OPTIMAL SHORT-TERM THERMAL UNIT COMMITMENT USING NEURAL NETWORK

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in
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CERTIFICATE

I hereby certify that the work which is being presented in the thesis entitled, **"Optimal Short Term Thermal Unit Commitment Using Neural Network"**, 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.Parag Nijhawan, Sr.Lecturer, EIED.*

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

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

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ABSTRACT

Unit commitment and economic dispatch, when combined together is a useful tool to find the most economic generation schedule with which demand and all generating unit constraints are satisfied. This developed unit commitment and economic dispatch program provide dispatchers a robust tool for planning both operation and market strategies with consideration of cost minimization, risk management.

Fuel cost savings can be obtained by proper commitment of the available generating units. This thesis describes a Dynamic programming method for the commitment of thermal units over a period of up to 24 hours. Back propagation neural network has been applied for solving the unit commitment schedule of thermal generating units of 3 thermal power plants with very promising results.

The total cost includes both the fuel cost and cost associated with the start up and shut down of units. A variety of spinning reserve requirements is observed and equality constraints of power balance, inequality plant generation capacity constraints. The inputs to the neural network contain the total load supplied. The electric power generation of 3 thermal power plants is taken as the output of the neural network. A MATLAB code has been developed to generate training and test pattern for the developed network. To conclude, the performance and time taken for execution of the neural network is compared with conventional dynamic programming method.

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CHAPTER 1

INTRODUCTION

1.1 OVERVIEW

The objective of the problem is to find the generation scheduling of three thermal units such that the total operating cost can be minimized, subjected to a variety of constraints using conventional dynamic programming and back propagation neural network. The total cost includes both fuel cost and start up cost. The input to the neural network contains the total load supplied. The electric power generation of three thermal units is taken as the output of the neural network. Comparison of results obtained from conventional dynamic programming and back propagation neural network are shown.

1.2 LITERATURE REVIEW

The main objective in the operation of any of today's complex electric power systems is to meet the demand for power at lowest possible cost, while maintaining safe, clean standards of environmental impact. In electric power system, Reliability and continuity of service are essential goals an engineer strives to meet at all times. There are some problems in the optimal economic operation of systems. The problems can be considered the part of the production scheduling activities. These activities are considered with economic hourly scheduling of the available energy resources so that the lowest total production cost is achieved while meeting system loads without rotating the system constraints [1, 4, 14].

Electric utility investment practices and operation have been designed to ensure affordable, reliable electricity service to consumers. Affordability and reliability require thoughtful, long term investments in generation and transmission as well as sophisticated operation of these assets. Economic dispatch focuses on short term operational decisions, specifically how to make optimum use of available resources to meet customer's electricity needs reliably and economically [26, 27].

Economic dispatch is the method of determining the most efficient, low cost and reliable operation of a power system by dispatching the available electricity generation resources to supply the load on the system. The primary objective of economic dispatch is to minimize the total cost of generation while honoring the operational constraints of the available generation resources. EPAct (energy policy act) defines “economic dispatch” as “the operation of generation facilities to produce energy at the lowest cost to reliably serve consumers, recognizing any operational limits of generation and transmission facilities”. Sakorn Panta and Suttichai Premrudeepreechacharn defines “economic dispatch as computational process where the total required generation is distributed among the generation units in operation, by minimizing the selected cost criterion, subject to load and operational constraints”. Economic dispatch is used in real time energy management power system control by most programs to allocate the total generation among the available units, unit commitment and in some other operation function [23].

Economic dispatch principles and operation are the same in both regulated utility operations and centralized wholesale markets. In centralized markets, the merit order of available resources is determined using offer schedules for each resource rather than the variable production costs that are used to dispatch a set of utility-owned resources.

Many factors influence economic dispatch in practice. These include contractual regulatory, environmental, scheduling, unit commitment, and reliability practices and procedures [26, 27] .It is useful to divide economic dispatch practices into separate stages: unit commitment and unit dispatch. Unit commitment takes place before real time operation and determines the set of generating units that will be available for dispatch. Unit dispatch occurs in real time and determines the amount of generation needed from each available unit [23].

Unit commitment and economic dispatch when combined together is a useful tool to find the most economical generation schedule with which demand and spinning reserve requirement are supplied and all generating unit constraints such as unit minimum and maximum generation capabilities, and unit minimum up and down time, over a time horizon. The available approaches for solving unit commitment economic optimization are priority list, dynamic programming and lagrangian relaxation. These approaches are integrated into unit commitment and economic dispatch to optimize the cost of generation and meet the needs of the restructured power industry [30, 31].

Test results are presented by using dynamic programming. Dynamic programming is defined as the cost-based scheduling algorithm to find optimal profit by selecting the market domain and determining the amount of power to be dispatched in that domain [10]. The approach, first used by Lowery [16], and later refined by Ayoub and Patton [2], selected unit generation output as a state variable and on-line capacity as the stages. Ayoub and Patton included probabilistic techniques for reserve determination in the developed code. Hobbs et al. [28] initialize their approach with options calculated for preceding periods. The truncated combination (DP-TC) described by Ouyang and Shahidehpour omits must run units and units not allowed or able to operate from the search range. Ouyang and Shahidehpour [15] use neural networks to enable the model to learn from previously made decisions. Dynamic programming approach is one of the widely employed methods but for a practical sized system, the fine step size and large units number often cause the ‘curse of dimensionality’. Neural networks and fuzzy logic techniques can be used to overcome the difficulties of classical method. Test results are presented using neural networks.

Neural networks have a well demonstrated capability of solving combinational optimization problem. The development of artificial neural network started 50 years ago. The paradigm of neural networks, which began during the 1940’s, promises to be a very important tool for studying the structure function relationship of the human brain. It has demonstrated great potential for various low level computations and embodies salient features such as learning, fault tolerance, parallelism and generalization. ANN can be defined as a class of mathematical algorithms designed to solve a specific problem. ANN is a parallel computational model which is comprised of densely interconnected adaptive processing units. ANNs learn the pattern on which they are trained [13, 24, 25].

In this work, a generation schedule for a typical load pattern would generally contain specific information regarding the optimization of unit commitment and ANN is trained with different load demands. Once it has been trained, it acquires the ability to give load scheduling pattern for any value for load demand. The method used is feed-forward back- propagation type of neural network to learn different condition in operation of each unit. So, the minimum operation condition is selected with less iteration and time.

1.3 OBJECTIVE

The objective of the proposed work is that unit commitment and economic dispatch, when combined together is a useful tool to find the most economic generation schedule with which demand and all generating unit constraints are satisfied. This developed unit commitment and economic dispatch program provide dispatchers a robust tool for planning both operation and market strategies with consideration of cost minimization, risk management. The proposed work includes formulation and coding using MATLAB.

1.4 ORGANIZATION OF THESIS

The thesis includes 6 chapters altogether. The chapters are organized as follows:

Chapter 1

This includes overview-brief outline of the problem, literature review and objective of the problem.

Chapter 2

This chapter provides an introduction to economic dispatch of thermal power systems. It includes comparison between economic dispatch and efficient dispatch and also includes how the problem is formulated for optimal generation scheduling. Benefits of economic dispatch are also included.

Chapter 3

This chapter elaborates unit commitment problem. It includes the introduction to unit commitment, constraints involved in the unit commitment to solve a numerical problem. It also includes a brief introduction to the solutions methods of unit commitment problem.

Chapter 4

Chapter gives an introduction to Neural Networks. Brief discussion on applications of ANN to various power systems problems has also been presented.

Chapter 5

This includes problem formulation i.e. how unit commitment is based on neural networks. The step-wise procedure to solve the thermal unit commitment problem and also step-wise procedure to solve the thermal unit commitment problem using neural network is presented.

Chapter 6

Chapter concludes this thesis work purely on the grounds of the results obtained.

CHAPTER 2

ECONOMIC DISPATCH

2.1 INTRODUCTION

Economic dispatch is the process of allocating the required load demand between the available generation units so as to minimize the cost of operation. It is a straight forward concept: costs to serve a given level of electricity demand are minimized by dispatching generation involving lower cost before dispatching higher cost generation. A number of considerations must be addressed to ensure that the resulting system operation is secure, reliable and cheap [1, 4, 6].

2.1.1 Planning for tomorrow's dispatch

- Scheduling generating units for each hour of the next day's dispatch
    - is based on forecast load for the next day
    - Selects generating units that should be running and are available for dispatching the next day (operating day)
    - Operating limits of each generating unit is recognized.
    - Recognize generating unit characteristics.
    - is performed by a generation group or an independent market operator.
- Reliability Assessment
    - Analyze forecasted load and transmission conditions in the area and ensures that scheduled generation dispatch meets the load reliably.
    - Revise the scheduled dispatch, if it is not feasible within the limits of the transmission system.
    - is performed by a transmission operations group.

2.1.2 Economic Dispatch vs. Efficient Dispatch

"Economic Dispatch", is an optimization process crafted to meet electricity demand at the lowest cost, given the operational constraints of the generation and the transmission system. Although economic dispatch will usually run higher efficiency gas-fired units before lower efficiency units. But it is not the case always, for a number of possible reasons. “Efficient Dispatch” modifies the practice of economic dispatch in a way that more efficient gas-fired units are always used before less efficient units.

The advantages of Efficient Dispatch are

1. The fundamental purpose of economic dispatch is to reduce consumers’ electricity costs whereas “Efficient Dispatch” would take off the dispatch process from this path and increase consumer’s electricity costs- for benefits that may not be large enough to offset these additional costs.
2. Economic Dispatch is a complex process, and modifications to it must be made with care in order to minimize the unanticipated consequences.

