REINFORCEMENT LEARNING APPROACHES TO POWER SYSTEM SCHEDULING

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By

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This is to certify that the thesis entitled **"Reinforcement Learning Approaches to Power System Scheduling"** is the record of bonafide research work done by Ms. Jasmin. E. A. under my supervision and guidance at School of Engineering in partial fulfillment of the requirements for the Degree of Doctor of Philosophy under the Faculty of Engineering, Cochin University of Science and Technology.

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DECLARATION

I, **Jasmin. E. A.,** hereby declare that the thesis entitled **"Reinforcement Learning Approaches to Power System Scheduling"** is based on the original work done by me under the guidance of **Dr. Jagathy Raj V.P,** Reader, for the award of Ph.D programme in the School of Engineering, Cochin University of Science and Technology. I further declare that this work has not been included in any other thesis submitted previously for the award of any Degree, Diploma, Associateship or Fellowship or any other title for recognition.

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Reinforcement Learning Approaches To Power System Scheduling

ABSTRACT

One major component of power system operation is generation scheduling. The objective of the work is to develop efficient control strategies to the power scheduling problems through Reinforcement Learning approaches. The three important active power scheduling problems are Unit Commitment, Economic Dispatch and Automatic Generation Control. Numerical solution methods proposed for solution of power scheduling are insufficient in handling large and complex systems. Soft Computing methods like Simulated Annealing, Evolutionary Programming etc., are efficient in handling complex cost functions, but find limitation in handling stochastic data existing in a practical system. Also the learning steps are to be repeated for each load demand which increases the computation time.

Reinforcement Learning (RL) is a method of learning through interactions with environment. The main advantage of this approach is it does not require a precise mathematical formulation. It can learn either by interacting with the environment or interacting with a simulation model. Several optimization and control problems have been solved through Reinforcement Learning approach. The application of Reinforcement Learning in the field of Power system has been a few. The objective is to introduce and extend Reinforcement Learning approaches for the active power scheduling problems in an implementable manner. The main objectives can be enumerated as:

(i) Evolve Reinforcement Learning based solutions to the Unit Commitment Problem.

(ii) Find suitable solution strategies through Reinforcement Learning approach for Economic Dispatch.

(iii) Extend the Reinforcement Learning solution to Automatic Generation Control with a different perspective.

(iv) Check the suitability of the scheduling solutions to one of the existing power systems.

First part of the thesis is concerned with the Reinforcement Learning approach to Unit Commitment problem. Unit Commitment Problem is formulated as a multi stage decision process. Q learning solution is developed to obtain the optimum commitment schedule. Method of state aggregation is used to formulate an efficient solution considering the minimum up time / down time constraints. The performance of the algorithms are evaluated for different systems and compared with other stochastic methods like Genetic Algorithm.

Second stage of the work is concerned with solving Economic Dispatch problem. A simple and straight forward decision making strategy is first proposed in the Learning Automata algorithm. Then to solve the scheduling task of systems with large number of generating units, the problem is formulated as a multi stage decision making task. The solution obtained is extended in order to incorporate the transmission losses in the system. To make the Reinforcement Learning solution more efficient and to handle continuous state space, a function approximation strategy is proposed. The performance of the developed algorithms are tested for several standard test cases. Proposed method is compared with other recent methods like Partition Approach Algorithm, Simulated Annealing etc.

As the final step of implementing the active power control loops in power system, Automatic Generation Control is also taken into consideration.

Reinforcement Learning has already been applied to solve Automatic Generation Control loop. The RL solution is extended to take up the approach of common frequency for all the interconnected areas, more similar to practical systems. Performance of the RL controller is also compared with that of the conventional integral controller.

In order to prove the suitability of the proposed methods to practical systems, second plant of Neyveli Thermal Power Station (NTPS II) is taken for case study. The performance of the Reinforcement Learning solution is found to be better than the other existing methods, which provide the promising step towards RL based control schemes for practical power industry.

Reinforcement Learning is applied to solve the scheduling problems in the power industry and found to give satisfactory performance. Proposed solution provides a scope for getting more profit as the economic schedule is obtained instantaneously. Since Reinforcement Learning method can take the stochastic cost data obtained time to time from a plant, it gives an implementable method. As a further step, with suitable methods to interface with on line data, economic scheduling can be achieved instantaneously in a generation control center. Also power scheduling of systems with different sources such as hydro, thermal etc. can be looked into and Reinforcement Learning solutions can be achieved.

Key words: *Power system, Reinforcement Learning, Unit Commitment, Economic Dispatch, Automatic Generation Control.*

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ε	-	Exploration parameter
α	-	Learning parameter
π	-	Policy
γ	-	Discount factor
Π	-	Policy space
β	-	Update parameter for probability
σ	-	Width of RBF network
χ	-	State space
$ag\_p_k^i$	-	Aggrgate state vector element corresponding ti i^{th} unit and k^{th} hour
p_k	-	String representing status in state x_k
ϕ_i	-	i^{th} Radial basis function
χ_k	-	Subspace of state space at k^{th} stage
$P_{max\ (i)}$	-	Maximum generation by i^{th} unit
$P_{min\ (i)}$	-	Minimum generation limit of i^{th} unit
$Q^*(x,a)$	-	Optimum Q value of state action pair *(x, a)*
$Q^n(x,a)$	-	Estimated Q value of state action pair *(x, a)* at n^{th} iteration
$V^{\pi^*}(x)$	-	Value function of state x corresponding to optimum policy π^*
$V^{\pi}(x)$	-	Value function of state x corresponding to policy π
a_g	-	Greedy action
a_k	-	Action at stage k
a_k^i	-	i^{th} element of action vector a_k
c_j^i	-	j^{th} centre of i^{th} RBF network
$p_{x_k}(a_k)$	-	Probability of action a_k at state x_k
p_k^i	-	i^{th} element of vector p_k
p_{xy}^a	-	Probability or reaching state y from state x on taking action a
ag_x_k	-	The aggregate state corresponding to x_k
$C_{i,t}\ (P_{i,t})$	-	Cost function of i^{th} generating unit for time slot t

D_i	-	Minimum down time of i^{th} unit
D_k	-	Demand at k^{th} stage
$D_{max\ (k)}$	-	Maximum possible demand at k^{th} stage
$D_{min\ (k)}$	-	Minimum possible demand at k^{th} stage
DR_i	-	Ramp Down rate of i^{th} unit
$g\ ()$	-	Reward function
ind_x_k	-	Index of state x_k
l_k	-	Load during k^{th} hour
Max_k	-	Maximum Power allocation possible at k^{th} stage
Min_k	-	Minimum Power allocation possible at k^{th} stage
m_k	-	Number of hidden nodes at k^{th} stage in RBF network
n_k	-	Number of actions at k^{th} stage
P_D	-	Total Load demand
$P_{i\,k}$	-	Power generated by i^{th} unit during hour k
P_L	-	Transmission loss in the system
$Q\ (a_k)$	-	Performance index of action a_k in N arm bandit problem
r_k	-	Reward received at instant k
$S_{c\,i}$	-	Cold start up cost of i^{th} unit
$S_{i\,i}$	-	Start up cost of i^{th} unit
$t_{OFF\ (i)}$	-	Number of hours i^{th} unit is OFF
$t_{ON\ (i)}$	-	Number of hours i^{th} unit is ON
$u_{i\,k}$	-	Status of i^{th} unit during hour k
U_i	-	Minimum up time of i^{th}unit
UR_i	-	Ramp up rate of i^{th} unit
W	-	Weight matrix
x_k	-	State at k^{th} stage
$?$	-	Parameter vector of RBF network
$Q(x, a)$	-	Q value of state action pair (x, a)
$\mathcal{A}$	-	Action space
$\mathcal{A}_k$	-	Subspace of action space at k^{th} stage

CHAPTER 1

INTRODUCTION

Power systems form the largest man made complex system. It basically consists of generating sources, transmission network and distribution centers. Secure and economic operation of this system is a challenging task. The primary concern of electric power system operation is to guarantee adequate optimal generation to meet load demand satisfying the numerous constraints enforced from different directions.

Active power or MW power generated in a power system is controlled in three time based control loops: Unit Commitment, Economic Dispatch and Automatic Generation Control. Unit Commitment and Economic Dispatch loops are to schedule the generating sources in economic manner to meet the forecasted load demand. Automatic Generation Control continuously monitors the load variations and adjusts the power output of the generators in optimum manner which results in efficient constant frequency operation for the equipments.

A variety of strategies have been developed to make the operation of these three control loops efficient and fast. In the present economic scenario, the growing sophistication of power systems motivates the development of more and more computationally faster methods, suitable for the existing systems.

Several methods have been employed for solving the various power scheduling problems. Dynamic Programming method has been widely used for solving Unit Commitment Problem and Economic Dispatch. However it suffers from the curse of dimensionality. Stochastic search methods like Genetic Algorithm, Evolutionary Programming and Simulated Annealing also have been used. However all these methods were demonstrated only for deterministic cost data.

All of the existing methods require a well defined model of the system to handle the control problems. But accurate model of the system may not be available for

all practical systems. Developing control methodology which is implementable in the practical environment is also a good direction in the power system control sector.

Reinforcement Learning is one popular method, which has been applied for the solution of many optimization problems. It is a learning strategy which relies on continuous interaction with the problem environment. Till now, application of Reinforcement Learning to power system problems has been a few (Imthias *et al.* [2002], Ernest and Glavic [2004], Gajjar *et al.* [2003]). The main objective of the research work is to extend existing Reinforcement Learning algorithms and to evolve new algorithms to the three control loops concerned with active power control. The three control problems belong to different classes. In this thesis, various efficient ways of using Reinforcement Learning to solve these problems will be explored. Expectation is that, this thesis will help to improve the understanding of various possibilities of applications of Reinforcement Learning in Power system.

In the following sections, the overall structure of power system control: Unit Commitment, Economic Dispatch and Automatic Generation Control are discussed. Then an outline of the presentation structure of the thesis is given. Finally the important contributions are highlighted in the concluding section.

