, inertia weight, random velocity and position of each particle and acceleration constant etc.

2. Calculate the water discharge using hydro power and volume constraints should be satisfied.

3. Calculate the fitness of each individual population using the fitness function or cost function.

$$J = \sum_{k=1}^{T} \sum_{i=1}^{N} t_k \; F_i\left(P_{ik} \right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4.5)$$

Where

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

4. Compute local best and global best fitness, corresponding note down their positions. And the weight function is also modified as

$$W_i = W_{max} - (W_{max} - W_{min}) * (i/iteration)$$

5. Modify the individual's velocity vid of each individual pi as

$$V_{id}^{k+1} = WV_{id}^{k} + c_1 r_1 \left(Pd_{id}^{k} - X_{id}^{k} \right) + c_2 r_2 \left(gb^{k} - X_{id}^{k} \right) \ldots\ldots\ldots (4.6)$$

6. Modify the individual's position pi as

$$pi(t) = pi(t - 1) + vi(t) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4.7)$$

7. Calculate the fitness of each individual in the population using the fitness function or cost function. After that compares these fitness values with each other.

8. Minimum value of fitness will be the global best fitness.

9. If the number of iteration reaches the maximum then go to step 10. Otherwise go to step 3.

10. The individual that generates the latest is the optimal generation power of each unit with the minimum total generation cost.