The economic dispatch problem involves two separate steps namely ‘unit commitment’ and ‘on-line economic dispatch’. The unit commitment selects those units that supply the anticipated load of the system over a required period of time at minimum cost as well as provide a specified margin of the operating reserve known as the spinning reserve. The on-line economic dispatch distributes the load among those operating units that are actually paralleled with the system in such a manner that the total cost of supplying the minute to minute requirements of the system is minimized.

For optimal generation of thermal system, the problem is to find the generation of different units so that the total fuel cost is minimum subjected to various constraints. Basically there are two types of constraints, namely, equality constraints and inequality constraints [26, 27].

2.2 OPTIMAL GENERATION SCHEDULING

The economic dispatch problem is defined as the one that minimizes the total operating cost of a power system while meeting the total load plus transmission losses within generator limits. When long distance transmission of power is involved, transmission losses do occur. If the transmission losses are neglected, then the total system load can be optimally divided among the various generating plants using the equal incremental cost criterion. A modern electric utility is capable of serving a vast area of relatively low load density [1, 4]. The transmission losses may vary from 5 to 15 per cent of total load. It is very necessary to keep an account for transmission losses while developing an economic load dispatch policy. Mathematically, the problem is defined as

Minimize $$F(P_{gi}) = \sum_{i=1}^{NG} (a_i P_{gi}^2 + b_i P_{gi} + c_i) Rs / hr \qquad \ldots(2.1)$$

Subject to

i. the energy balance equation

$$\sum_{i=1}^{NG} P_{gi} = P_D + P_L \qquad \ldots(2.2)$$

ii. and the inequality constraints

$$P_{gi}^{\min} \le P_{gi} \le P_{gi}^{\max} \qquad \ldots(2.3)$$

where

a_i, b_i and c_i are the cost coefficients

P_D is the load demand

P_{gi} is the real power generation and will act as decision variable

NG is the number of generation buses

P_L is the transmission power loss

The transmission loss can be expressed as a function of generator powers through B-coefficients. Under normal operating conditions, the transmission loss is found to be quadratic in the injected bus real powers. Loss formulae using B-coefficients can be generalized as

$$P_L = \sum_{i=1}^{NG} \sum_{j=1}^{NG} P_{gi} B_{ij} P_{gj} \qquad \ldots(2.4)$$

where

P_{gi} and P_{gj} are the real power injections at the ith and jth buses

B_{ij} are the loss coefficients which are constant under certain assumed conditions

NG is the number of generation buses

This converts the constrained optimization problem into an unconstrained optimization problem. Lagrange multiplier method is used where the function is minimized (or maximized) using side conditions in the form of equality constraints.

Using Lagrange multipliers, an augmented function is defined as

$$L(P_{gi},\lambda) = F(P_{gi}) + \lambda\left(P_D + P_L - \sum_{i=1}^{NG} P_{gi}\right) \qquad \ldots(2.5)$$

where

λ is the Lagrangian multiplier

The incremental cost can be obtained as

$$\left(\frac{\partial F(P_{gi})}{\partial P_{gi}}\right) L_i = \lambda \qquad \ldots(2.6)$$

where

$$L_i = \frac{1}{1 - \frac{\partial P_L}{\partial P_{gi}}} \qquad \ldots(2.7)$$

L_i is called the penalty factor of the *i*th plant.

The value of P_{gi} can be obtained as

$$P_{gi} = \frac{\lambda\left(1 - B_{i0} - \sum_{j=1}^{NG} 2B_{ij}P_{gj}\right) - b_i}{2\left(a_i + \lambda B_{ii}\right)} \qquad \ldots(2.8)$$

Without transmission losses

The value of P_{gi} can be obtained as

$$P_{gi} = \frac{\lambda\left(1 - B_{i0} - \sum_{j=1}^{NG} 2B_{ij}P_{gj}\right) - b_i}{2\left(a_i + \lambda B_{ii}\right)} \qquad \ldots(2.9)$$

The incremental cost can be obtained as

$$\lambda = \frac{P_D + \sum_{i=1}^{NG} \frac{b_i}{2a_i}}{\sum_{i=1}^{NG} \frac{1}{2a_i}} \qquad \ldots(2.10)$$

2.3 THE BENEFITS OF ECONOMIC DISPATCH

Economic dispatch benefits electricity users in a number of ways:

1. By systematically seeking the lowest cost of energy production that consistent with electricity demand, economic dispatch reduces total electricity cost. To minimize cost, economic dispatch typically increases the use of ‘ the more’ efficient generation units, that leads to better fuel utilization, lower fuel usage, and reduced air emissions comparative to that done using less-efficient generation

2. If the geographic and electrical scopes integrated under unified economic dispatch are increase, then additional cost savings result from pooled operating reserves, which allow to meet the loads reliably using less total generation capacity in an area.

3. Economic dispatch requires operators to pay close attention to system conditions and maintain secure grid operation, thus increasing operational reliability without increasing costs.

4. Economic dispatch methods are incorporate policy goals such as promoting fuel diversity or respecting demand as well as supply resources very flexibly.

5. Economic dispatch encourages new investment both in generation and transmission expansion and upgrades them in order to enhance both reliability and cost savings [26, 27].

CHAPTER 3

UNIT COMMITMENT

3.1 INTRODUCTION

In the operation of power systems, solutions of various problems are usually determined on the experience and judgment of experts (operators) formulated as a set of heuristic rules. Very likely an inference machine is anticipated which would be able to apply these rules logically, and solve these problems according to the procedure followed by human experts. The implementation of this automation procedure for replacing or reducing the amount of thinking in critical circumstances is known as ‘expert system’ approach. Implementation of an expert system not only reduces human work load in decision making process but it also resolve various difficulties in a much shorter period of time. Hence, reducing human errors in a systematic and well developed manner.

In this regard, those problems have been considered whose solutions can be easily formulated into sets of rules by this fascinating approach. These problems include power system restoration, security analysis, alarm processing, fault diagnosis etc.

There are a number of problems associated with power system operation which cannot be handled directly by a set of rules. Most of them are related to economic operation, where the optimization of the objective functions is usually governed by complex constraints, and hence it is difficult to develop an appropriate set of rules to trace out the optimal solution for each of these problems [8, 21, 24, 28].

The formulation of a generation allocation plan, for power system operations, suffers from various problems such as increase in the number, type and size of generating facilities, and variations in load demands. These complexities, pose a wide range of decision-making problems for power system operators. One of the problems is the scheduling of generators in a power system at any given time. It proves uneconomical for a power system if all the units that are required to satisfy the peak load during low load periods run simultaneously. The unit commitment problem draws out a plan for selecting only those units from the generating facilities that are capable of meeting the predicted demand in a reliable and an economical manner.

One of the most important problems in operational scheduling of electrical power generation is the unit commitment (UC) problem. It determines the start-up and shut-down schedules of thermal units to be used to meet forecasted demand over a future short term (24-168 hour) period. The main motive is to minimize total production cost while addressing to a large set of operating constraints. The UC problem is a complex mathematical optimization problem that involves both integer and continuous variables. The exact solution to the problem can be obtained by complete enumeration. But it cannot be applied to realistic power systems because it involves excessive computation time. It is difficult to solve the unit commitment problem for a large system, since large numbers of units of commitment are involved. The problem amplifies if all the units are involved simultaneously in the search for the optimal solution, as it leads to the exhaustion computational [1, 14].

To “commit” a generating unit implies to “turn it on;” that is, to bring it upto the desired speed, synchronize it and connect it to the system so that it can deliver power to the network. The problem of “commit enough units and leave them on line” is one of economics.

3.2 CONSTRAINTS IN UNIT COMMITMENT

Many constraints can be placed on the unit commitment problem. Each individual power system, power pool, reliability council, and many more can impose different rules on the scheduling of units, depending on the generation makeup and load-curve characteristics.

3.2.1 Spinning reserve requirements

Spinning reserve requirements are essential for minimizing load interruption in the operation of power system. This interruption occurs partly, due some unpredictable load fluctuations and partly due to possible outages of equipment. Spinning reserve requirements can be specified in terms of excess megawatt capacity or some form of reliability measures. The practice of allocating the amount and distributing the spinning reserve requirements may vary from company to company and from pool to pool.

For on-line thermal units, the spinning reserve of a unit is equivalent to that unit capacity which is less than the unit generation or a fixed percentage of the capacity, whichever is lower. In the case of hydro units and pumped storage units in the generating mode, the spinning reserve of a unit is calculated as the difference between the unit capacity and the unit generation. But when a pumped storage unit is in the pumping mode, its spinning reserve is equal to the pumping load [3, 31].

The amount of spinning reserve is an important factor that assures an uninterrupted supply to the customers. The distribution of the spinning reserve relative to the load centers and among the various generating plants in the system also holds a similar importance. Therefore additional spinning reserve requirements are also imposed in order to ensure adequate distribution of spinning reserve throughout the system.

Different types of spinning reserve requirements that shall be in the commitment of units are as follows:

- Fixed total spinning reserve
- Minimum spinning reserve for each area
- Maximum spinning reserve from any one plant
- Maximum spinning reserve from each unit

3.2.2 Thermal Unit Constraints

Thermal units usually require a crew to operate them, especially when turned on and turned off. Since the thermal unit can undergo only gradual temperature changes, hence this gets translated into a time period of some hours which are essential to bring the unit on-line.