1.1 Power system control

Customer's Load demand in electric power systems is not steady and is subject to change because of the change in human activities with time. Economic production of electric energy is one of the challenging tasks in the power generation sector due to the limited and variant generating resources. A great deal of effort is required to maintain the electric power supply quality and quantity within the requirements of various types of consumers being served. The requirements of consumers include mainly availability, quality, reliability and reasonable cost for the power. As electric energy can't be stored, the loads should be met by variations in the power generation. It is required to commit enough number of generating units to meet the load demand in real time. In short, the load demands are to be met while operating the power system in the most economic manner.

A modern power system consists of several kinds of generating resources of which Hydro, Thermal and Nuclear sources form the major part. These different generating stations are connected to various load centers through transmission lines. Hydro and nuclear sources need more investment in setting up, which contributes to the fixed cost of power generated. The cost of thermal power is mainly dependent on the variable cost, majority of which is due to the fuel cost.

The economic production of power relies on mainly two stages of scheduling. Long term scheduling which involves resource acquisition and allocation for a long duration, commonly one year in advance and short term planning involving the scheduling for one day or one week. At a load control centre, the load demand profile is studied from the past history or experience and based on that, a pre – dispatch schedule is prepared in advance. This scheduling involves the selection of sources of generation available, depending on the constraints and the amount of thermal power to be generated.

Thermal power is usually used to meet the base load during the peak hours. Since the cost of thermal power is more, proper selection and scheduling of these units has become the essential step in power generation planning. Also the different thermal generating units have different fuel characteristics and hence the cost of production varies from unit to unit (Elgerd [1984], Wood and Wollenberg [2002]). Apart from this, the cost of generation in any existing power system is not deterministic. It varies instantaneously. Therefore, economic production of electric energy from a thermal power plant demands the optimum selection of units and also the generation levels considering the stochastic nature of cost. In this thesis, focus is made on the economic scheduling of thermal generating stations.

Scheduling the thermal stations is a two step procedure. In the first step termed as *Unit Commitment*, decision is made on which all generating units are to be operated during each slot of time. This is normally done for separate intervals of one hour each. While deciding the commitment status, cost of production is minimized by accounting the various system and unit constraints. The second part of scheduling is to find the

real power generation of the different generating units and is termed as *Economic Dispatch.* Through the dispatch solution, generation levels of the units are set for duration of several minutes. Power generation from the different units should be so as to satisfy the different constraints and in the most economic manner.

The load on a power system varies instantaneously. Meeting the instantaneous variations of load needs a continuous change in the generation. When a load is suddenly added to the system, initially the kinetic energy stored in the rotating parts of the generators will be utilized to meet the same. Consequently the speed and hence frequency drops. Then the governor mechanism act to increase the fuel input to the system in order to meet the increased load. The primary governor control alone cannot bring the frequency to the scheduled value. The function of real time control or on-line scheduling, termed as *Automatic Generation Control* (AGC) in a power system, is changing the control valve or gate openings of the generator prime movers in response to load variations so as to maintain the scheduled frequency.

In short, active power or MW control in a power system is done in three time based loops. First two loops termed as Unit Commitment and Economic Dispatch are parts of pre dispatch and the third loop or Automatic Generation Control is part of on-line or real time control.

1.2 Research Focus

Economic scheduling is very important in the power industry since the saving of even several paise per unit of generated power will accumulate to an electric utility profit of thousands of rupees per day. A variety of solution strategies have been evolved for handling the power generation control problems.

Mathematical programming methods like Dynamic Programming suffer from the curse of dimensionality. Other methods like Genetic Algorithm, Simulated Annealing, etc. take more computation time and are proved only for deterministic cost data. Also the existing strategies find difficulty in implementing in a practical power

system. Main focus is to develop a practically implementable solution for the generation scheduling problems.

Reinforcement Learning is one solution strategy which had been applied for solution of several search and optimization problems. The capacity of this solution method in the economic scheduling of power generation has not yet been fully explored. The direction of this research work is to develop solutions through Reinforcement Learning approaches to the three control loops in the generation control, in a way more suitable for implementation in an existing power system. In the next sections, these three control problems are described.

1.2.1 Unit Commitment Problem

The general objective of Unit Commitment Problem is to minimize the system operating cost by selecting the units for operation in each slot of time. It determines the combination of available generating units in order to meet the forecasted load demand with minimum production cost. At the same time the various operating constraints enforced by the system should be satisfied during the period mentioned. The period of forecasting varies from 24 hours to one week. Forecasting is based on the previous history, environmental factors, social factors etc. On deciding the commitment schedule to achieve minimum production cost, a number of operating constraints are to be satisfied. Some of these are listed below:

(i) **Power generation constraints**

System generation constraints include power balance, spinning reserve, import/export, transmission line constraints etc. Active power generation should be equal to the total power demand plus losses. Demand in one control area includes the load to be met in that area, transmission losses, scheduled interchange power etc. Total maximum capacity of on-line units must include some spinning reserve also. This spinning reserve is necessary to fulfill the unexpected increase in demand or forced outage of any of the generating units. The amount of the required spinning reserve is usually determined by the

maximum capacity of the largest generating unit in the system or a given percentage of the forecasted peak demand during the scheduled period.

(ii) **Minimum and Maximum generation output constraints**

There exist a number of physical and economical considerations regarding the operating range of a generating unit. A range of power outputs is specified for each machine by either machine output limits or economic operation of other associated units.

(iii) **Minimum Up time / Down time constraints**

Each individual thermal unit has its own constraints which include initial condition, minimum and maximum generation output limits, minimum up time/ down time, unit status restrictions etc. Initial condition of a generating unit includes the number of hours that it has been continuously on-line or off-line and its generation output at the starting instant of present scheduling slot. Minimum up time refers to the number of hours a unit has to be on-line before it can be shut down. Minimum Down time is the number of hours a unit must be off before it can be started up. Both the initial number of on-line or off- line hours and the initial generation output associated with other constraints limit the present status and generation output of the unit.

(iv) **Unit status restriction**

Unit status restrictions include must run and must off restrictions. Generating units with such restrictions will be pre defined and must be excluded while finding the commitment schedule. Some units must be forced to run or to be on line due to various practical and economic reasons. Such units may be using expelled steam from other machinery or units or from some renewable energy sources or may be necessitated due to coupling with other units. The units which are under maintenance are termed as must off units. Also the availability of fuel forces certain plants to be on / off during a particular period. These two

sets of units must be excluded while finding a commitment schedule in the Unit Commitment Problem.

1.2.2 Economic Dispatch

The Economic Load Dispatch problem is a problem of minimizing the total fuel cost of generating units for a specified period of operation so as to accomplish optimal generation dispatch among operating units and at the same time satisfying the various constraints. The fuel cost of the different thermal generating units can be smooth or non smooth.

The cost functions will usually be given in quadratic or higher order polynomial forms. Due to the use of multiple fuel options for the generating units, the cost functions will sometimes be super position of piecewise quadratic functions or in other words will be non smooth over the generation range.

The Economic scheduling of generators for any slot of time will be subject to a variety of constraints. These constraints include:

(i) **Power balance constraints or Demand constraints**

This constraint is based on the balance between the total system generation and the total connected load and the losses in the transmission system.

(ii) **Generator constraints**

The output power of each generating unit has lower and upper bounds so that it should lie within these limits at any point of time.

(iii) **Ramp rate limits**

Ramp rate limit restricts the operating range of all the on line units for adjusting the generator operation between two operating periods. The generation can be changed according to the increasing and decreasing ramp rate limits only.

(iv) **Prohibited operating zones**

The generating units may have certain ranges where the operation is restricted on the grounds of physical limitations of machine components or operational instability.

(v) **Valve point effects**

The valve opening process of multi valve steam turbines produce a ripple like effect in the heat rate curve of the generators and it is usually taken into account by some modifications in the cost functions of the units.

(vi) **Transmission loss**

While finding an optimum schedule of generation, transmission loss is one important constraint since the generating centers and the connected load exist in geographically distributed fashion.

1.2.3 Automatic Generation Control

In a power system, turbo generators must be continuously regulated to match the active power demand, failing which the machine speed will vary with a consequent change in frequency, which is highly undesirable. Also the excitation of the generators must be continually regulated to match the reactive power demand with reactive power generation; otherwise the voltages of the system buses will vary (Elgerd [1982]).

By Unit Commitment and Economic Dispatch solutions, the required active power generation is distributed among the different generating units in an optimum manner leading to the minimum cost of generation. The final and on-line control of generation in a power system is done through the control of frequency measured from the system bus. This third or inner control loop is Automatic Generation Control (AGC) or more specifically Load Frequency control. This control loop handles the instantaneous variations in the customer load.

Power system loads and losses are sensitive to frequency. Therefore for satisfactory operation, a nearly constant frequency is necessary. The frequency of the

system is dependent on active power balance. Therefore any imbalance in the active power is reflected as a change in system frequency. In an isolated power system, generation control is just controlling of the frequency by means of changing the fuel intake by the governor.

Once a generating unit is tripped or a block of load is added to the system, the power mismatch is initially compensated by the extraction of kinetic energy from system inertial storage which causes a decline in system frequency. As the frequency decreases, power taken by loads decreases. Equilibrium for large systems is often obtained when the frequency sensitive reduction of loads balances the output power of the tripped unit or that delivered to the added block of load at the resulting new frequency (Athay [1987]).

If the frequency mismatch is large enough to cause the frequency to deviate beyond the governor dead band of the generating units (generally in the range of 30-35mHz.), their output will be increased by the governor action. For such mismatches, equilibrium is obtained when the reduction in the power taken by the loads plus the increased generation due to governor action compensates for the mismatch. Such equilibrium is often obtained within 10-12 seconds. Typical speed droop are in the range of 5% and therefore at the expense of some frequency deviation, generation adjustment is carried out by governors. In order to compensate for the offset deviation and to bring back the system to the original scheduled frequency, a manual or automatic (through AGC) follow up and corresponding control are required.

The Automatic Load Frequency Control is done based on the concept of tie line bias control in which the Area Control Error (ACE) is calculated at specified discrete intervals of time and control action in the form of change in the reference setting of the governor is carried out. The control decision has been developed by several mathematical and soft computing methods by various researchers. Imthias *et al.* [2002] proposed a Reinforcement Learning control strategy for the load frequency control problem. For the completeness of the attempt to develop Reinforcement Learning based strategies for all the control loops in the power generation control, a

Reinforcement Learning algorithm for Automatic Generation Control (AGC) with a new approach is presented.