4.2.2 Flowchart of hydrothermal scheduling using PSO :

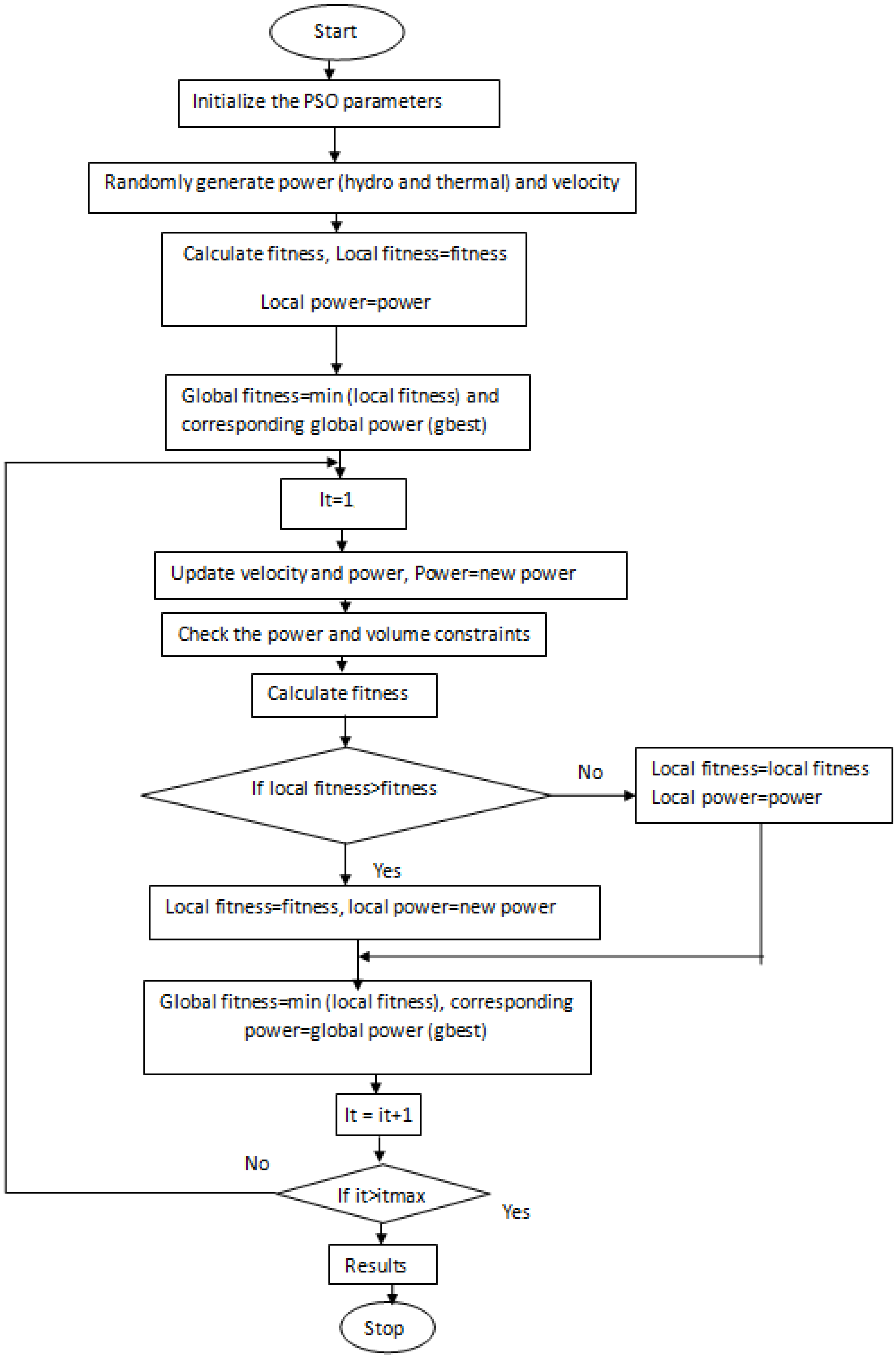


Figure4.1: Flow –chart of PSO in hydrothermal scheduling

Chapter 5
Results and Discussions

In this section, the results of Short-term hydrothermal scheduling problem are discussed. In this section we intend to introduce a problem in optimal operation of systems with hydro as well as thermal generation. It is important to realize that in case of a hydro unit no variation, in operating cost can be attributed to variation in output power.

Consequently the criterion of minimum operating cost for thermal plant cannot be used for hydro plant in the system. Instead it is usual to specify an allowable volume of water for release over a certain interval of time. This for the short range can vary from one day to one week. Hydro resources modeling are an important aspect of hydrothermal scheduling. The algorithms are implemented in MATLAB to solve the problem. The main objective is to minimize the cost of generation of thermal plants.

We will now discuss the simplest model used for optimal operation studies purposes.

5.1 Problem Constraints

The performance is evaluated for the following:-

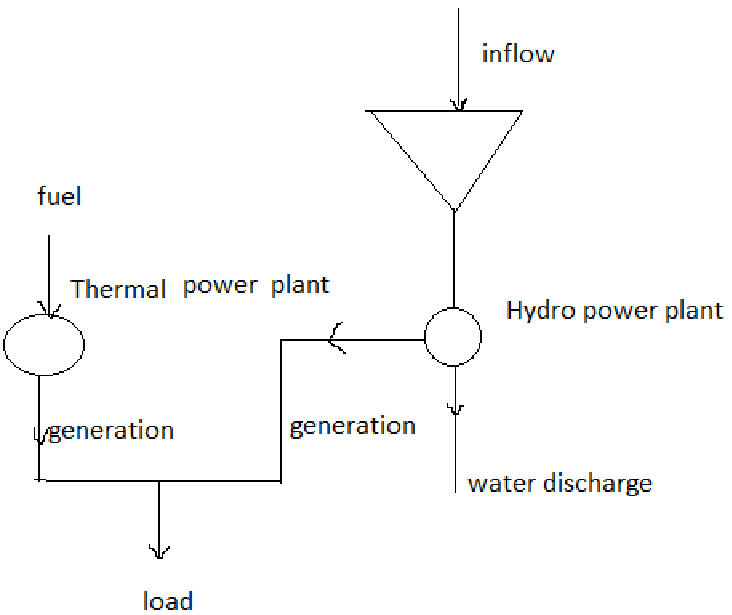


Figure: 5.1 Schematic diag. of hydrothermal scheduling

As we are taking Glimn Kirchmayer model for the hydrothermal scheduling. The test system consists of one thermal and one hydro generating station as shown in figure. The operating cost of thermal-power plant is given by-

$$F_i(P_{ik}) = a_i P_{ik}^2 + b_i P_{ik} + c_i \quad \text{.......(5.1)}$$

The rate of discharge of hydro generating station is given by-

$$q_{jk} = x_j P_{j+N}^2 + y_j P_{j+N} + z_j \ m^3 \quad \text{.......(5.2)}$$

According to Glimn-Kirchmayer model discharge is

$$q_{jk} = K_j \phi(P_{mk}) \psi(h_{jk}) \quad \text{.......(5.3)}$$

where

ψ and Φ are two independent function of head and hydro generation.

k_j constant proportionality.