As a result of these restrictions, various constraints arise, in the operation of a thermal plant, such as:

- **Minimum up time and minimum down time**: in the operation of units, engineering consideration and manufacturer specification normally requires that a unit should for at least a certain amount of time before it is shut down. In a similar fashion, a minimum down time is imposed on individual units between successive operations.
- **Crew constraints on plants**: certain plants may have limited crew size which prohibits the simultaneous starting up and/or shutting down of two or more units at the same plant. Such constraints would be further specified by the times required to bring a unit on-line and to shut it down.

In addition, a certain amount of energy is consumed to bring the unit on-line, since it is required to slowly vary the temperature and pressure of the thermal unit.
This energy does not result in any MW generation from the unit and is brought into the unit commitment problem as a "start-up cost."

The start-up cost can vary from a maximum "cold-start" value to a much smaller value if the unit is only turned off only recently and is still relatively close to operating temperature. There are two approaches for treating a thermal unit during the period it is off. The first approach allows the unit's boiler to first cool down and then to get heated up to operating temperature in the scheduled turn on time. The second approach (called banking) requires sufficient energy input to the boiler to just maintain operating temperature. The costs for the two are then compared so that, if possible, the best approach (cooling or banking) can be chosen.

Start up cost when cooling is given by

$$C_c\left(1-\varepsilon^{-t/\alpha}\right)\times F+C_f \qquad \ldots(3.1)$$

where

C_c = cold-start cost (MBtu)

F = fuel cost

C_f = fixed cost (includes crew expense, maintenance expenses) (in R)

α = thermal time constant for the unit

t = time (h) the unit was cooled

Start-up cost when banking is given by

$$C_t\times t\times F+C_f \qquad \ldots(3.2)$$

Where

C_t = cost (MBtu / h) of maintaining unit at operating temperature

Up to a certain number of hours, the cost of banking will be less than the cost of cooling. But, the capacity limits of thermal units may change frequently, due to maintenance or unscheduled outages of various equipment in the plants. This must also be taken into account in unit commitment [1, 32].

3.2.3 Must run units

These units include pre-scheduled units which must be on-line, due to operating reliability and/or economic considerations.

3.2.4 Must out units

Units which are on forced outages and maintenance are unavailable for commitment and are referred as must out units.

3.2.5 Units on fixed generation

These are units which have been pre-scheduled but their generation has been specified for certain time period. A unit on fixed generation automatically turns into a must run unit for the designated time period.

3.2.6 Changes in unit generating limits and capacity

Partial outages and component maintenance can reduce the unit generating limits and capacity. On the other hand, completion of maintenance and restoration of failed components increases the limits and capacity.

3.2.7 Hydro-constraints

Unit commitment cannot be completely separated from the scheduling of hydro units whereas the hydro thermal scheduling can be separated from the unit commitment problem. But we cannot assert that the result will be an optimal solution.

3.2.8 Fuel constraint

A system in which some units have limited fuel, or else have constraints that require them to burn a specified amount of fuel in a given time, presents a most challenging unit commitment problem.

3.2.9 Fuel cost computation

Fuel cost in unit commitment problem may be divided into two categories. First is the transitional cost while the other is the production or generation cost. Generally the transitional cost is the cost associated with the startup of the unit. Sometimes it may also include the shut down cost as well. The production cost is the fuel cost required to meet the load, and this depends on the unit loading, heat rate and fuel price.

3.3 UNIT COMMITMENT SOLUTION METHODS

The unit commitment problem determines the combination of available generating units. It schedules their respective outputs in order to satisfy the forecasted demand with a minimum total production cost under the operating constraints, enforced by the system, for a specific period of time that usually varies from 24 hrs to one week. Attempts to develop rigid unit operating schedules in advance for more than one week are extremely curtailed due to uncertainty in hourly load forecasts at lead time greater than week.

Besides achieving minimum total production cost, a generation schedule is required to satisfy a number of operating constraints. These constraints reduce freedom in their choice of starting up and shutting down of generating units. Usually the constraints to be satisfied are usually the status restriction of individual generating units, minimum up time, minimum down time, capacity limits, generation limits for the first and last hour, power balance constraint, spinning reserve constraints, hydro constraints, etc.

The high dimensionality and combinatorial nature of the unit commitment problem curtails the attempts entire to make develop any rigorous mathematical optimization method, which is capable of solving the whole problem for any real-size system. The available approaches for solving unit commitment problem can usually be classified into *heuristic methods* and *mathematical programming methods.* The proposed mathematical programming approaches are *dynamic programming and Langragian relaxation* [10].

These two approaches are most widely used to develop industry grade unit commitment programs. The major advantage is the reasonable computation time involved as compared to other approaches. The most talked about techniques for the solution of the unit commitment problem are:

- Priority-list schemes.
- Dynamic programming (DP)
- Lagrange relation (LR)

3.3.1 Priority-List Methods

The simplest unit commitment solution method consists of creating a priority list of units. The priority list could be obtained in a much simpler manner by noting the full-load average production cost of each unit. A full-load average production cost is calculated as the net heat rate at full load multiplied by the fuel cost.

3.3.2 Dynamic Programming Solution

In dynamic programming, it is relatively easy to add constraints (such as power balance constraints) that affect operations in an hour mainly the economic dispatch and solution methods. However, the dynamic programming suffers from the curse of dimensionality. Hence, it is required to limit the commitments considered at any hour through the simplification techniques such as truncation and fixed priority ordering. These simplifications, particularly for large scale systems, can lead to suboptimal solutions. Dynamic programming decomposes a problem into a number of smaller problems, solves them and hence develops an optimal solution of the original problem in a step wise manner. The optimal solution is developed from the subproblem recursively.

In its fundamental form, the dynamic programming algorithm for unit commitment problem examines every possible state in each interval. Some of these states are rejected instantly because they are found infeasible. But even, for an average size utility, a large number of feasible states will exist and the requirement of execution time will stretch the capability of even the largest computers.

Dynamic programming has many advantages over the enumeration scheme. The chief advantage being the reduction in the dimensionality of the problem. Suppose units are found in a system and any combination of them could serve the (single) load. There would be a maximum of 2^N-1 combinations to test.

The imposition of priority list arranged in order of the full load average cost rate would result in a theoretically correct dispatch and commitment only if:

1. No load costs are zero.
2. Unit input-output characteristics are linear between zero output and full load.
3. No other restrictions are there.
4. A fixed amount is set for start-up costs.

In the dynamic programming approach that follows, we assume that:

1. A state consists of an array of units with only specific units operating and rest off-line.
2. The start-up cost of a unit is independent of the time it has been off-line (i.e., it is a fixed amount).
3. There are no costs for shutting down a unit.

4. There is a strict priority order, and in each interval a specified minimum amount of capacity must be operating.

A feasible state is one in which the committed units can be supply the required load and that meets the amount of capacity at each period [11].

3.3.2.1 Forward Dynamic Programming Approach

One could set up a dynamic-programming algorithm to run backward in time starting from the final hour back to the initial hour. Conversely, the algorithm can be made to run forward in time from the initial hour to the final hour. The forward approach has distinct advantages in solving generator unit commitment problem. For example, if the start-up cost of an off line unit is a function of time (i.e., its temperature), then a forward dynamic-program approach is more suitable since it helps in computing the previous history of the unit at each stage. There are other practical reasons as well for going forward. It easily specifies the initial conditions and the computations can go forward in time as long required [1, 22].

3.3.3 Lagrange Relaxation Solution

The dynamic programming method for solving the unit commitment problem has many disadvantages for large power systems that have many generating units. This is because of the necessary force on the dynamic programming solution to search for a way in order to reduce the number of combinations that must be tested in each time period, among a small number of commitment states.

However, these disadvantages disappear in the Lagrange relaxation technique. This method is based on a dual optimization approach. The utilization of Lagrangian relaxation in production unit commitment problem is much more recent than the dynamic programming methods.

Defining the variable U_i^t as

$U_i^t = 0$ if unit i is off-line during period t

$U_i^t = 1$ if unit i is on-line during period t

Several constraints and the objective function of the unit commitment problem are defined as:

1. Loading constraints:

$$P_{load}^{t} - \sum_{i=1}^{N} P_i^t U_i^t = 0 \quad \text{for} \quad t = 1.....T \qquad \ldots(3.3)$$

2. Unit limits:

$$U_i^t P_i^{\min} \le P_i^t \le U_i^t P_i^{\max} \quad \text{for} \quad i = 1.....N \quad \text{and} \quad t = 1.....T \qquad \ldots(3.4)$$

3. Unit minimum up and down time constraints. Note- However other constraints can also be easily formulated and added to the unit commitment problem such as transmission security constraints, generator fuel limit constraints, etc.
4. The objective function is:

$$\sum_{t=1}^{T}\sum_{i=1}^{N}\left[F_i\left(P_i^t\right) + startup\cos t_{i,t}\right]U_i^t = F\left(P_i^t, U_i^t\right) \qquad \ldots(3.5)$$

The Lagrange function obtained:

$$L\left(P, U, \lambda\right) = F\left(P_i^t, U_i^t\right) + \sum_{t=1}^{T}\lambda^t\left(P_{load}^t - \sum_{i=1}^{N} P_i^t U_i^t\right) \qquad \ldots(3.6)$$

It has many advantages:

1. It has the capability of getting modified easily in order to model the characteristics of specific utilities.
2. It is more advantageous due to its flexibility in dealing with different types of constraints.
3. It is flexible and can incorporate additional coupling constraints that have not been considered so far.
4. It is also more adaptive than dynamic programming because no priority ordering has been mentioned.
5. Computationally more attractive for large systems.