1.3 Objectives

Efficient and Economic solution of the above discussed three control problems: Unit Commitment, Economic Dispatch and Automatic Generation Control is the main focus of the research work. The objective is to introduce Reinforcement Learning approaches for the economic scheduling problem in an implementable manner and extend the Reinforcement Learning solution to Automatic Generation Control. The main objectives can be enumerated as:

(i) Evolve Reinforcement Learning based solutions to the Unit Commitment Problem.

(ii) Find suitable solution strategies through Reinforcement Learning approach for Economic Dispatch.

(iii) Extend the Reinforcement Learning solution to Automatic Generation Control with a different perspective.

(iv) Check the suitability of the scheduling solutions to one of the existing power systems.

1.4 Outline of the thesis

The thesis focuses on introducing Reinforcement Learning based approaches to various power system control problems. Power scheduling problems and the constraints enforced are studied. Different existing methodologies for the solution to the power scheduling problems are reviewed in detail emphasizing the advantages and limitations.

As the first step towards applying Reinforcement Learning strategy to Unit Commitment problem, the problem is formulated as a multi stage decision making task. Review of the basic solution introduced by Imthias [2006 a] is done and the solution is extended to make it implementable in a practical power system. These

algorithms in general are denoted as RL_UCP. Minimum up time and down time constraints are first neglected to introduce the new solution strategy. Efficient solution methods are then put forth taking into account the start up and shut down constraints. State aggregation method is also used to develop efficient solution to this constrained optimization problem. Solutions are verified for different standard test systems. A comparison with other solution methods including Simulated Annealing and Genetic Algorithm are made to prove the efficacy of the proposed method.

Economic Dispatch solutions are obtained through Reinforcement Learning algorithms considering different types of complexities of the problem. For simplicity of introducing the new algorithms, transmission loss in the system are first neglected. Then the transmission losses are incorporated. In order to make learning efficient function approximation method is used. Verification and validation are carried out for several systems having different types of cost functions and constraints. The solution given by the proposed algorithms (termed as RL_ED) are compared with other stochastic techniques.

A control strategy for Load Frequency Control in an interconnected power system is also proposed. The control areas connected are considered to operate at a common system frequency. The reference power setting is changed by the control action proposed by the RL controller which acts according to the variation in the Area Control Error (ACE).

Finally, one of the existing thermal generating stations (Neyveli Thermal Power System Corporation) is considered for case study to check the suitability of the developed solutions to a practical system.

The different chapters of the thesis are organized as follows:

Unit Commitment is a combinatorial optimization problem which has been solved earlier by several numerical as well as soft computing methods. Numerical methods include Lagrange Relaxation, Priority List, Dynamic Programming etc. and soft computing strategies include Neural Network, Simulated annealing, Genetic Algorithm, Evolutionary Programming etc. For finding the schedule of generation

through Dispatch solution, a number of methods including lambda iteration, genetic algorithm, simulated annealing, evolutionary programming etc. have been proposed by various researchers. *Chapter II* gives a review of the existing solution strategies for the three control problems. Implementation details of the different techniques are also looked into. Reinforcement learning method and a few of the applications existing in the various fields are also explained.

Reinforcement Learning is explained in detail in *Chapter III*. The different components of Reinforcement Learning problem include state, action, reward and value function. A discussion on these components, the different solution strategies including Q learning and the different ways of exploring the action space including ε - greedy and pursuit are discussed. Function approximation method using Neural Networks is also explained. A review of application of Reinforcement Learning to some of the power system problems is also given.

Formulation of Unit Commitment Problem as a multi stage decision making problem and Reinforcement Learning based solutions are given in *Chapter IV*. First the basic algorithm is reviewed. An efficient solution through exploration using pursuit method is introduced without considering minimum up time and down time constraints. Then more efficient algorithms suitable for existing power systems are proposed considering minimum up time and down time limitations.

In *Chapter V*, Economic Dispatch problem is solved using Reinforcement Learning strategy. The first set of algorithms neglect the constraint enforced by the transmission losses in the system. Then the transmission losses are also included and an extended algorithm is put forth to get economic distribution. A function approximation method using Neural Network is proposed to make the dispatch solution more efficient one. Simulation studies are also presented.

To give completeness of formulating Reinforcement Learning solution to the power generation control problems, the on line dispatch problem or Load Frequency Control is solved using Reinforcement Learning method in *Chapter VI*. Comparison of the results with an integral controller for the same parameters is given.

A practical power system: Neyveli Thermal Power Station is taken for case study and the simulation results of the developed algorithms applied to the system is given in *Chapter VII.* The results obtained are compared with two of the recent techniques: Fuzzy Dynamic Programming and Evolutionary programming with Tabu search.

The important contributions are given in the concluding chapter, *Chapter VIII.* Also the limitations and scope for further work are explained.

CHAPTER 2

A REVIEW OF TECHNOLOGIES FOR POWER SYSTEM SCHEDULING

2.1 Introduction

A thorough literature survey has been conducted to study the various approaches existing for the solution of the three major scheduling problems: Unit Commitment, Economic Dispatch and Automatic Generation Control. Applications of Reinforcement Learning to the various fields are also reviewed.

Unit Commitment is the process of determining the optimal schedule of generating units over a period subject to system operating constraints. Various approaches to the solution of this combinatorial optimization problem have been proposed. The different methodologies applied for the same are discussed in the next section.

Economic Dispatch is the problem of scheduling the committed units so as to meet the desired load at minimum cost. Due to the non convexity of cost functions and the different constraints existing on the operation of thermal power plants, solution of this optimization problem is difficult. A number of classical and soft computing techniques have been developed over years for solution of this problem. The different techniques and solution strategies are reviewed in section 2.3

Control strategy for adjusting the reference power setting in Automatic Generation Control is adopted in several ways. A brief review of the different models and solution strategies are also detailed in section 2.4.

Reinforcement Learning is a good learning strategy which relies on interactive learning. It has found applications in several fields. A brief discussion on the different existing applications is also included in section 2.5.

2.2 Solution Methodologies for Unit Commitment

Unit Commitment Problem is a very challenging optimization problem. This is because of the huge number of possible combinations of ON / OFF status of the generating units in the power system over the different time periods considered. Solution to this combinatorial optimization problem has been developed by several exact and approximate methods. Padhy [2004] gives a good survey on the different solution methods for Unit Commitment Problem. Some of the existing solution methods are discussed below:

2.2.1 Priority list

It is one of the simplest Unit Commitment solution methods (Wood and Wollenberg [2002]). Priority list is obtained after enumerating the various combinations of the units possible at each load demand. The generating unit priorities are determined according to their average production cost. For every slot/ period of time, units are committed one by one according to their priorities until the power balance and security constraints are satisfied. Each time, minimum up time and down time are checked before commitment. This is a one simple and efficient method and has been widely used in several practical power industries. One limitation is that the solution obtained need not be optimal always since the initial status and start up cost of the different units are not considered in preparing the list.

In order to obtain an optimal Unit Commitment solution, an adaptive list method is suggested (Lee [1988]). The units are grouped based on their initial unit operating characteristics, minimum shut down and start up times, spinning reserve etc. At each hour to be scheduled, within each group, the units are ranked according to the economic cost of production and prior system operation. Comparison is made in terms of a cost index which accounts the prior system marginal cost and production cost. Initial set of units (initial feasible solution) at each hour consists of top ranked units from the different groups. At each iteration, based on the relative economic cost, the dominated unit in the set is identified and removed from further consideration. The load balance condition is evaluated. Additional comparison will be made among the

[redacted] units and the 'next unit to commit' is found. Comparison and refinement is continued to get the optimum solution satisfying the load demand.

2.2.2 Dynamic Programming

Dynamic Programming (DP) is another major approach introduced in 1960s to the solution of several optimization problems (Bellman and Dreyfus [1962]). Dynamic Programming is a method based on well known "Bellman's optimality principle". Based on the same, an optimization problem is first divided into a number of stages. Possible states and solutions of the problem at each stage are identified.

According to the optimality principle, an optimal decision made at one stage does not depend on the policy or decisions made at its previous stages. To achieve the optimum, starting from the first stage the various solutions at each stage are enumerated. Each decision will make a transition of the system to one of the states at the next stage. Enumeration of the decisions or solutions at each stage corresponding to the states encountered is continued, until the final stage is reached.

A variety of Dynamic Programming (DP) solutions have been proposed by a number of researchers. The basic steps in the Dynamic Programming based solution to Unit Commitment (Wood and Wollenberg [2002]) are:

(i) Identify the number of stages in the scheduling problem. It is same as the number of hours to be scheduled.

(ii) Define the possible states at each stage of the problem. The states are defined as the possible combinations of the units or the ON/ OFF status of one particular unit.

(iii) Filter the feasible or permissible states for each time slot based on the constraints enforced in the problem. This is dependent on the load demand to be met at the particular time slot and the operating limitations.

(iv) Starting from the initial state (status of the units), find the feasible solutions (unit combinations) at each stage to make stage transition. Corresponding to

each state, the cost is calculated by considering the production cost and start up cost of the units.

(v) Reaching the final stage, backtrack from the optimum combination (having minimum cost) till the initial stage to obtain the optimum schedule.

The solutions proposed by the different methods based on DP are a slight variation of this basic procedure. Some of them are reviewed here. In the simplest DP approach (Ayoub and Patton [1971]), the commitment of generating units is determined independently for every time period. For every unit, the start up and shut down costs are assumed to be constant and the total cost of every output level is the sum of production and start up costs. In this method, time dependence of start up cost is not considered. It cannot take into account the minimum up time and down time of the generating units.

In 1976, Pang and Chen suggested a DP based algorithm considering the start up costs. In this, each stage represents a particular time period, and in every stage, corresponding states represent different combinations of commitment status during that period. The solution procedure considers the interdependence between the different time slots and hence the start up cost is considered as dependent on the transition information. Also the minimum up / down time constraints are incorporated.

In order to consider the huge dimension arising for large systems, additional techniques with DP are proposed (Pang *et al.* [1981]). In each period subset of the states are identified to get optimal policy. This subset is formed based on the constraints forced on the status of the generating units, which is dynamic in nature. This truncated DP approach efficiently reduces the computation time. But the limiting of the state space is not always optimum. Hence the solution does not turn to be optimum in many cases.