$$\psi(h_j(t)) = s*h_j^2 + d*h \quad \text{.......(5.4)}$$

$$\Phi(P_m) = n*P_m^2 + o*P_m + y \quad \text{.......(5.5)}$$

5.1.1 Power balance constraint

$$\sum_{i=1}^{N+M} P_{ik} = P_{Dk} \quad \text{.......(5.6)}$$

Where

$P_{ik} = P_{ik}$ is the output of hydro and thermal unit durning the k^th^ interval

$P_{dk} = P_{dk}$ is the demand during the k^th^ interval

5.1.2 Generation limit constraint

$$P_i^{\min} \le P_{ik} \le P_i^{\max} \quad (i=1,2,\ldots\ldots N) \quad \text{.......(5.7)}$$

P_i^{min} is the lower limit of i^{th} generartor output

P_i^{max} is the upper limit of i^{th} generartor output

5.1.3 Water Discharge constraint

$$\sum_{k=1}^{T} t_k \, q_{jk} = V_j \quad (j=1,2,3,\ldots..M) \quad \text{......(5.8)}$$

q_{jk} is the rate of discharge from the j^{th} hydro-unit in interval k and is defined-

$$q_{jk} = x_j P_{j+N}^2 + y_j P_{j+N} + z_j \ m^3/h$$

Where

x_j,,y_j, z_j are discharge coefficient.

V_j is the pre-specified volume of water available for unit j for whole of the period.

5.2 Hydrothermal Scheduling problem

The coefficients of fuel cost are given in table 5.2(a). The discharge coefficients of hydro plants are given in table 5.2(b). Maximum and minimum power limits are given in table 5.2(c). Maximum and minimum discharge limits are given in table 5.2(d). The load demands, thermal power, error and hydropower for 24-hour intervals are shown in table 5.2(e). Table 5.3(a). The load demands thermal power and hydro power for 24-hour intervals [18].

Assume that the transmission losses are zero and the reservoir is large. The water available in the reservoir is given by-

Vs = 2559.6 m^3

Thermal Unit	a_1(Rs/MW^2 h)	b_1(Rs/MWh)	c_1(Rs/h)
1	0.001991	9.606	373.7

Table 5.2(a). The coefficients of fuel cost

Hydro Unit	x_1(m^3/MW^2 h)	y_1(m^3/MWh)	z_1 (m^3/h)
2	0.0007749	-0.009079	61.53

Table 5.2(b). The discharge coefficients of hydro plants

Unit	Maximum(MW)	Minimum(MW)
P_1	550	150
P_2	300	100

Table 5.2(c). Maximum and minimum power limits

Hydro Unit	Maximum(m^3/h)	Minimum(m^3/h)
q	120	90

Table 5.2(d). Maximum and minimum discharge limits

Interval(hours)	Demand(MW)	Interval(hours)	Demand(MW)
1	455	13	580
2	425	14	605
3	415	15	616
4	407	16	653
5	400	17	721
6	420	18	740
7	487	19	700
8	604	20	678
9	665	21	630
10	675	22	585
11	695	23	540
12	705	24	503

Table 5.2(e). showing the input demand with the interval

5.3 Results

Interval (hours)	Demand (MW)	Thermal Power(MW)	Hydro Power(MW)	Discharge (m^3/h)	Error
1	455	217.5761	237.4238	103.05560	0.00001
2	425	182.4907	242.5092	104.9007	0.00001
3	415	169.6252	245.3746	105.9580	0.0011
4	407	180.5349	226.4604	99.2141	0.00027
5	400	171.2448	228.7552	100.0028	0.0000
6	420	174.1100	245.8901	106.1495	-0.00014
7	487	250.4997	236.5503	102.7427	-0.0009
8	604	371.1950	232.8049	101.4145	0.0001
9	665	408.4786	256.5215	110.1920	-0.00013
10	675	417.0945	257.9054	110.7311	0.0001
11	695	437.2365	257.7633	110.6756	0.0011

12	705	444.0826	260.9175	111.9147	-0.00015
13	580	335.2858	244.7141	105.7131	0.0002
14	605	361.5663	243.4336	105.2404	-0.00272
15	616	380.2142	235.7859	102.4699	0.1002
16	653	393.5169	259.4830	111.3493	0.0013
17	721	466.1678	254.8320	109.5380	0.001
18	740	476.1663	263.8337	113.0741	-0.0009
19	700	443.1487	256.8512	102.3202	0.00001
20	678	408.9924	269.0076	115.1634	-0.0009
21	630	373.9437	256.0563	110.0115	-0.0003
22	585	342.3796	242.6202	104.9414	0.00001
23	540	303.0835	236.9165	102.8737	-0.0009
24	503	268.6658	234.3340	101.9541	0.0001

Table 5.3(a). The load demands, thermal power, error and hydro power for 24-hour intervals

Volume =2559.60037 m^3

Volume error=-0.00037 m^3

From the above results the operating cost (thermal power plant) is given by

Operating cost = 91,377.61601 Rs.