Disadvantages:

1. Its weakness is that the optimal solution obtained using this method seldom satisfies the once relaxed coupling constraints.
2. Another weakness is the sensitivity problem that may cause unnecessary commitments of some units. Hence, only a nearly optimal feasible solution can be expected. However, the degree of suboptimality decreases alongside as the number of units increases.

CHAPTER 4

NEURAL NETWORKS

4.1 INTRODUCTION TO NEURAL NETWORKS

Neural networks represent a different and meaningful approach for using computers in the workplace. A neural network is used to learn patterns and relationship in data. It may be any kind of data. Like the result of a market research effort, a production process given varying operational conditions, or the decisions of a loan officer given a set of loan applications.

While computing, programmer or an analyst specifically develops the code for every facet of the problem. However, this is not the case with neural networks. They do not require explicit coding of the problems. NNs can compute any computable function, especially those that can be represented as a mapping between vector spaces and can be approximated to arbitrary precision by feed forward NNs [5, 25].

4.2 AIM OF NEURAL NETWORKS

The aim of the neural networks is to mimic the human ability to adapt to changing circumstances and the current environment. This depends heavily on the capability to learn from events that have happened in the past and then apply it to future situations.

Artificial Neural Network (ANN) is a system that is loosely modeled on the human brain. The field goes by many names, such as, connectionism, parallel distributed processing, neurocomputing, natural intelligent systems, machine learning algorithms, and artificial neural networks. It is an attempt to simulate, within the specialized hardware or sophisticated software, the multiple layers of simple processing elements called neurons. Each neuron is linked to a certain number of neighbors with varying coefficients of connectivity that represent their connection strength. Learning is accomplished by adjusting these strengths and hence achieving appropriate results. For the overall network all natural neurons have four basic components: dendrites, soma, axon, and synapses. Basically, a biological neuron receives inputs from other sources, combines them in some way, performs an operation, generally non-linear, on the result, and then output the final result. Neural networks are mainly categorized by their architecture (number of layers), topology (connectivity pattern, feed forward or recurrent etc) and learning regime [6, 25].

In general, the neural net can be a single layer or a multi-layer net. The structure of the simple artificial neural net is shown

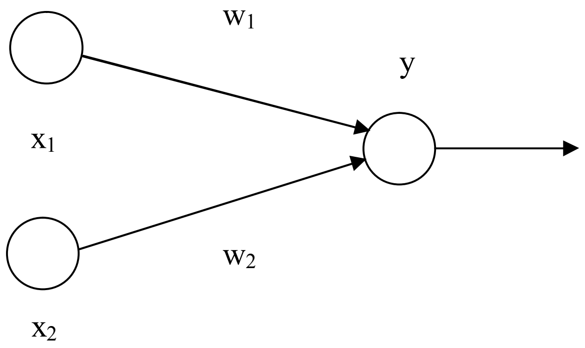


Fig 4.1: A Simple Artificial Neural Net

Fig 4.1 shows a simple artificial neural net with two input neurons (x_1, x_2) and one output neuron (y). w_1 and w_2 are the interconnecting weights. In a single layer net, there is a single layer of weighted interconnections.

A typical multi-layer artificial neural network, MNN, comprises of an input layer, output layer and a hidden (intermediate) layer of neurons. MNNs are often called layered networks. They can implement arbitrary complex input/output mappings or decision surfaces separating different patterns. A block diagram representation of a three layered MNN is shown in fig 4.2

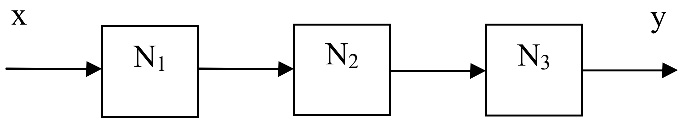


Fig 4.2: A Block Diagram Representation of a Three-layered MNN

Artificial neural networks are non linear information (signal) processing devices that are built from interconnected elementary processing devices called neurons.

It is an information processing paradigm that is inspired by the way biological nervous system, such as the brain, processes information. The key element of this paradigm is the novel structure of the information processing system. To solve specific problems, it is compared to the large number of highly interconnected processing elements (neurons) working in union. ANNs, like people, learn by an example. An ANN can be configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning in biological systems involves adjustment to synaptic connections that exist between the neurons.

A neural network is a massively distributed parallel. It has a natural propensity for experimental knowledge and making it available for use. It resembles the brain in two respects:

1. knowledge is acquired by the network through a learning process, and,
2. Inter-neuron connection strengths, known as synaptic weights, are used to store the knowledge.

An artificial neuron is characterized by:

1. Architecture (connection between neurons)
2. Training or learning (determining weights on the connections)
3. Activation function

4.3 WHAT ARE FEED FORWARD NETWORKS

One can differentiate between two basic types of networks, networks with feedback and those without it. In networks with feedback, the output values can be traced back to the input values. However there are networks wherein for every input vector laid on the network, an output can be calculated and can be read from the output neurons. There is no feedback. Hence only, a forward flow of information is present. Networks having this structure are known as feed forward networks. There are various nets that come under the feed forward type. One of the most important types of feed forward network is the back propagation network.

4.3.1 Back propagation network

Back propagation is a systematic method for training multi layer artificial neural networks. It has a strong mathematical foundation, though not highly practical. It is a multi layer forward network and uses extend gradient descent based delta-learning rule, commonly known as back propagation (of errors) rule. Back propagation provides a computationally efficient method for changing the weights in a feed forward network, with differentiable activation function units, to learn a training set of input –output examples. This network aims at training the net to achieve a balance between the ability to respond correctly to the input patterns that are used for training. It is capable of providing good responses to the inputs that are similar [25].

Applications

The back propagation algorithm covers wide area of applications, viz.

- optical character recognition
- image compression
- data compression
- load forecasting problems in power system area
- control problems
- non linear simulation
- fault detection problems

This can also be extended to face recognition, avionic problems, etc.

4.3.2 Architecture

A multilayer feed forward network, often known as Multilayer Perceptron (MLP), is distinguished from others by the presence of one or more hidden layers. Hidden neurons in hidden layers intervene between external input and the network outputs. The addition of hidden layers in MLP increases its capability of extracting higher-order statistics, which further helps to deal with high degree on non-linearity and complex situations. MLPs can be either fully connected or partially connected. In fully connected multilayer feed forward networks, every neuron in each layer is connected to every other neuron in the adjacent forward layer. Fig 4.3 shows a fully connected multilayer feed forward network [17].

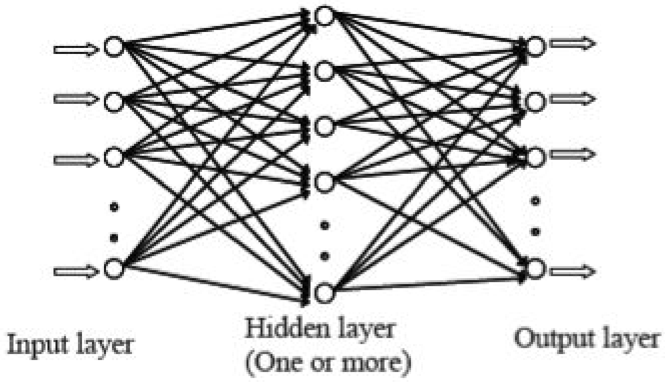


Fig 4.3: Fully Connected Multi Layer Feed Forward Network

4.4 APPLICATION OF NEURAL NETWORKS IN POWER SYSTEMS

4.4.1 Introduction

Neural networks have been used in a broad range of applications including: pattern recognition, pattern classification, optimization, prediction and automation control. In spite of different structures and paradigms, all NN applications are special cases of vector mapping. The application of NNs in different power system operation and control strategies has led to the quite acceptable results.

Here is an overview of application of NNs in power system operation and control. The comparison of a number of published papers, in IEEE proceedings and conference papers in this field, from 1990-1996 with the ones published during 2000-2005 has showed that the following fields has attracted great attention in the past five years:

1. load forecasting
2. fault diagnosis/fault location
3. economic dispatch
4. security assessment
5. transient stability

The electricity industry is a huge, growing business, based on the supply and demand routine of electricity. There are many benefits in knowing the future load on the system by the way of forecasting future load demand [12, 18].