Another modified DP termed as sequential DP combines the Priority List and the conventional Dynamic Programming approach (Meeteran [1984]). In this method, in order to increase the speed of computation, search space is reduced to certain subspaces termed as windows. But, the optimality is to be attained regarding the

accuracy and window size. For large scale systems, a large search range is required to get proper solution. Even if window size or subset range is selected by several heuristic techniques, the computational efficiency is very poor.

A variable priority ordering scheme is proposed (Synder *et al.* [1987]) to enhance the computational efficiency. The approach again suffers from the dimensionality as the state space becomes enormously large with the number of generating units. An enhanced Dynamic Programming method considering the reserve constraints is proposed by Hobbs *et al.* [1988].

The power system dynamic stability problem is also considered and a Dynamic Programming solution to multi area unit commitment is proposed (Hsu *et al.* [1991]). Eigen values are used to find the stability of the units at the optimum generation point obtained at each hour.

Ouyang [1991] proposed an intelligent Dynamic Programming method, which eliminates infeasible states and reduces the decision space in each hour of the problem. The variable window Dynamic Programming suggested, adjusts the window size according to the received load increments.

The spinning reserve constraints form an important part in the solution of Unit Commitment problem. Scheduling of hydro electric plant is done through Dynamic Programming considering the reserve constraints (Finandi and Silva [2005]).

2.2.3 Lagrange Relaxation

Lagrange Relaxation technique is a numerical solution method based on dual optimization. The method decomposes the linear programming problem into a master problem and more manageable sub problems. Sub problems are linked by Lagrange multipliers which are added to the master problem to get the dual problem. This low dimension dual problem is then solved. For the same, Lagrange multipliers are computed at the master problem level and are passed to the sub problems. The updating of Lagrange multipliers is done by either analytical methods or heuristic methods.

The solution strategy can eliminate the dimensionality problem encountered in the Dynamic Programming by temporarily relaxing the coupling constraints and separately considering each sub problem. It provides the flexibility for handling the constraints and is computationally efficient.

For obtaining the optimum solution, Unit Commitment Problem is formulated, in terms of the cost function, set of constraints associated with each unit and the set of coupling (system) constraints, into one primal problem and one dual problem. The primal sub problem is the objective function of the Unit Commitment Problem. Dual problem incorporates the objective function and the constraints multiplied with the Lagrange multipliers.

Lagrangian dual function is formed by adjoining the power balance and security constraints into the cost function, via two sets of Lagrange multipliers. Equality constraints are incorporated by one set of multipliers (usually denoted by λ) and inequality constraints by another set (denoted by μ). The dual procedure attempts to maximize the dual function (minimum of Lagrange function) with respect to Lagrange multipliers. In the solution process, at each iteration, the Lagrange multipliers are taken as fixed. Once the values of multipliers have been fixed, each sub problem is solved (minimized) with those constraints which represent the operating characteristics of the corresponding unit.

For the minimization procedure, any of the linear programming method is used. Corresponding to the obtained values of the system variables, the dual function and primal function are evaluated to obtain the duality gap which is the measure of convergence. When the duality gap is more, the Lagrange multipliers are updated to start the next iteration in the solution process. Tolerable value of duality gap indicates the convergence of the algorithm.

From the early 1970's, researchers focus on developing solution to Unit Commitment Problem using Lagrange Relaxation. Muckstadt and Koeing [1977] have provided a Lagrange Relaxation solution using branch and bound decision making technique. A node in the branch and bound tree represents the problem 'P' with

appropriate set of variable $x_{i\,t}$ *($x_{i\,t}$ = 0 or 1)*. The Lagrangian Relaxation of the problem at each node is solved with shortest path algorithm solving each of the single generator sub problems. This provides the lower bound for the optimal solution of the problem at each node. The bounds are used to direct the search through the decision tree. At each node in the tree, sub gradient method is used to update the values of the Lagrange Multipliers so as to make the bounds better. The updated multiplier values are used to compute the next solution of Lagrange Relaxation. The method has proved to give optimal solutions to smaller problems and with acceptable tolerance limit to a bit larger problems. But for lager problems the number of nodes in the decision tree is very large in number which increases the computational complexity.

A modified solution strategy was proposed by Lauer *et al.* [1982]. In this case in addition to the lower bound, an upper bound is also obtained at each node in the branch and bound tree. The lower bounds are provided by the solution of the dual problem and then the upper bounds are fixed using dynamic priority lists which depends on time, state of the units and the demand. The sub gradient method of solution to dual problem does not provide sufficient information for getting optimal solution to primal problem and this makes the number of nodes to be examined is very large for a satisfactory solution of complex and real world problems.

To address the large size and real world problems, another approach was suggested by Bertsekas *et al.* [1983]. In this case, the dual problem is approximated to a twice differentiable problem and then solved by constrained Newton's method. The solution to dual problem gives the values of Lagrange Multipliers to solve the relaxed primal problem. Since the number of iteration required in Newton's method is insensitive to the number of generation units, computational requirement for getting the optimal solution is much less (10 – 12 minutes for 200units and 24 hour load pattern)

Cohen and Sherkat [1987] have reported the solution to general Unit Commitment problem using Lagrange multipliers. Bard [1988] also solved the short term Unit Commitment of thermal generators using Lagrange multipliers.

Solution through Lagrange Relaxation method depends on the values of Lagrange multipliers. Therefore setting the initial Lagrange multipliers and updating them are significant to the optimality of the solution The solution from the simple Lagrange Relaxation method is not optimal always due to improper adjustment of the Lagrange multipliers. The non convexity of the problem is also not handled satisfactory by simple Lagrange Relaxation method.

To handle the non convexity of the Unit Commitment problem, modifications have been proposed to the basic method of Lagrange Relaxation. A three phase method is proposed by Zhaung and Galiana [1988]. Lagrangian dual of the problem is maximized using sub gradient technique in the first phase. A reserve feasible dual solution is developed in the second phase and the third phase solves the Economic Dispatch.

Unit Commitment solution is obtained considering the transmission constraints (Bataut and Renaud [1992]). The solution often oscillates around the global optimum point. The non convexity of solution method is overcome in the modified method termed as Augmented Lagrange Relaxation (Wang *et al.* [1995]). In this solution, quadratic penality terms are considered and added with the objective function in order to handle the convexity of the problem. These multipliers relax the system demand multipliers and the oscillations of the solution are avoided.

Peterson and Brammer [1995] suggested a Lagrange Relaxation method considering the various constraints including ramp rate constraints of the generating units. Beltran and Heredia [2002] also proposed an Augmented Lagrange Relaxation with a two phase method of solution to improve the convergence of the short term Unit Commitment problem. But it is more complicated and slower due to the updating needed for each of the Lagrange multipliers and penalty factors at each step, which increases the time for convergence.

Lu and Schahidehpur [2005] used the Lagrange method considering the generating unit with flexible constraints. A case of Lagrange Relaxation and mixed integer programming are proposed by Li and Shahidehpour [2005]. The method is to

find the global optimum using the classical Lagrange Relaxation method and to obtain local optimum through Augmented Lagrange Relaxation method.

Stochastic methods are also developed for the updating of Lagrange multipliers. Cheng *et al.* [2000] employed genetic algorithm in the calculation of Lagrange multipliers. Balci and Valenzuela [2004] proposed Particle Swarm Optimization for the computation of the multipliers.

Lagrange Relaxation is an attractive and efficient method due to the flexibility of incorporating the constraints in the problem and suitability for large systems.

2.2.4 Decommitment method

Decommitment method determines the Unit Commitment schedule by decommitting the units from an initial state in which all the available units are brought on line over the planning horizon. A unit having the highest relative cost is decommitted at a time until there is no excessive spinning reserve or minimum up time. Tseng *et al.* [1997] demonstrated that the decommitment method is reliable, efficient and quick approach for solving Unit Commitment Problem. Tseng *et al.* [2000] and Ongasakul and Petcharakas [2004] applied decommitment method as an additional step along with Lagrange Relaxation.

2.2.5 Artificial Neural Networks

Artificial Neural Networks (ANN) offers the capability of parallel computation. They are computational models composed of interconnected and massively parallel processing elements. For processing information, the neurons operate concurrently and in parallel and distributed fashion. The interconnection of the different neurons in the network is through the parameters termed as weights which are modified during the training phase of Neural Network. Once trained, the network gives the optimum output for the input data supplied to the network. Several models and learning algorithms associated with Neural Networks have been developed.

The network learning is generally of three types: Supervised Learning in which learning is carried out from the set of examples or known input – output pairs,

Unsupervised Learning in which without the use of examples the network learn for optimum weights and Reinforcement Learning where learning is carried out through interaction, getting rewards for actions at each time step.

Of the different Neural Network architectures, Hopfield Neural Network and Radial Basis Function networks are most commonly used for optimization tasks. Hopfield Neural Network is one recurrent network that operates in unsupervised manner. Radial Basis Function (RBF) networks are used as interpolating networks, used mainly for function approximation tasks.

Several Neural Network solutions have been proposed for Unit Commitment Problem. Unit Commitment can be treated as a discrete optimization problem since the ON / OFF status is the decision to be carried out. In the early work by Ouyang and Shahidehpour [1992], a pre schedule according to the load profile is obtained using a three layer Neural Network and supervised learning. The input layer of the network consists of T neurons for a T hour scheduling task and accepts the load demand profile. The input neurons are normalized by the maximum swing in the MW. The neurons in the output layer provide the output schedule which is an N x T matrix, N being the number of machines to be scheduled. Since the status variable can take only '1' or '0'corresponding to ON / OFF, output matrix is having only these two elements corresponding to the different variables. Training of the network is carried out using representative load profile and commitment schedule obtained through mathematical programming technique. After training, Neural Networks gives the commitment schedule for any load demand. But the limitation is that the training pattern is to be properly selected to get the accurate scheduling of the units.

In order to make the solution more efficient, Hopfield Neural Network is used for solution of Unit Commitment problem and results are obtained for scheduling of 30 units (Sasaki *et al.*[1992]). Discrete energy function is associated with the different neurons in the network so as to handle the discrete nature of Unit Commitment Problem.