5.4 Discussion

Classical technique like Newton-Rapsion, initial guess method and Lagrange relaxation method etc. have uses the local search but in case of particle swarm optimization (PSO) every search is random in nature. Hence it will search the optimal best in large random search space rather than start with single initial values. The classical techniques depend upon the step size and take some initial values for further computation to get the optimal solution, which may initially take to be wrong. But this is not in case of PSO, as it is randomly based technique.

Due to its random in nature fast convergence will takes place, but the global solution obtained from this technique is not assure that these results are exact or not.

Conclusion

An optimal scheduling of short-range fixed head hydro and thermal plants using particle swarm optimization (PSO) has been presented. The algorithm requires small computing resources and is fast, robust and reliable. By the use particle swarm optimization; the optimal value of fitness is obtained which is our operating cost of thermal power plant. On the basis fitness value, optimal power values are obtained with the satisfaction of equality and inequality constraints.

Future work

The particle swarm optimization technique applied on short range fixed head hydrothermal scheduling with the satisfaction of all the equality and inequality constraints. The particle swarm optimization technique applied on short range fixed head hydrothermal scheduling, not including the transmission losses. So we can apply PSO technique on variable head including losses and get the optimal solution. As we have already heard about the "Cophegen Sameleen" which is held in Denmark country. Nearly all the countries are participating in this Sameleen and discussing how we protect our environment, and to avoid the "Global Warming". There is lot of constraints (controlling the SO_2, NO_2 etc.), which you can include in the hydrothermal scheduling.

References:

[1]. Kirchmayer L.K., “Economic Control of Interconnected Systems,” *Wiley*, 1959.

[2]. Drake J.H., Kirchmayer L.K., Mayall R.B., Wood W., “Optimum Operation of a Hydrothermal System,” *AIEEE Transaction*, Vol.-85, pp.242-250, Aug. 1962.

[3]. Dahlin E.B., D.N.C. Shen, “Optimal Solution to the Hydro-Steam Dispatch Problem for Certain Practical systems,” *IEEE Trans. on Power Apparatus Systems*, Vol.85, , pp.437-458. May 1966.

[4]. Arvanitidis N.V., Rosing J., "Optimal Operation of Multireservoir Systems Using a Composite Representation", *IEEE Trans. on Power Apparatus and Systems*, Vol.89, No.2, February 1970.

[5]. Davist C.E., Pronovost R., "The Stochastic Dynamic Programming Procedures for Long Term Reservoir Management", *IEEE Trans. on Power Apparatus and Systems*, Vol.91, No.6, Nov/Dec 1972.

[6]. Agarwal S.K., Nagrath I.J.,“Optimal Scheduling of Hydrothermal Systems,” *Proc.on IEEE Trans.*, Vol .119, pp. 169-173. 2, Feb.1972

[7]. Turgeon A.,"Optimal Operation of Multireservoir Power Systems with Stochastic Inflows", Water Resources Research, Vo1.16,2, April 1980.

[8]. Soares S., Lyra C., Tavares H.” Optimal Generation Scheduling of Hydrothermal Power Systems,” *IEEE Trans. on Power Apparatus Systems*, Vol. 99,No.3, pp.1107-1175. May/June 1980

[9]. Quintana V.H., Chikhani A.Y., "A Stochastic Model for Mid-term Operation Planning of Hydrothermal Systems with Random Reservoir Inflows", *IEEE Trans. on Power Apparatus and Systems*, Vol.100, No.3, March 1981.

[10]. Maidment D.R., "Stochastic State Variable Dynamic Programming for Reservoir System Analysis”, *Water Resources Research*, Vo1.17, No.6, December 1981.

[11]. Lyra ,"Modelling and Optimization of Hydrothermal Generation Scheduling", *IEEE Trans. on Power Apparatus and Systems*, Vol.103, No.8, August 1984.