Fig 4.4: Neural Networks applications in Power systems;2000-April 2005

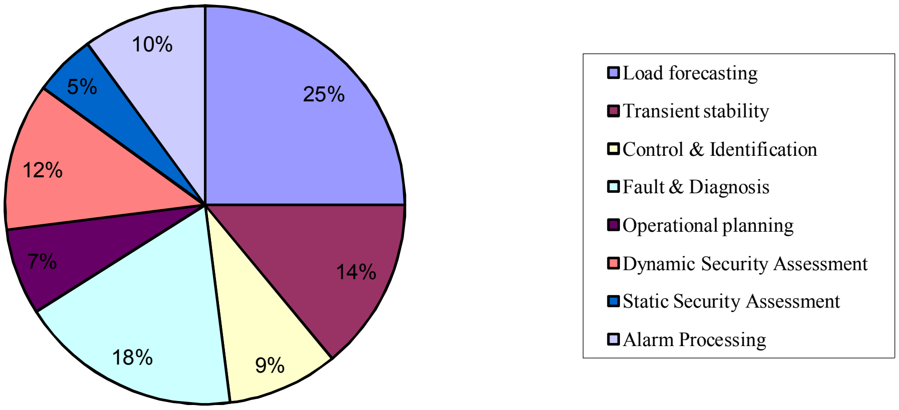
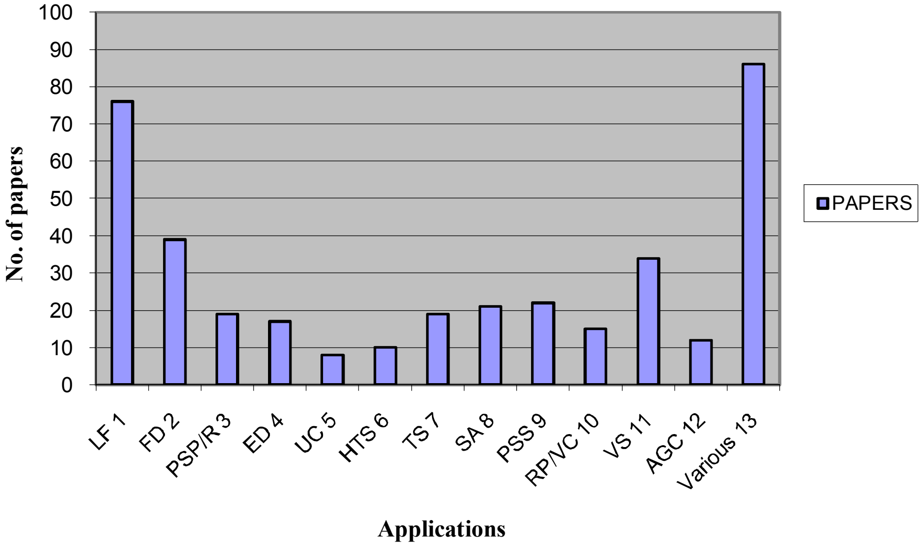


Fig 4.5 shows the classifications of papers on ANN application in power systems. From the figure shown below, it can be clearly seen that load forecasting and fault diagnosis are main areas in which ANN have been used followed by voltage stability/contingency analysis, power system stabilizer, security assessment, power system protection/relaying, transient stability, economic dispatch, reactive power/voltage control, etc.

1. Load forecasting = 76
2. Fault diagnosis = 39
3. Power system Protection/relaying = 19
4. Economic dispatch = 17
5. Unit Commitment = 8
6. Hydro thermal scheduling =10
7. Transient stability = 19
8. Security assessment = 21
9. Power system stabilizer = 22
10. Relative power/voltage control = 15
11. Voltage stability/contingency analysis = 34
12. Automatic generation/load frequency control = 12

13. Various other areas of power systems = 86

Fig 4.5 Classifications of papers on ANN applications in power systems



Load forecasting can be broadly classified in three categories:

i. Short term load forecasting (STLF): half hourly or hourly data with a horizon of one day to seven days ahead. It addresses the problem of unit commitment, scheduling and operating reserve,

ii. Medium term forecasting (MTF): weekly or monthly data with a horizon of one week to three years. It addresses the problem of operation planning, maintenance, energy contracts, fuel management and revenue from sales,

iii. Long term forecasting (LTF): weekly, monthly or annual data with a horizon of greater than three years for the problem of capacity expansion planning and strategy planning.

STLF, in particular, has become increasingly important since the rise of the competitive energy markets. Loads in power system depend on various factors like weather conditions, economic situation, holiday’s geographical locations, daylight hours, etc.

ANN is a very attractive and the most commonly applied approach for load forecasting problem now a days, because it can combine both time series and regression approaches to predict the load demand. A functional relation between weather variables and electrical loads does not hold much importance because ANN can generate this functional relationship by learning and training data.

4.5 VARIOUS POWER SYSTEM PROBLEMS

Brief overview of various power system problems in which ANN has been applied is as follows:

4.5.1 Fault diagnosis

Fault diagnosis means to identify the faulty components in power system by using the information of the operation of protective relays and circuit breakers. However, this task is difficult, especially for the cases where the relay or circuit breaker fails to operate or multiple faults occur. Fault diagnosis has been a traditional area for expert systems (ES). ANN has also been an important application area for fault diagnosis problems. To enhance service reliability and reduce the power outage, of power system is required to have a rapid restoration of capability. As a first step of restoration, the fault section should be estimated quickly and accurately.

4.5.2 Power system protection relaying

The reliable operation of large power systems is highly dependent on various protective devices. Protective relays are the hardware devices that sense the over currents and tripping the circuit breakers to isolate the faulty section as soon as possible. Setting the operating parameter is a knowledge intensive problem. It often requires the experience of senior relay engineers. It also involves comprehensive and repetitive routine work dealing with a large database, which is a tedious and time consuming task. The complexity of the problem is compounded when various relay types from different manufacturers are involved. Moreover, the increasing complexity of modern power system adds an extra burden to the relay setting process. Since major parts of the relay setting knowledge is available in rule style, hence, an ES lends itself naturally to the purpose of facilitating/ optimizing relay settings. The fast response of a trained ANN and its generalization abilities is very useful for this application.

4.5.3 Economic dispatch

The basic objective of economic dispatch (ED) is to generate adequate electricity to meet continuously changing consumer load demand at the lowest possible cost, subjected to a number of constraints. In ED problem, generation costs are represented as curves, usually piecewise linear, and the overall computation minimizes the operating cost by locating a point where the total output of the generations equals the total power that must be delivered, when the incremental cost of power generation is equal for all generators.

4.5.4 Unit commitment

Unit commitment (UC) is an important sub problem of production scheduling which relates the determination of the generating units in service (on/off) during each interval of the scheduling period (a day or a week) in order to meet system demand and reserve requirements at minimum/optimal cost for the total scheduling period, subject to a variety of equipment, system/operation and environmental constraints.

4.5.5 Hydrothermal scheduling

Generation scheduling problem is a combination of UC and ED problems. The scheduling problem must be defined in terms of cost function. The cost function consists of the objective function (fuel cost, idling cost, and start-up cost etc) subject to the constraints of fuel, load balance, etc. Operation of a system having both hydro and thermal plants is more complex. This is so because hydro plants have negligible operating cost, but are required to operate under the constraints of water available for hydro generation in a given period of time [12, 18].

CHAPTER 5

PROBLEM FORMULATION

5.1 UNIT COMMITMENT USING NEURAL NETWORKS

The growing application of artificial intelligence techniques to power engineering has the potential of using the state of art technology in scheduling the short term power generation. In recent years, the neural network supported systems have started a new era of engineering technology holding its integrity. Simulation of neural networks and various expert system shells via computer software has provided powerful tools for developing new systems. The neural network computing enhanced by expert systems has opened up a new route for the optimization of generation scheduling. With proper and sufficient training, the information regarding the optimal operation of a system can be stored in the network as such, and the output can be obtained in a much shorter time [3, 4, 32].

5.1.1 Formulation of Thermal Unit Commitment

As the size of the system grows and more complicated constraints are imposed, it is often insufficient to rely on human intuition for the achievement of optimal solution. Therefore more rigorous programming techniques are utilized. The analytical methods treat the unit commitment problem as a mixed integer/real variable optimization problem. The existing methods, such as dynamic programming, Priority listing, and Lagrangian relaxation, provide effective alternatives for evaluating commitment plans. However, they demand a vast amount of calculating power.

Unit commitment problem is formulated as the production cost of units considering the fuel cost and the transition (start-up) cost [1, 13, 19].

Model of fuel cost

The fuel cost is the production cost of operating generators that arise while meet the load demand of a system during a specified time period. This cost depends on the heat rate, fuel price (constants) and unit-load curves. A unit-load curve represents the incremental or total operating cost of generation as the function of megawatt power level.

Minimum and maximum limits are important to model the curve that is assumed to be non-linear.

The curves are approximated by the quadratic function

$$F(P_{gi}) = \sum_{i=1}^{NG} (a_i P_{gi}^2 + b_i P_{gi} + c_i) Rs / hr \qquad \ldots(5.1)$$

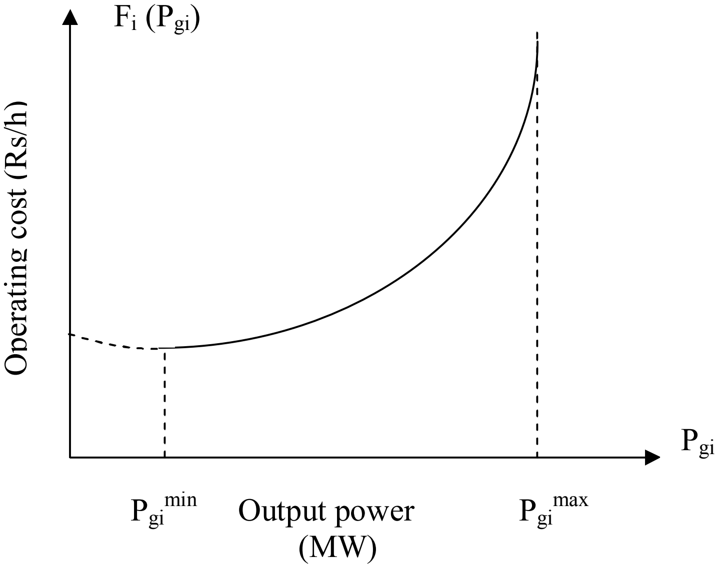


Fig 5.1: Operating costs of a fossil fired generator

Model of Start-up cost

A simplified time dependent start up cost is taken as follows:

Hot start up cost if down time is less than or equal to cold start hours

Start up cost=cold start cost, otherwise.