Ramp rate constraints are also incorporated in finding the Unit Commitment schedule by Wang and Shahidehpor [1993]. To handle the problem more accurately, Walsh and Malley [1997] proposed Augmented Hopfield Neural Networks. In this case, energy function comprises both the discrete and continuous terms to handle the problem more efficiently considering the optimum dispatch for the generating units.

To provide more flexibility and to adaptively adjust the weights in the network, an evolving weight method is suggested (Chung *et al.* [1998]). Genetic Algorithm is used to evolve the weights and interconnections.

One limitation of using Neural Network alone is the need for larger time for convergence. By using Neural Network as a classification network and then using Dynamic Programming in the smaller space obtained, convergence is easily obtained (Daneshi *et al.* [2003]).

The attractive feature of the method suggested by Swarup and Simi [2006] is the use of separate discrete networks (instead of neurons in the previous cases) for each of the constraint in the Unit Commitment Problem and a continuous Hopfield network for solving Economic Dispatch problem. The two sorts of networks remain decoupled, but learnt simultaneously. This avoids the use of complex unified energy function. It provides more flexibility on adding more constraints, without affecting the objective function block. But the major limitation comes from larger state spaces, difficult to be learnt while finding the schedule of a number of units and for a large profile of load data.

2.2.6 Evolutionary Programming

Evolutionary Programming and Genetic Algorithm are optimization tools developed motivated by the natural evolution of organisms. Each of them maintains a set of solutions called population, through modification and selection. They differ in the representative technique, type of alteration and selection procedure adopted. The basic idea behind is to mathematically imitate the evolution process of nature.

Evolutionary Programming algorithm considers evolution as a change in adaptation and diversity of population (Fogel [1995]). Unlike Genetic Algorithm, Evolutionary Programming imposes no restriction on the coding that may be employed for the optimization task.

An Evolutionary Programming algorithm for solving simple Unit scheduling task is proposed by Juste *et al.* [1999]. Each population is having a set of n individuals. Each individual represents a solution to the problem. The populations are evolved considering the entire state space, without giving any priority to the evolved generations and individuals. Each individual is a matrix representing the status of the units for the forecasted load period. Binary encoding is used and the decimal equivalent of the binary string representing the status for T hours is used for each of the units. Each individual is thus encoded as a vector of N decimal numbers. Therefore each population is represented by a matrix of N x n decimal numbers.

From the initial population, randomly selected as having n individuals, the next population is evolved through selection. The fitness value of each individual is calculated using the cost functions associated with the units. From each parent individual, an offspring is created by adding a Gaussian random variable to the elements. The parameter of the Gaussian distribution takes into account the fitness values of the parent population. The evolved members and the parent individuals together are ranked according to their fitness value and the best n individuals are selected as the next population. As a number of populations are evolved through this iterative procedure, the individuals will approach to the optimum status for the units.

Evolutionary Programming algorithms are also developed which differ in the generation and selection of the offspring from the parent population. By incorporating a search technique along with Evolutionary Programming, Rajan and Mohan *et al.* [2004] proposed an algorithm to find Unit Commitment schedule at much lesser time. They also considered the cooling and banking constraints and optimum schedule is obtained through a hybrid approach of Tabu search and Evolutionary Programming.

Due to the use of Evolutionary Programming, the search complexity in the Tabu list is reduced.

Since a large number of populations are to be generated for getting the optimum schedule, the time complexity is more in all Evolutionary Programming methods.

2.2.7 Genetic Algorithm

Genetic Algorithms (GA) are well-known stochastic methods of global optimization based on the evolution theory of Darwin. The various features that characterize an individual are determined by its genetic content, represented as chromosomes. In GA based solution strategies a population of chromosomes are considered and evaluated. Each chromosome is represented as a string.

In case of Evolutionary Programming the off springs are generated by using a Gaussian distribution while in case of genetic algorithm the next generation is evolved by changing of the chromosome string through mutation and cross over operations.

The individuals in the population are encoded using either binary or real numbers. The population in GA is treated with genetic operations. At iteration i, the population X_i consist of a number of n individuals or solutions x_j where n is called as population size. The population is initialized by randomly generated individuals. Suitability of an individual is determined by the value of the objective function, called fitness function. A new population is generated by the genetic operations selection, crossover and mutation. Parents are chosen by selection and new off springs are produced with crossover and mutation. All these operations include randomness. The success of optimization process is improved by elitism where the best individuals of the old population are copied as such to the next population.

Kazarilis *et al.* [1996] applied simple Genetic Algorithm for solution of Unit Commitment problem. Binary encoding representing the status of the generating units is used and the non linear cost function is employed to calculate the fitness value of the individuals. Binary numbers '1' and '0' indicate ON / OFF status of the generating

units. Each individual is a solution corresponding to N generating units and T hours. Therefore it is represented as $N \times T$ matrix of binary numbers. There are *'n'* such candidate solutions in one population. Through the genetic operators mutation, cross over and selection among the parent individuals, new population is created from parent population. Recombination of the binary strings is made through cross over which exchanges portions between strings. Mutation makes random alteration of the bits in a string and thus provides diversification in the competing solutions. A new population is produced by selecting the best individuals after applying cross over and mutation. Fitness or goodness of a particular individual is measured through evaluation of the cost function.

Since the size of the matrix representing the individual increases with the increase in the number of hours and generating units, search space becomes huge.

Orera and Irving proposed a hybrid genetic algorithm [1997] to handle the huge space of variables. A priority order commitment is employed which gives a sub optimal solution to generate the initial GA population. The problem is decomposed in the hourly basis to reduce the search space from 2^{NT} to 2^{N}. Starting from the first hour, the algorithm sequentially solves the scheduling problem by limiting the search to one hour and considering the minimum uptime and down time constraints. For the remaining hours, solution for the previous hour is taken as an initial solution instead of taking in random. To make the solution more efficient a hybrid method incorporating Tabu search and Genetic Algorithm is also proposed by Mantawy *et al.* [1999 a].

Considering the competitive market and import / export constraints, a solution to Unit commitment is found (Richter and Sheble [2000]). But the solution neglected many other constraints such as cooling period. Cheng *et al.* [2000] incorporated the Genetic Algorithm into Lagrange relaxation method to update the Lagrange multipliers and thus to obtain efficient solution.

A cooperative co evolutionary Programming solution is proposed by Chen and Wang [2002]. The algorithm is more powerful in handling more complex problems. The method is a two phase method. In the first level, sub gradient method is used to

solve the Lagrange multipliers and in the second level, GA is used to solve the system variables.

Xing and Wu [2002] considered the energy contracts while finding the commitment schedule. Senjuy *et al.* [2002] considered the unit characteristics more precisely and found a schedule through Genetic Algorithm. Swarup *et al.* [2002] considered the constrained Unit Commitment problem and solution is obtained using problem specific operators. Damousis *et al.* [2004] used an integer coded genetic algorithm, which used coding in terms of integer rather than binary as in conventional genetic algorithm. Dudek *et al.* [2004] explained the application of some improved search facilities to improve the performance.

Genetic method involves extensive computation time since a large number of populations with sufficient number of individuals are to be generated to reach the optimum. Therefore this method is not much suitable for larger systems. Also optimal solution is not always guaranteed.

2.2.8 Tabu search

Tabu search technique applies a meta heuristic algorithm, which uses the search history for a good solution among a set of feasible solutions. It uses a flexible memory system. The adaptive memory system avoids the trapping to local optimum points, by directing the search to different parts of the search space. Tabu search can be treated as an extension of steepest descent algorithm. It selects the lowest cost neighbour as the starting point in the next iteration. At each step, the algorithm maintains a list of recent solutions.

Tabu search begins with a randomly chosen initial solution. The initial solution is treated as the current solution and the corresponding cost as the current cost. This current solution is then modified randomly to get a set of neighbourhood solutions. The best solution in the neighbourhood is selected for transition. Each transition through the solution space is termed as 'move'. The move is chosen based on the cost of the neighbourhood solutions. Usually the lowest cost neighbour is selected for the move

even if it is costlier than the current solution. But if the move has been already encountered in the near history, it will be discarded if having higher cost. A lower cost move will be accepted even if it is already present, to provide sufficient exploration in the search space.

For comparing the moves and to ascertain the acceptance a list called *Tabu list* is created. In every iteration, the move corresponding to the selected solution is inserted in the Tabu list. When an entry is inserted, the earliest one is deleted and the cost of the current solution is inserted as the aspiration level of the list to compare the cost in the next iterations. This refinement of the list and selection is carried out iteratively to reach the optimum solution.

For solving Unit Commitment problem several solutions based on Tabu search are proposed (Mantawy *et al.* [1998]). Tabu list created is of size Z x N, where Z is the list size chosen and N being the number of generating units. Each vector in the matrix represents the Tabu List for one generating unit. That is, each vector records the equivalent decimal number of the binary representation of a specific trial solution (u_{it}, $t = 1,.....T$) corresponding to unit i. On iterative solution, the infeasible solutions are removed from the list and the list reduces to optimal solutions.

Borghetti *et al.* [2001] compared the strength and weakness of Lagrange Relaxation and Tabu search for models of competitive electricity market. It revealed that there is no guarantee that the Tabu search will yield the global optimal result in large systems. Mitani *et al.* [2005] proposed a combined approach of Lagrange relaxation and Tabu search for obtaining the schedule. This method guaranteed the optimality, but due to complexity, computational speed is less.

2.2.9 Particle Swarm Optimization

In 1995, a solution method termed as Particle Swarm Optimization (PSO), motivated by social behavior of organisms such as fish schooling, bird flocking was introduced. PSO as an optimization tool provides a population based search procedure

in which individuals called particles change their position with respect to time. In a PSO system, particles fly around a multi dimensional search space. During flight, each particle adjusts its position according to its own experience and the experience of its neighbouring particles, making use of the best position encountered by itself and its neighbours. The swarm direction of a particle is defined by the set of particles neighbouring the particle and its history or experience. PSO can generate high quality solutions in less convergence time, compared to other stochastic methods.