[12]. Dyncan ,"Optimal Hydrothermal Coordination for Multiple Reservoir River Systems", *IEEE Trans. on Power Apparatus and Systems*, Vol.104, No.5, May 1985.

[13]. Pereira, M. V. F. "Optimal Scheduling of Hydrothermal Systems - Na Overiew". *Symposium on Planning and Operation of Electric Energy Systems* - Preprints.Rio de Janeiro, pp.1-9, July. 1985

[14]. Amado S.M and Rebeiro C.C., "Short-Term Generation Scheduling of Hydraulic Multi Reservoir Multi Area Interconnected Systems," *IEEE Trans. on power systems,* Vol. 2, No.3, pp.758-763. Aug.1987

[15]. Yang J.S and N. Chen, "Short Term Hydrothermal Coordination Using Multi-Phase Dynamic Programming," *IEEE Trans. on Power systems,* Vol. 4, No.3, , pp.1050-1056. Aug. 1989.

[16]. Bond P S and Carneiro A.A.F.M., 'A Large Scale Application Of An Optimal Deterministic Hydrothermal Scheduling Algorithm',' *IEEE Transactions on Power Systems*, Vol. *5,* No. 1,pp.204-211, February 1990

[17]. Abdul Halim Abdul Rashid and Khalid Mohamed Nor, "An Efficient Method for Optimal Scheduling of Fixed Head Hydro and Thermal Plants", *IEEE Transactions on Power Systems,* Vo1.6, No. 2, May 1991.

[18]. W.W-G. Yeh ,"Optimization of Real Time Hydrothermal System Operation," *journal of water resources planning and management*, Vol.118, No., pp.636-653. 6, Nov./Dec. 1992

[19]. Kit Po Wow and Yin Wa Wong,'Short-Term Hydrothermal Scheduling With Reservior Volume Constraints. Part I: Simulated Annealing Approach.' *IEEE 2nd International Conference on Advances in Power System Control, Operation and Management,* pp.559-564, December 1993.

[20]. Kennedy James and Eberhart Russell,' A New Optimizer Using Particle Swarm Theory',' *IEEE Transactions on Power Systems,* pp.7803-2676,Aug.95.

[21]. Wood A., Wollenberg B., "Power Generation, Operation and Control," New York:*Wiley*, 1996.

[22]. Luh Peter B.'An Optimization-Based Algorithm for Scheduling Hydrothermal Power Systems with Cascaded Reservoirs and Discrete Hydro Constraints', *IEEE Transactions on Power Systems*, Vol. 12, No. 4, ,pp.1775-1780 November 1997

[23]. Hamdan A.R.’ Comprehensive Algorithm For Hydrothermal Co-ordination’ *IEEE Proc-Gener Transm Distvib.*, Vol. 144, No. **5,** ,pp.482-488, September 1997

[24]. Ferrero R.W.’ A Dynamic Programming Two-Stage Algorithm For Long-Term Hydrothermal Scheduling Of Multi reservoir Systems’,’ *IEEE Transactions on Power System*. Vol. 13. No., pp.1534-1540, 4,November 1998

[25]. Yuan’ A hybrid chaotic genetic algorithm for short-term hydro system scheduling’,’ *Mathematics and Computers in Simulation* .Vol.59.,pp.319–327(2002)

[26]. Kothari D.P., Dhillon J.S., “Power System Optimization”, *Prentice Hall of India Private Limited*, New Delhi, 2004.

[27]. Lakshminarasimman L. and Subramanian S.,'Short-term scheduling of hydrothermal power system with cascaded reservoirs by using modified differential evolution', *IEEE Proc.-Gener. Transm. Distrib.*, Vol. 153, No. 6, November 2006

[28]. Suman D.S.‘A Novel Approach for Short-Term Hydrothermal Scheduling Using Hybrid Technique’ *IEEE Transactions on Power System*, pp.1534-1540,5/06/2006

[29]. Sreeni.T.S ’ Hydro Thermal Scheduling using Particle Swarm Optimization’, *IEEE Transactions on Power System*,pp.1350-1353,3/08/2008

[30]. Costas G. Baslis and Anastasios G. Bakirtzis,’ A MIP(mixed-integer programming) Approach to the Yearly Scheduling Problem of a Mixed Hydrothermal System’, *IEEE Transactions on Power System* ,Vol. 978,5/08/2008