The function to be minimized for unit commitment problem can be expressed in mathematical form as follows:

$$\sum_{t=1}^{T} \sum_{i=1}^{N} \left[F_i\left(P_i^t\right) + startup \cos t_{i,t} \right] U_i^t = F\left(P_i^t, U_i^t\right) \qquad \ldots(5.2)$$

Transmission losses

Simple method to calculate the total transmission losses for generator economic allocation is the loss coefficients method. These coefficients or constants are in fact not constants but depend on the loading conditions as well as on the configuration of the power system.

$$P_L = \sum_{i=1}^{k}\sum_{j=1}^{k} P_{Gi}B_{ij}P_{Gj} + \sum_{i=1}^{k} B_{0i}P_{Gi} + B_{00} \qquad \ldots(5.3)$$

Subject to the following major constraints:

1. Power balance constraint:

   Generation should meet the load demand and the spinning reserve plus transmission losses.

   $Pi = PD + spinning\_reserve + losses$

   where Pi is the real power generation of ith plant and PD is the total power demand.

2. Power generation limits:

   These limits define the region within which a unit must be dispatched.

   $P_{gi}^{\min} \leq P_{gi} \leq P_{gi}^{\max}$

   where $P_{gi}^{\min}$, the lower limit of the real power output of ith unit and $P_{gi}^{\max}$,the upper limit of the real power output of the ith unit.

3. Minimum up time:

   This constraint signifies the minimum time for a committed unit to be turned off and removed from online.

4. Minimum down time:

   This constraint signifies the minimum time for a decommitted unit to be turned on and brought on-line.

5. Spinning reserve constraints:

   Spinning reserve is the term used to describe the total amount of generation available from all the synchronized units on the system minus the present load plus the losses that have occured. Spinning reserve must be carried out in such a mannerso that the loss of one or more units does not cause too far a drop in system frequency.

5.2 ALGORITHM OF UNIT COMMITMENT PROBLEM

1. Read the constant a_i, b_i and c_i, loss coefficients B_{ij}, B_{0i}, constant B_{00}, power demand P_D, maximum $P_{Gi}^{\max}$, minimum $P_{Gi}^{\min}$ generators real power limits, Start

up costs (Hot + Cold), No Load cost, Spinning reserve, Load data and Generator data.

2. Initialize.
3. Consider hour 1.
4. Assume a suitable value of $\lambda = \lambda_0$. Calculate $P_{G1}, P_{G2}, \ldots, P_{Gi}$ based on equal incremental cost.
5. Calculate the generation at all buses using

$$P_{Gi} = \frac{1 - B_{0i} - \frac{b_i}{\lambda} - \sum_{j=1}^{k} 2B_{ij}P_{Gj}}{\frac{2a_i}{\lambda} + 2B_{ii}} \quad i = 1, 2, \ldots, k \qquad \ldots(5.4)$$

6. Calculate the losses using the relation

$$P_L = \sum_{i=1}^{k}\sum_{j=1}^{k} P_{Gi}B_{ij}P_{Gj} + \sum_{i=1}^{k} B_{0i}P_{Gi} + B_{00} \qquad \ldots(5.5)$$

7. Calculate,

$$\Delta P = \sum_{i=1}^{k} P_{Gi} - P_D - P_L \qquad \ldots(5.6)$$

8. Update λ as $\lambda^{(k+1)} = \lambda^{(k)} - \Delta\lambda^{(k)}$, where $\Delta\lambda$ is the step size.
9. Update new power demand using spinning reserve and transmission losses, P_D^{new}
10. For the new power demand display all the feasible combinations.
11. The Start- up cost of a unit is independent of the time it has been off line (it is a fixed amount).
12. Satisfy operating constraints and spinning reserve requirements.
13. Calculate cost of generation with values of powers using the fuel cost and extra cost for all states FC, HS and CS.

$$F_{cost} = S_{cost} + (noload\_cost) \qquad \ldots(5.7)$$

14. Compute total cost, store most economical strategy and do for all states.

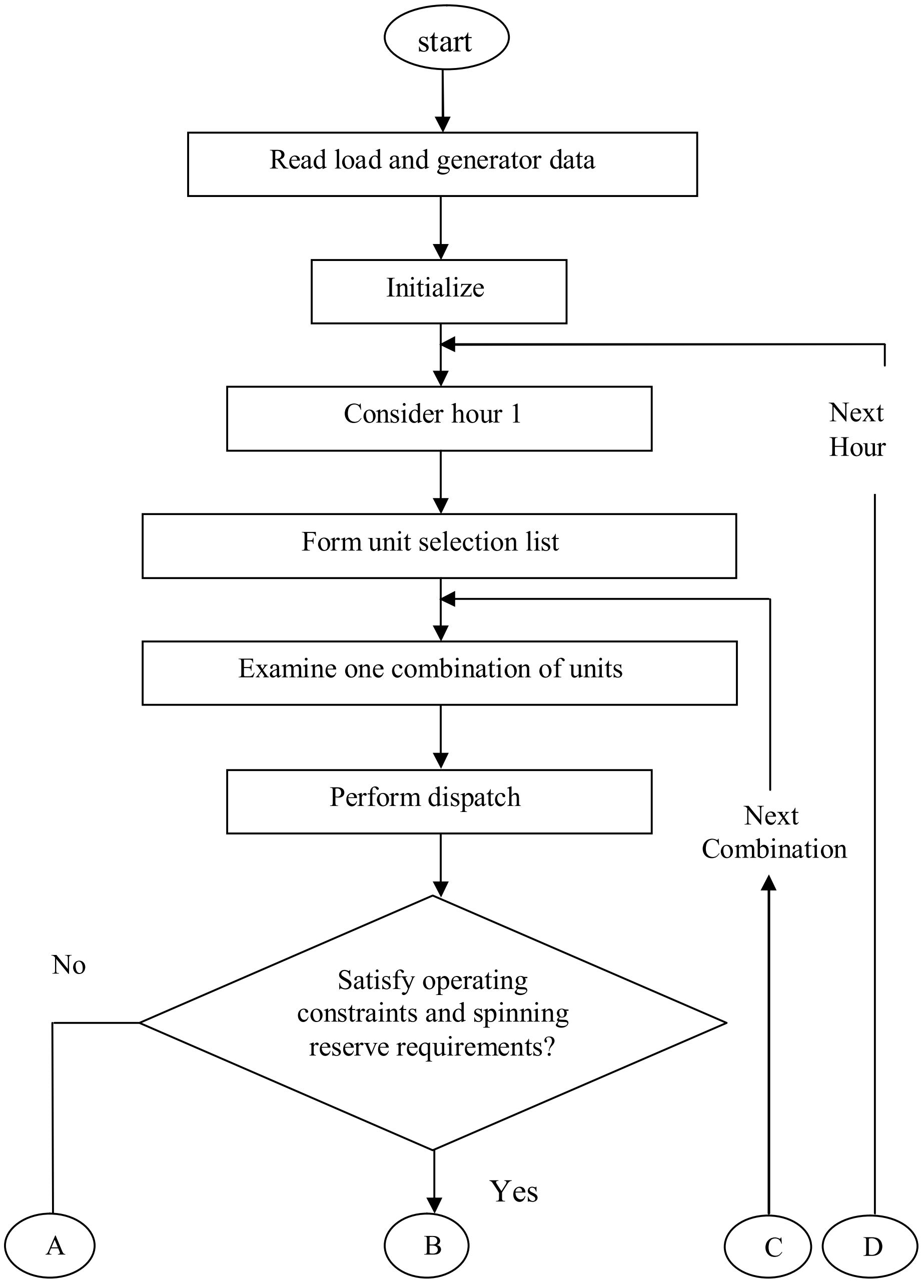
$$F_{cost} = \min\left[S_{cost} + (noload\_cost)\right] \qquad \ldots(5.8)$$

15. Save lowest cost strategies.
16. Trace optimal schedule.

5.3 FLOWCHART OF UNIT COMMITMENT PROBLEM

A recursive search technique, called dynamic programming, is used to find the most economic feasible commitment schedule. The outline of the approach is shown by the flowchart in figure 5.3

The unit commitment procedure is divided into two major parts. The first involves the formation of a unit selection list (figure 5.2), and the other part consists of a search technique which determines optimal feasible schedules for a given study period.