Xiaohui *et al.* [2005] used the discrete particle swarm algorithm for solving Unit Commitment Problem for a ten generating unit system and 24 hour load pattern. Each particle is having the elements corresponding to the ON / OFF of the units. Starting from a random initial position (state) of the particle, at each position of the particle the fitness function (which accounts the production cost and start up cost) is evaluated. The best particle position P_{best} and also the global best position (on comparing P_{best} value with the previous best values) are stored. Then the particles change their position based on 'velocity' parameter. The velocity parameter of each particle accounts the deviation of the current position from the best observed value, at the same time accounting the unvisited positions of the solution space. Through the iterative procedure, the entire solution space is searched to get the optimum position. This updating of particle position flight is continued for each slot of time.

An adaptive strategy for choosing parameters is proposed in the improved particle swarm optimization method suggested by Zhao *et al.* [2006]. It proved to give higher quality solutions compared to Evolutionary Programming.

Even though Particle Swarm Optimization gives a better solution than other methods for simpler systems, for large and complex space the particles do not move always towards the optimum point.

2.2.10 Simulated Annealing

Simulated Annealing is one powerful stochastic search technique, suitable for solution of many optimization problems, derived from material science. The method is based on the process of annealing of the metals through heating to a high temperature followed by slow cooling, in steps, to obtain the low energy state of the solid.

In applying this technique to such combinatorial optimization tasks, the basic idea is to choose one feasible solution at random and then move to another solution in the neighborhood. A neighbouring solution is generated by perturbation to the current solution. The fitness value of the neighbouring solution and that of the present solution are calculated at each iterative step of the procedure. The neighbouring solution is accepted whenever it seems to be better (having less cost). Also some of the higher cost solutions are accepted based on a probability distribution and considering their fitness values.

The probability of acceptance of a higher cost solution is decided by the control parameter. The value of the control parameter, 'temperature' is initially chosen as a high value and reduced in the iterative steps in order to approach to the optimum point. Higher temperature at the initial points ensures the proper exploration of the solution space and as the temperature is reduced the convergence of the solution is achieved. Therefore in order to reach the optimum solution with sufficient exploration, a good cooling schedule is to be formulated.

Zhuang and Galiana [1990] first proposed a Simulated Annealing algorithm to solve Unit Commitment problem. The algorithm is a direct implementation of the basic Simulated Annealing procedure. The initial solution is obtained using a priority list method. In the subsequent iterations, the current solution is perturbed by changing the status of an arbitrary unit at an arbitrary hour to generate the next solution. The feasibility of the solution is then checked and the cost function is calculated to accept or not the same. The temperature is reduced by multiplying the current temperature by a factor (in the range 0.8 -0.9).

An Enhanced Simulated Annealing is proposed by Wong [1998]. Instead of random perturbation, next solution is developed by applying one of the specific steps in random. Mantawy *et al.*[1999] proposed a hybrid algorithm for solution of Unit Commitment Problem using combined Simulated Annealing, Genetic Algorithm and Tabu search. The algorithm is superior to the individual methods.

Purushothama and Lawrence Jenkins [2003] made use of local search method to select the best neighbouring solution. At each temperature, a number of neighbouring solutions are generated and using local search method best among these is selected. The solution obtained is optimum, but computation time is increased.

2.3 Economic Dispatch - Solution strategies

Economically distributing the load demand among the various committed units at each hour / time slot is one optimization task in power generation control. It has been solved by many researchers using different methodologies. The complexity of this problem comes from the non convexity of cost functions, piece wise incremental cost functions associated with many of the units, transmission loss associated with the system etc. A number of classical and stochastic methods have been proposed for the solution of this constrained optimization problem.

Chowdhury and Rahman [1990] gave a detailed review of the methods developed till 1990. After that a variety of techniques have been developed of which most of them are soft computing techniques. A brief review of the latest methods is given here with an evaluation point of view.

2.3.1 Classical Methods

Lambda iteration is one of the conventional methods for solving the constrained optimization problem (Wood and Wollenberg [2002]). It has been very successfully implemented for the solution of the problem by many researchers. In this method, a Lagrange function is formulated by adding with the objective function, the constraint function multiplied by the multiplier 'lambda'. The iterative adjusting of the parameter lambda is carried out. When the difference between the total generation and

demand falls within a tolerable limit or after sufficient large number of iterations, the updating of the parameter lambda is stopped. This method is found to be good, but has a slow convergence or yield an unacceptable result if the initial lambda and the method of updating of lambda are not properly selected. Also for effective implementation of this method, the cost functions need to be continuous.

Base point participation factor method is one of the earlier methods used in Economic Dispatch solution. In this case, each generating unit is having a participation factor associated with it depending on its generation and cost constraints. Incorporating this weighted constraint function along with the objective function a new objective function is formulated. Solution of the function is then carried out using iterative or graphical methods. This method is simple, but not capable of accommodating larger number of units and complex cost functions.

Gradient method is one analytical method in which the objective function is minimized by finding the steepest descent gradient. The solution depends on the initial starting point. If the initial solution is better, it gives the optimum result very easily. But if the initial solution points in a wrong direction, getting an optimum result is much difficult.

Also, these methods require the generator cost curves to be continuous functions, which is not possible in the case of practical situations. Also these methods have oscillating tendency in large scale mixed generating unit systems leading to high computation time. A lot of other techniques have been evolved to tackle the non convexity of the cost functions.

2.3.2 Dynamic Programming

Dynamic Programming (DP) is a good solution method for solving non linear and discontinuous optimization tasks. It is an efficient method for solving of the Economic Dispatch problem also (Wood and Wollenberg [2002]). DP works with the unit input output information directly by enumerating all possible solutions. It consists of evaluating the problem in stages corresponding to each unit for choosing the optimal allocation for a unit.

On solving Economic Dispatch, first a forward approach is carried out to generate tables of costs. In the first step considering a power demand D the first two units (considered in random) are scheduled to find the minimum cost. For the same, some power (say P_1) is assumed to one of the generating unit and the balance $(D - P_1)$ to one from the remaining set (2^{nd} unit) as P_2. This constitutes a table of discrete values and corresponding costs. From the table of values corresponding to each value of power minimum cost and the corresponding distribution among the two units can be found. Then the next unit is considered. The power allotment to the third unit is then made in the next step by allocating P_3 to it and allocating power $D - P_3$ economically among the first two units (finding the allocation schedule P_1,P_2 corresponding to the minimum cost from the previous table). This generates the second table of values. This is continued till the last unit, to get the cost distribution tables corresponding to different power allocation to the different generating units. Then a backward search is carried out through the distributions to obtain the minimum cost allocation to each of the units.

This backward dynamic programming method has been successfully applied to several systems. It gives an optimum solution for smaller systems. But as the number of generating units and the constraints of the system increases, it becomes difficult to generate and manage the larger number of entries in the discrete tables. Therefore when number of units and scheduled power range increases Dynamic Programming method fails. In other words, Dynamic Programming method suffers from the curse of dimensionality. It leads to higher computational cost even when incorporating the zoom feature (Liang and Glover [1992], Shoults *et al.* [1996]). The method leads to local optimal solutions when avoiding the problem of dimensionality.

2.3.3 Neural Networks

The ability of Neural Networks to realize some complex non linear functions makes them attractive for system optimization including Economic Dispatch problem. Hopfield Neural Networks have been successfully applied to the solution of Economic Dispatch problem. Since the allocation of power to the different generators comes from

a continuous space, Hopfield Neural Networks with continuous activation functions are found suitable for dispatch problem. Energy function of the continuous Hopfield Network is defined differently by different researchers.

Kasangaki *et al.* [1997] proposed Hopfield Neural Network solution for handling Unit Commitment and Economic Dispatch. The problem variables are first modeled as stochastic differential equations considering the constraints. Then Hopfield Neural Network with augmented cost function as energy function find the optimum values of these variables.

Su and Lin [2000] also proposed a Hopfield Neural Network as a solution method for simple Economic Dispatch problem. They considered some of the security constraints and used simple back propagation algorithm to obtain the optimum solution. The energy function is formulated by combining the objective function with the constraint function using appropriate weighting factors.

Yalcinoz and Cory [2001] developed Hopfield Neural Network solutions for various types of Economic Dispatch problems. In this case also, the constraints are handled by modification of the activation functions. Radial Basis Function networks are used by Aravindhababu and Nayer [2002] to get an optimum allocation. Farooqui *et al.* [2003] proposed an algorithm based on Hopfield Neural Networks considering ramp rate constraints. Balakrishnan *et al.* [2003] considered the emission constraints also in thermal dispatch. Later, Silva *et al.* [2004] introduced one efficient Hopfield Neural Network solution with transmission system representation.

Senthilkumar and Palanisamy [2006] suggested a Dynamic Programming based fast computation Hopfield Neural Network for solution of Economic Dispatch problem. Swarup and Simi [2006] proposed the solution using continuous Hopfield Neural Networks in which weighting factors are calculated using adaptive relations. But the computational effort is high in these methods due to the large number of iterations needed to obtain optimality.

2.3.4 Genetic Algorithm

While applying GA for solution of Economic Dispatch, the encoding commonly used is the binary encoding, representing the MW generation as the corresponding binary string. The fitness function is the cost function considering the ramp rate constraints, prohibited operating zones etc.

A variety of GA based algorithms are developed to get the economic schedule. Walters and Sheble [1993] used this method for solving Economic Dispatch problem. A hybrid form of Genetic Algorithm and Back propagation network is given by Ping and Huanguang [2000]. Ongasakul and Tippayachai [2002] suggested a modified Genetic Algorithm termed as Micro Genetic Algorithm for solution. He considered different types of cost functions to prove the flexibility of the algorithm. Basker *et al.* [2003] proposed a real coded algorithm, instead of binary coding. Won and Park [2003] worked out an improved genetic algorithm solution and found to be better than conventional genetic algorithm due to the improved selection operator based on Gaussian distribution chosen for generating a new population.

2.3.5 Evolutionary Programming

Evolutionary Programming (EP) method is capable of rendering a global or near global optimum without gradient information. For generating units having non convex cost function, Evolutionary Programming seems to be a good method.

In solution of Economic Dispatch, the initial parent is generated as the MW distribution in proportion to the generation capacity of the different generating units. The successive populations are generated from the parent using the different distribution patterns. The fitness values of the off springs are mostly evaluated based on the cost function or cost distribution. Then n fittest off springs are selected for generating the next generation. The iterative procedure is continued till optimum allocation is obtained after generating a number of populations.