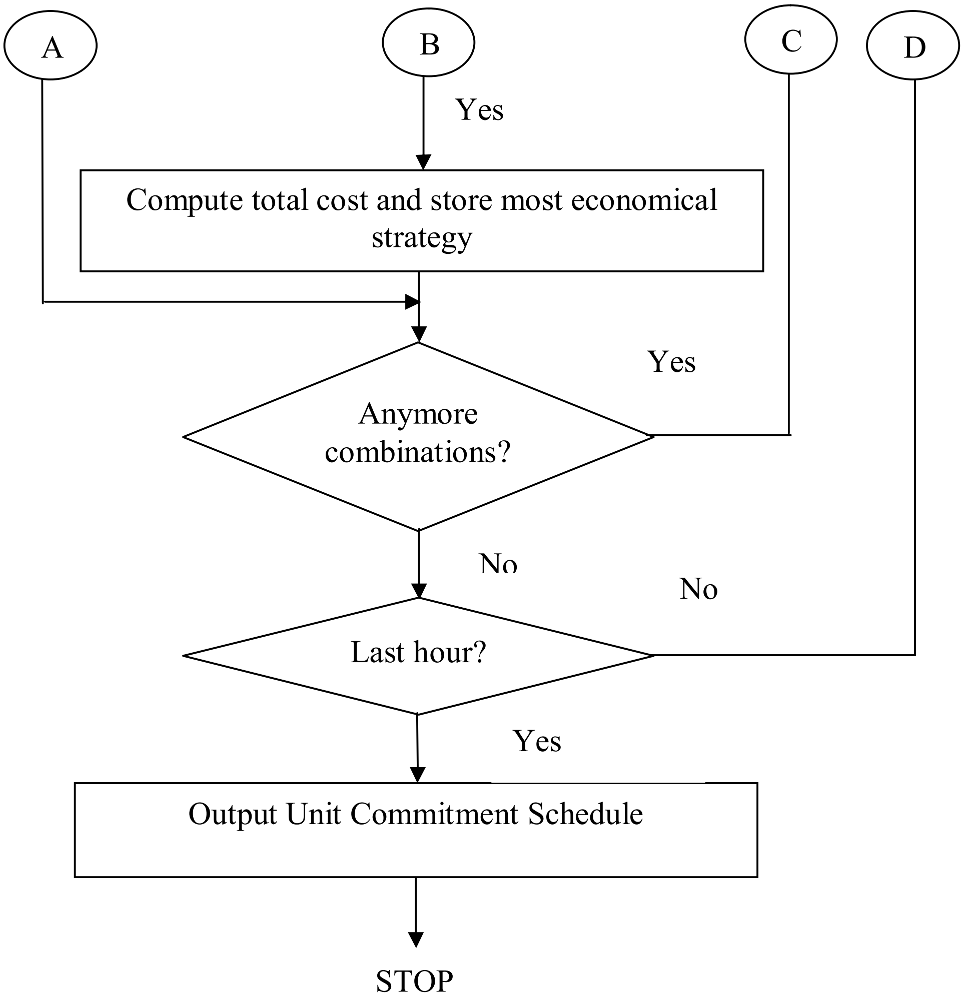


Fig 5.2: Simplified Flow Chart of Unit Commitment Procedure

5.4 NEURAL NETWORK COMPUTING

An artificial neural network basically consists of a large number of highly connected but relatively simple processing elements communicating via messages. Each element (neuron) being a replicate of the human neuron in performance. Artificial neural networks have made progress by employing models based on the same ability as of human brain. Artificial neural networks are characterized as.

1. The architecture

A neural network is formed by interconnected slabs arranged in a particular manner. A feed forward neural network receives inputs through the input slab and yields outputs through the output slab.

2. Highly parallel distributed control

Control is the transfer function that describes the output of a neuron at given inputs.

3. Learning paradigm

Learning is a training technique that adjusts the underlying network's parameters appropriately to respond to the problem that is to be learned, until it is fully learned or some termination criteria are met.

Proposed approach

In the problem, multilayer feed forward network using back propagation error of learning determine variables corresponding to the operating level of generators and production cost. Load demand profile is input to the neurons in the input layer. Generation is the output of the neurons in the output layer.

Training details:

The network is trained by the back propagation learning algorithm. A set of load profiles and their corresponding commitment schedules satisfying all the constraints are used to train the neural network. A major concern in the application of a neural network to a specified problem domain is to converge the network to the global minimum and prevent it from being trapped in local minima. A common approach for overcoming this problem is to make the slope of the sigmoid function sharper with time. In other words, a careful selection of control parameters such as learning rate and momentum helps to solve the problem.

Too many parameters (a large network) and a few training patterns will allow the network to fit the training data very closely but will not necessarily lead to an optimal generalization. The gradient learning process employed by the back propagation algorithm works as follows: initially all hidden nodes in the network do the same work, i.e. they all attempt to fit the major features of the data. The nodes then start to differentiate, with some of the nodes beginning to fit the second most important aspect of data. This differentiation process continues as long as the error remains in the network and training continues [23, 25].

5.4.1 Back Propagation Algorithm

1. Read the input values,(X), target values,(T) learning rate coefficient,(η) tolerance limit of error,(ε), momentum constant,(α) maximum number of iterations,(*itrmax*) neurons in hidden layer,(n) ,input nodes,(m), output nodes,(z),maximum value of input,($x\_\max$), maximum value of target,($t\_\max$)
2. Normalize the input and target vector.
3. Activate the first node of the input by *1.0* and the rest by the normalized inputs.
4. Generate the random weights.
5. Set all the elements of error weight matrices $dW1$ and $dW2$ equal to zero.
6. Set $epoch = 0.0$
7. Set $serr = 0.0$
8. Calculate output $Y1$ using

   $$Y1(k) = X(1,i) * W1(i,k) \quad \text{where} \quad i = 1,2,......,m\,; k = 1,2,.....,n \qquad ...(5.9)$$

10. Process output of hidden layer through a non linear activation function (positive sigmoid function) to produce output of hidden layers.

    $$Y11(k) = 1/\left(1+\exp\left(-Y1(k)\right)\right) \quad \text{where} \quad k = 1,2,.....,n \qquad ...(5.10)$$

11. Calculate the final output using

    $$Y2(j) = Y11(1,k) * W2(k,j) \quad \text{where} \quad j = 1,2,.....,z\,; k = 1,2,.....,n \qquad ...(5.11)$$

12. Process again through sigmoid function to find output of network.

    $$Y22(j) = 1/\left(1+\exp\left(-Y2(j)\right)\right) \quad \text{where} \quad j = 1,2,.....,z \qquad ...(5.12)$$

13. Calculate square error as

    $$\left.\begin{aligned} e(s,1) &= T(s,1) - Y22(s,1) \\ serr+ &= e(s,1) * e(s,1)^T \end{aligned}\right\} \text{where } s = 0.0 \qquad ...(5.13)$$

14. Adjust the weight of output layer

$$d12(j) = Y22(j) * (1 - Y22(j)) * e(s,1)^T$$
$$dW2(j,1) = \eta * d12(j) * (Y22(j)) + \alpha * dW2(j,1) \qquad \ldots(5.14)$$
$$W2(j,1) += dW2(j,1)$$

15. Adjust the weight of hidden layer

$$sum\_w = 0;$$
$$sum\_w += d12(j) * W2(j,1)$$
$$d11(k) = sum\_w * Y11(k) * (1 - Y11(k)) \qquad \ldots(5.15)$$
$$dW1(i,k) = \eta * d11(k) * X(1,i) + \alpha * dW1(i,k)$$
$$W1(i,k) += dW1(i,k)$$

16. Check for tolerance, if $serr > \varepsilon$ then go to step 7.

17. Test the stopping condition.

The stopping condition may be the minimization of errors, number of epochs, etc.

5.4.2 Flowchart of Proposed Back Propagation Algorithm

The outline of the approach is shown by the flowchart in fig 5.4

1. Initialization of weights
2. Feed forward
3. Back propagation of errors
4. Updation of the weights.

During the first stage, which is the initialization of weights, some small random values are assigned. During feed forward stage each input unit receives an input signal and transmits this signal to each of the hidden units. Each hidden unit then calculates the activation function and sends its signal to each output unit. The output unit then calculates the activation function to form the response of the net for the given input pattern.

During back propagation of errors, each output unit compares its computed activation with its target value to determine the associated error for that pattern with that unit. During final stage, the weights are updated.

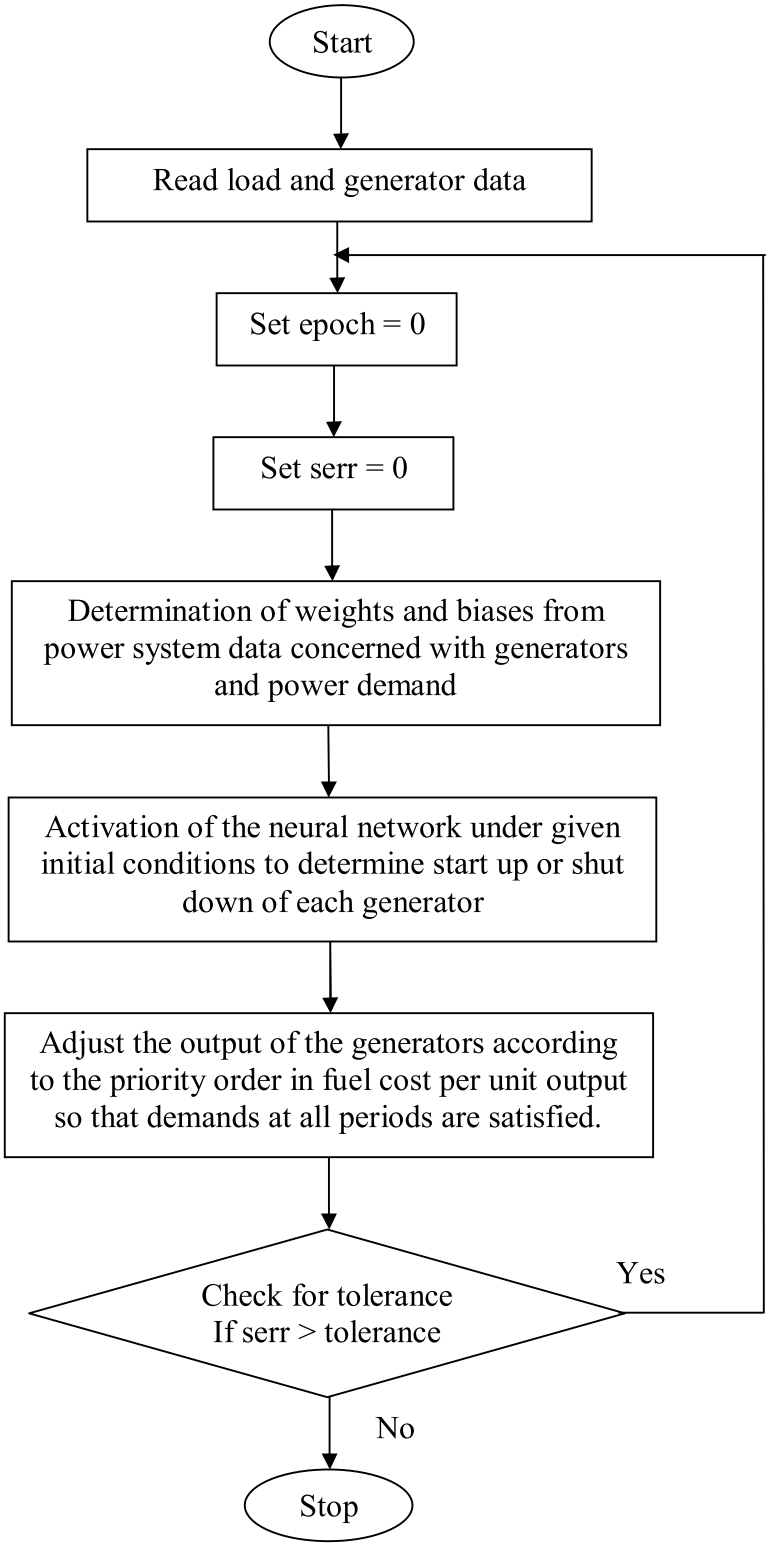


Fig 5.3: Flowchart of the Proposed Back Propagation Algorithm

CHAPTER 6

RESULTS AND DISCUSSION

6.1 RESULTS OBTAINED BY CONVENTIONAL DYNAMIC PROGRAMMING APPROACH

The approach mentioned in Chapter 5 is applied to a system comprised of 3 generating units whose input data like Load Pattern of 24 hr, Cost functions, Unit Characteristics, B-coefficients matrix and neural network training data are shown in APPENDIX A

Costs obtained from the Load pattern shown in Table A1 by conventional dynamic programming (ignore losses and spinning reserve) are shown in Table 6.1:

Table 6.1: Costs obtained from the Load pattern shown in Table A1 by conventional dynamic programming (ignore losses and spinning reserve)

Load demand (MW)	Optimal combination	Dynamic approach
400	1 0 0	440
	1 1 0	**432.76**
	1 0 1	887.93
	0 1 1	895.76
450	1 1 0	**485.65**
	1 0 1	699.07
	0 1 1	674.05
700	1 1 0	**750.089**
600	1 0 0	660
	1 1 0	**644.3**
	1 0 1	667.5
550	1 0 0	605
	1 1 0	**591.4**
	1 0 1	611.4

500	1 0 0	550
	1 1 0	538.5
	1 0 1	555.2
	0 1 1	**527**
750	1 1 0	**802.975**
650	1 1 0	**697.2**
	1 0 1	723.6

According to Power generation-load balance constraint,

Generation should meet the load demand and the spinning reserve plus transmission losses. In this work, both are considered.

$Pi = PD + spinning\_reserve + losses$

Spinning reserve is taken as 50 MW (constant)

Transmission losses have been calculated, 17.864699 MW by using Table A4 and equation (5.5)

Costs obtained by conventional dynamic approach (considering losses and spinning reserve) are shown in Table 6.2

Table 6.2: Costs obtained by conventional dynamic approach (considering losses and spinning reserve)

Load demand (MW)	Unit combination	Dynamic approach
467.86	1 0 0	514.65
	1 1 0	**504.55**
	1 0 1	964.12
517.86	1 0 0	569.65
	1 1 0	**557.43**
	1 0 1	775.26
767.86	1 1 0	**1397.138**
667.86	1 1 0	**716.098**
617.86	1 1 0	**663.21**

	1 0 1	687.54
567.86	1 0 0	624.65
	1 1 0	**610.32**
	1 0 1	632.20
817.86	1 1 0	**1506.964**
717.86	1 1 0	**2275.95**

A MATLAB code developed for solving neural network based unit commitment problem is used to solve the above problem.

6.2 RESULTS OBTAINED BY NEURAL NETWORKS

The input-output data for training neural network is the variation of load, incremental cost and transmission losses. Optimal generated power of each generator is output obtained by the conventional method.

The neural network is trained using MATLAB program and training data used is shown in Table A5.

After training, results obtained are as follows:

Total epoch performed = 10

Error = 0.027893

Final weight matrix (v)

$$\left\{\begin{matrix} 0.11663 & 0.1163 & 0.11663 & 0.11663 \\ 0.23303 & 0.11654 & 0.23303 & 0.23303 \\ 0.34954 & 0.11656 & 0.23305 & 0.11656 \end{matrix}\right\}$$

Final weight matrix (w)

$$\left\{\begin{matrix} 0.011831 & 0.01183 & 0.011831 \\ 0.02348 & 0.01183 & 0.011831 \\ 0.035129 & 0.023479 & 0.011831 \\ 0.035129 & 0.023479 & 0.02348 \end{matrix}\right\}$$

Table 6.3: Testing the response of the network on each of the input pattern

Inputs		
X_1	X_2	X_3
0.4	0.08107259	0.17864699
0.45	0.08177329	0.17864699
0.7	0.08527675	0.17864699
0.6	0.08387537	0.17864699
0.55	0.08317467	0.17864699
0.5	0.08247398	0.17864699
0.75	0.08597745	0.17864699
0.65	0.08457606	0.17864699

Error = (t-Y) ^2

Error = 0.47833

Table 6.4: Results (Costs obtained from neural networks)

Load (MW)	Total cost (Rs)
400	909.524
450	910.4743
700	921.0281
600	920.9738
550	913.9218
500	910.4743
750	921.0281
650	921.0281
Total cost of operation (Rs)	7328.4525

The CPU time for computing neural network is much less than conventional dynamic programming approach.

From the above obtained results, the cost obtained by conventional method is more as compared to neural networks.

6.3 CONCLUSION

This work aim to carry out development for ANN based method to determine generation scheduling such that the total operating cost can be minimized considering transmission losses of thermal power plants very efficiently and accurately. In a power system there is a large variation in load from time to time and it is not possible to have the load scheduling pattern for every possible load demand. As there is no general procedure for finding out the economical load scheduling pattern. This is where ANN plays an important role as we need small number of training data sets for the training of ANN. A trained ANN can then be applied to find out the economical load scheduling pattern for a particular load demand in a fraction of second.

This thesis work is an attempt to compare the total cost obtained by the conventional dynamic programming and neural networks applied to it. For costs obtained by conventional dynamic programming, the ON/OFF states of the units have been considered in order to meet the load demand. Whereas, for cost obtained by neural network technique, only the ON states of units have been assumed. After assessment, it is observed that both costs obtained and computation time by conventional dynamic programming is more as compared to neural networks. Hence, neural network is found to be very efficient as compared to conventional dynamic programming.

6.4 FUTURE SCOPE

Due to flexibility in ANN several other practical constraints can also be easily incorporated as input-output information of the training sets. For future work, it is suggested to design a general ANN for such problems. Also, methods can be thought of which reduce the training time. The effect of complexity of the neural network on the performance of system may also be studied. The proposed technique can be further improved by committing each unit separately.

APPENDIX A

The input data used for the results shown in Chapter 6 is as follows:

For solving the problem using conventional Dynamic programming initial conditions are taken as follows:

1. Unit 1 and unit 2 are initially ON.
2. Unit 3 is OFF from the last three hours
3. Initially losses and spinning reserve are ignored.

Gap is of 3hrs, load pattern starts from 12midnight. (*Courtesy:* "Power generation, operation and control", A.J.Wood and B.Wollenberg)

Table A1: Load Pattern

Hrs	Load (MW)
12-3	400
3-6	450
6-9	700
9-12	600
12-3	550
3-6	500
6-9	750
9-12	650

Table A2: Cost functions

Unit no.	a_i (Rs/MW^{2}h)	b_i (Rs/MWh)	c_i (Rs/h)
1	0.00142	7.2	510
2	0.00194	7.85	310
3	0.00482	7.97	78

Table A3: Unit characteristics

Unit no.	Max (MW)	Min (MW)	No load cost(Rs/hr)	Start up cost,Rs (hot)	Start up cost, Rs (cold)	Fuel cost (Rs/MW)
1	600	150	213	250	400	1.1
2	400	100	175	175	300	1.0
3	200	50	115	100	200	1.2

Table A4: The B- coefficients (MW^{-1}) for the calculation of Transmission losses.

0.0001363	0.0000175	0.0001839
0.0000175	0.0001545	0.0002828
0.0001839	0.0002828	0.0016147

Data used for the computation of the cost using Neural Networks

No. of neurons in the input layer = 3

No. of neurons in the hidden layer = 4

No. of neurons in the output layer = 3

Non linearity factor = 0.0015

Learning rate = 0.5

Momentum factor = 0.9

Max. Error = 0.00005

Initial weights (v) between input and hidden layer

$$1e\text{-}4* \left\{ \begin{matrix} 1\ 1\ 1\ 1 \\ 2\ 1\ 2\ 2 \\ 3\ 1\ 2\ 1 \end{matrix} \right\}$$

Initial weights (w) between hidden and output layer

$$1\text{e-}5* \begin{Bmatrix} 1 & 1 & 1 \\ 2 & 1 & 1 \\ 3 & 2 & 1 \\ 3 & 2 & 2 \end{Bmatrix}$$

Table A5: Training Pattern (used to train the neural network)

Inputs			Targets		
x_1	x_2	x_3	T_1	T_2	T_3
0.105	0.10233	0.19864	0.7869	0.1974	0.0656
0.150	0.10587	0.19864	0.9635	0.3446	0.1918
0.255	0.11411	0.19864	1.3757	0.6881	0.4862
0.350	0.12157	0.19864	1.7485	0.9988	0.7525
0.4	0.12549	0.19864	2.329	1	0.671
0.5	0.13334	0.19864	2.500	1	1.5

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