Yang *et al.* [1996] suggested a solution for Economic Dispatch problem using a Gaussian distribution for generation of off springs. Later, an evolutionary programming algorithm for a utility system having fuel restricted and fuel unrestricted units has been suggested by Kumarappan and Mohan [2003]. They also considered the transmission losses by executing the fast decoupled load flow for the system. Even though it gives one optimum allocation schedule, the computation seems to be more expensive and a lot of memory is required.

Sharkh *et al.* [2003] combined the approaches of Evolutionary Programming with fuzzy logic and formulated an algorithm which considered the uncertainty in the constraints.

Evolutionary Programming method is applied for Economic Dispatch problem by Somasundaram and Kuppusamy [2005] incorporating the efficiency of conventional lambda iteration method. In this, system lambda is taken as the decision variable and power mismatch is taken as the fitness function. The method used two steps of computation, one to find the optimum decision space and then the second finding the optimum decision point.

Jayabarathi *et al.* [2005] explored evolutionary programming algorithms for the solution of various kinds of Economic Dispatch problems such as considering prohibited operating zones, ramp rate limits etc.. Classical Evolutionary Programming, Fast Evolutionary Programming and Improved Fast Evolutionary Programming methods are developed for the solution of the problem. Classical and Fast Evolutionary Programming methods take more computation time and Improved Fast Evolutionary Programming requires more complex computations.

Ravi *et al.* [2006] proposed a fast evolutionary programming technique for handling heuristic load patterns. A modification of this method named as clonal algorithm is applied by Panigrahi *et al.* [2006]. Coelho *et al.* [2007] gave an Evolutionary Programming technique for solution of security constrained Economic

Dispatch problem. The line flow and bus voltage constraints are taken into consideration.

These methods seem to have the disadvantages of slow convergence due to a large number or generations to be manipulated and also need a large number of decision variables. It also suffers from indeterministic stopping criteria.

2.3.6 Particle Swarm Optimization

Particle Swarm Optimization (PSO) is one of the heuristic algorithms which can be used to solve the non linear and non continuous optimization problems. Therefore many researchers find it suitable for solution of Economic Dispatch problem. The individuals called particles change their position based on its own previous experience and the experience of the neighbouring particles.

Each individual or particle is represented as a string representing the power allocation to the different units. If there are N units to be dispatched then i^{th} individual is represented as $P_{(i)} = [P_{i1}, P_{i2}, \ldots\ldots, P_{iN}]$. The dimension of the population is n x N, where n is the number of particles in the population. The evaluation of fitness function is the reciprocal of the cost function in order to obtain the minimization of the problem. The fitness value of each individual f_i is calculated and compared with that of the remaining individuals in the population. The best value among these is stored as the particle best vale. Also comparison is made with the best value already found in the already generated populations and it is stored as the global best value of the optimization function. A velocity parameter is updated based on the deviation of each particle fitness value from the best value and the positions of the particles are updated. This basic PSO method for Economic Dispatch is used with modifications in the updating of the velocity parameters, the number of individuals and populations stored and selection of individuals for the population.

Giang [2003] proposed the algorithm for solution through basic PSO method. Selvakumar and Thaushikodi [2007] proposed a modified algorithm for solution of Economic Dispatch problem. In this method, along with particle's best position worst

position is also stored. This gives more exploration of search space. Performance evaluation proved it to be better than classical PSO method.

2.3.7 Taguchi method

Taguchi method involves the use of orthogonal arrays in estimating the gradient of cost functions. The controlled variables are called factors. The method involves an analysis that reveals which of the factors are most effective in reaching the goals and the directions in which these factors are most effectively adjusted. This is done by varying the factors in a disciplined manner and recording the corresponding values of the objective function. When the factors reach the optimum, optimum solution is obtained.

This method provides with a solution having reduced complexity for solving the Economic Dispatch problem (Liu and Cai [2005]). A vector having N elements, $[a_1, a_2, \ldots\ldots a_N]$ which corresponds to the relative contribution of the generator to the total power is taken as the factors to be optimized. The values of these factors are iteratively computed using the method of orthogonal array. The algorithm is found to provide better performance and lesser solution time than Evolutionary Programming and Neural Networks. But the computational complexity is more due to the large matrices to be handled and hence more difficult to incorporate additional system constraints.

2.3.8 Direct search method

This is a search technique which achieves the global optimum point by searching the solution space through exploration. Search technique seems to give optimum result always since the entire solution space is considered without elimination. Chen proposed an algorithm to apply this method for Economic Dispatch problem (Chen [2005], [2007]). For improving the performance of the direct search procedure, a novel strategy with multi level convergence is incorporated in search method to minimize the number of iterations and achieve faster convergence.

2.3.9 Tabu search

The search method provided by Tabu search is applied to Economic Dispatch problem (Lin *et al.* [2002]). It takes care to avoid trapping in the local minima points by using an adaptive size for the tabu list. A number of searches are carried out inside each of the iterations of the algorithm and the best solution point is fixed. Also the different individuals are ranked in descending order according to their fitness scored, by a sorting algorithm. This ensured the optimum solution to the constrained problem. But the search space which is large for larger systems leads to take more computer memory and thus sometimes is difficult to get converged.

2.3.10 Decision trees

Inductive Inference system is used to build the decision tree by classifying the samples to different learning sets (Sapulveda *et al.* [2000]). For generating the successive learning sets certain values of attributes are considered. The power generation values of the units are used as attributes to define the learning set and the refinement and intensifying is done by evaluating the objective function. Sapulveda *et al.* [2003] suggested an objective function comprising of the power mismatch, total fuel cost and transmission line losses. The weighting factors associated with the terms are adjusted through lambda iteration method. The algorithm seems to be suitable for many systems considering transmission losses. But there exists a chance of trapping in local optimum points.

A similar technique termed as Partition Approach algorithm was proposed by Lin and Gow [2007]. The method gave optimum result in lesser time, but for obtaining the same, a number of trials are to be executed out of which average has to be calculated.

2.4 Automatic Generation Control

Automatic Generation Control which is the third loop in the generation control scheme tries to achieve the balance of generation and load in each area and maintain the system frequency and tie line flows at the scheduled values. Load frequency action

is guided by the Area Control Error (ACE), which is a function of the system frequency and the tie line interchange. AGC studies are generally carried out using simulation models.

2.4.1 Automatic Generation Control – Models of Power system Network

AGC studies are widely done using simulation model proposed by Elgerd [1982]. According to this approach, in each area, a group of generators are closely coupled internally and swing in unison. Also, the generator turbines tend to have the same response characteristics. Then each control area is represented by a single loop. The turbine, generator and load parameters represent the equivalent values considering all the generators in that area. The different control areas are connected by loss less tie lines. The power flowing through the tie line appears as a load decrease / increase in the other area, depending on the direction of flow. A change of power in one of the areas is met by a change in generation of all interconnected areas followed by a change in the tie line power. Correspondingly, the frequency change will occur in all the interconnected areas.

In a practical network, the interconnected power system operate at a single frequency and this common frequency (common to all areas) is determined by the net generated power and connected load of all the areas. In such a system, the tie line power of each area is computed as the difference of generated power and load power of that area (Divya and Nagendra Rao [2005])

Advantages of such a system are enumerated as

(i) The system model is closer to practical power system network.

(ii) It does not require the calculation of tie line constant (which depends on the nature and no: of lines of interconnection)

(iii) Model does not require a composite prime mover model representing the entire area.

2.4.2 AGC – Control strategies

The basic control strategy is, to set the reference point in each area of the interconnected system. The change in the set point is guided by the variation in the frequency resulting from the addition or removal of a load. The various control strategies make the decision on the reference set point, by calculating the Area Control Error (ACE).

Classical as well as modern control strategies are being used in AGC. Athay [1987] gives a review of the early works done in this area. Also several soft computing techniques have been applied for finding the control strategy for AGC.

Abdel Magid and Dawoud [1997] proposed the Generation control using Genetic Algorithm. Neural Networks is used for the control solution by Zeynelgil *et al.* [2002]. Fuzzy Logic controllers which take into account the uncertainty in the instantaneous variations are developed (Demiroren and Yesil [2004]). Simulated Annealing is used as the solution method in a multi area thermal generating system (Ghosal [2004]). Imthias Ahamed *et al.*[2002] proposed a Reinforcement Learning approach to a two area system. But the models used in all these assume different frequencies for the two areas (model proposed by Elgerd).

Automatic Generation Control, considering the same frequency for all the areas has not yet been developed by any of the stochastic techniques till now. Since in the practical system, all the areas have a common frequency, it is worth to think in this direction.

2.5 Reinforcement Learning and Applications

Reinforcement learning theory is a formal computational model of learning through continuous interaction (Sutton and Barto [1998]). It forms a way of programming agents by reward and punishment without needing to specify how the task is to be achieved. It relies on a set of learning algorithms to trace out the pay offs at each interaction and analyzing the same. In the standard Reinforcement Learning framework, a learning agent which can be a natural or artificially simulated one

repeatedly observes the state (present status in terms of a set of parameters or observations) of its environment and performs an action from the many choices possible. Performing an action changes the state or 'a transition of state' is said to occur. Also, the agent obtains an immediate (numeric) pay off, based on the state and the action performed. The agent must learn to maximize a long term sum of the reward that it can receive.

One reason that Reinforcement Learning is popular is that it mimics the natural behavior. It serves as a theoretical tool for studying the principles of agents learn 'how to act'. It has also been used by many researchers as an effective computational tool for constructing autonomous systems for various fields of control. Since the learning agent improves through experience, it has been found as a good tool for closed loop control action which is the fundamental behavior of all the learning systems. Reinforcement Learning can also be viewed as an approximation to Dynamic Programming.

Si *et al.* [2004] have given a good detailed description of Approximate Dynamic Programming. Description on neuro dynamic programming and linear programming approaches for Adaptive Dynamic Programming are explained. Multi objective control problems, Robust Reinforcement Leaning and Supervised actor critic Reinforcement Learning concepts are also detailed. Along with the design concepts, the book is having one separate section dedicated for the different applications of these adaptive optimization concepts including missile control, heating and ventilation control of buildings, power system control and stochastic optimal power flow.

The applications where Reinforcement Learning has been applied include combinatorial search and optimization problems like game playing, industrial process control and manufacturing, robotics, medical image processing, power system etc. These practical applications have proved Reinforcement Learning as a useful and efficient learning methodology. In the next section, a review of some of the

applications where Reinforcement Learning has been successfully applied is discussed.

2.5.1 Game playing

Artificial Intelligence (AI) has been providing several solutions to one of the search problems in computer science: Game playing. It varies from single player to multi player games. These problems are formulated as optimization problems in AI. Many researchers applied Reinforcement Learning algorithms for various classes of game playing. Tesauro and Gammon [1994] applied the temporal difference algorithm to Backgammon. Two types of learning algorithms were developed, one with little knowledge of the board positions in the game and the other with more knowledge about the board positions or the game environment (Tesauro and Gammon [1995]). In these algorithms, no exploration strategy was used. It took more computation time but guaranteed convergence and best reward position in finite time. Since it mimics the human play at top level, the algorithms were impressive among AI researchers.

Reinforcement Learning combined with function approximation provided by Neural Network is a very effective tool while dealing with large state spaces. The implementation of board game Othello by Nees and Wezel [2004] is a very good proof for the same.

2.5.2 Robotics And Control

Since the emergence of Reinforcement Learning, it has been successively applied by many researchers in the derivation of suitable control strategy for robot. Mataric [1992] described robotic experiments which learned from Q learning.

Crites and Barto [1997] applied the Q learning strategy in an elevator control task. The problem involved several elevators servicing the various floors. The objective is to minimize the average squared wait time for passengers. This discounting problem is effectively solved using Reinforcement Learning and take less computation time than other methods. Handa and Ninimy [2001] proposed a robust controller, through temporal difference learning method.

Autonomous helicopter flight represents a challenging control problem with complex and noisy dynamics. Andrew *et al.* [2004] described a successful application of Reinforcement Learning to autonomous helicopter flight.

Kehris and Dranidis [2005] investigated the generation of an entry control policy for an assembly plant using a Reinforcement Learning agent. The assembly plant consists of ten workstations and produces three types of products. The objective is to control and sequence the machines in an optimum manner, ensuring the correct combination in production mix. The RL optimization gives a better allotment to the various work stations.

2.5.3 Computer Networking

Effective network routing is a complex task in the interconnected system. Along with other intelligent methods, Reinforcement Learning has also been used in this area. Kelley [2005] proposed Q learning strategy for achieving an efficient and fast routing strategy. Another traffic handling method is suggested by Sahad [2005]. He proposed an intelligent method which used the concept of fuzzy logic along with Reinforcement Learning strategy.

2.5.4 Process management

A Job scheduling problem has been solved by Zhang [1995] .This gives a general framework for applying the Reinforcement Learning strategy to delayed reward situations. Q learning with exploration strategy is applied for achieving the computationally effective solution.

2.5.5 Medical images

One widely used technique for medical diagnosis is ultra sound imaging. The difficulty with the diagnosis is due to poor image contrast, noise and missing or diffuse boundaries which makes difficult for segmentation. Reinforcement learning scheme is effectively applied for transrectal ultra sound images by Sahba and Tizhoosh [2008] very recently.

2.6 Conclusion

A detailed review of the existing methodologies in the field of power system scheduling has been carried out in this chapter. Several classical and heuristic methodologies adopted for the solution of scheduling problems have been looked at. Even though numerous solution methodologies exist, thinking of more efficient and computationally faster stochastic strategy is still relevant. In the next chapter the Reinforcement Learning problems and learning method are discussed.

CHAPTER 3

REINFORCEMENT LEARNING

3.1 Introduction

Reinforcement Learning (RL) is the study of how animals and artificial systems can learn to optimize their behavior in the face of rewards and punishments. One way in which animals acquire complex behaviors is by learning to obtain rewards and to avoid punishments. Learning of a baby to walk, a child acquiring the lesson of riding bicycle, an animal learning to trap his food etc. are some examples. During this learning process, the agent interacts with the environment. At each step of interaction, on observing or feeling the current state, an action is taken by the learner. Depending on the goodness of the action at the particular situation, it is tried in the next stage when the same or similar situation arises (Bertsekas and Tsitsikilis [1996], Sutton and Barto [1998], Sathyakeerthi and Ravindran [1996]).

The learning methodologies developed for such learning tasks originally combine two disciplines: Dynamic Programming and Function Approximation (Moore *et al.* [1996]). Dynamic Programming is a field of mathematics that has been traditionally used to solve a variety of optimization problems. However Dynamic Programming in its pure form is limited in size and complexity of the problems it can address. Function Approximation methods like Neural Networks learn the system by different sets of input – output pairs to train the network. In RL, the goal to be achieved is known and the system learns how to achieve the goal by trial and error interactions with the environment.

In the conventional Reinforcement Learning frame work, the agent does not initially know what effects its actions have on the state of the environment and also what the immediate reward he will get on selecting an action. It particularly does not know what action is best to do. Rather it tries out the various actions at various states,

gradually learns which one is the best at each state so as to maximize its long term reward. The agent thus tries to acquire a control policy or a rule for choosing an action according to the observed current state of the environment. One most natural way to acquire the above mentioned control rule would be the agent to visit each and every state in the environment and try out the various possible actions. At each state it observes the effect of the actions in terms of rewards. From the observed rewards, best action at each state or best policy is manipulated. However this is not at all practically possible since planning ahead involves accurate enumeration of possible actions and rewards at various states which is computationally very expensive. Also such planning is very difficult since some actions may have stochastic effects, so that performing the same action at two different situations may give different reward values.

One promising feature in such Reinforcement Learning problems is that there are simple learning algorithms by means of which an agent can learn an optimal rule or policy without the need for planning ahead. Also such learning requires only a minimal amount of memory: an agent can learn if it can consider only the last action it took, the state in which it took that action and present state reached (Sutton and Barto [1998]).

The concept of Reinforcement Learning problem and action selection is explained with a simple N – arm bandit problem in the next section. A grid world problem is taken to discuss the different parts of the RL problem. Then the multi stage decision making tasks are explained. The various techniques of solution or learning are described through mathematical formulations. The different action selection strategies and one of the solution methods namely Q learning are discussed. The few applications of RL based learning in the fields of power system are also briefly explained.

3.2 N – Arm bandit Problem

The N arm bandit is a game based on slot machines. The slot machine is having a number of arms or levers. For playing the game, one has to pay a fixed fee. The player will obtain a monetary reward by playing an arm of his choice. The monetary reward may be greater or lesser than the fee he had paid. Also the reward from each arm will be around a mean value with some value of variance. The aim of

the player is to obtain maximum reward or pay, by playing the game. If the play on an arm is considered as an action or decision, then the objective is to find the best action from the action set (set of arms). Since the reward is around a mean value, the problem is to find the action giving highest reward or the arm with highest mean value which can be called as best arm.

To introduce the notations used in the thesis, action of choosing an arm is denoted by "a". The goodness of choosing an arm or quality of an arm is the mean value of arm and is denoted by $Q(a)$. If the mean of all arms are known the best arm is given by the equation,

$$a^* = \underset{a \in \mathcal{A}}{argmax}\, Q(a)^1,$$

where $\mathcal{A} = \{1,2,\ldots\ldots\ldots N\}$ (3.1)

As mentioned earlier, the problem is that the $Q(a)$ values are unknown. One simple and direct method is to play each arm a large number of times. Let the reward received in playing an arm in k^{th} trial is $r^k(a)$. Then an estimate of $Q(a)$ after n trials is obtained using the equation,

$$\hat{Q}^n(a) = \frac{1}{n}\sum_{k=1}^{n} r^k(a)$$

By law of large numbers,

$$\lim_{n\to\infty} \hat{Q}^n(a) = Q(a) \tag{3.2}$$

Now the optimal action is obtained by equation (3.1). To make the notation less cumbersome, the estimate of $Q(a)$ will also be denoted by $Q^n(a)$.

The above method termed as Brute force is time consuming. As a preliminary to understand an efficient algorithm for finding Q values (mean values corresponding to each arm), a well known recursive method is now derived.

As explained earlier, average based on n observations is given by,

[1] $a_g = argmax_{a\in\mathcal{A}}\, Q(a) \Rightarrow Q(a_g) \geq Q(a) \forall a \in \mathcal{A}$

$$\hat{Q}^n(a) = \frac{1}{n}\sum_{k=1}^{n} r^k(a) \tag{3.3}$$

Therefore,

$$\hat{Q}^{n+1}(a) = \frac{1}{n+1}\sum_{k=1}^{n+1} r^k(a)$$

$$= \frac{1}{n+1}\{\sum_{k=1}^{n} r^k(a) + r^{n+1}(a)\}$$

$$= \frac{1}{n+1}\{\frac{n}{n}\sum_{k=1}^{n} r^k(a) + r^{n+1}(a)\}$$

Then, using equation (3.3),

$$\hat{Q}^{n+1}(a) = \frac{1}{n+1}\{n\hat{Q}^n(a) + r^{n+1}(a)\}$$

$$= \frac{n}{n+1}\hat{Q}^n(a) + \frac{1}{n+1}r^{n+1}(a)$$

$$= \left(1 - \frac{1}{n+1}\right)\hat{Q}^n(a) + \frac{1}{n+1}r^{n+1}(a)$$

$$= \hat{Q}^n(a) + \frac{1}{n+1}[r^{n+1}(a) - \hat{Q}^n(a)]$$

That is,

$$\hat{Q}^{n+1}(a) = \hat{Q}^n(a) + \frac{1}{n+1}[r^{n+1}(a) - \hat{Q}^n(a)] \tag{3.4}$$

The above equation tells that the new estimate based on $n+1^{th}$ observation, $r^{n+1}(a)$ is old estimate $Q^n(a)$ plus a small number times the error, $(r^{n+1}(a) - Q^n(a))$.

There are results which say that under some technical conditions a decreasing sequence $\{\alpha_n\}$ can be used instead of $\frac{1}{n+1}$ to get a recursive equation (Robbins and Monro [1951]). That is,

$$\hat{Q}^{n+1}(a) = \hat{Q}^{n}(a) + \alpha_n\left[r^{n+1}(a) - \hat{Q}^{n}(a)\right]$$

The sequence α_n is such that $\sum \alpha_n = \infty$; $\sum \alpha_n^2 < \infty$.

Different variants of the above equation are used throughout the thesis.

Now, an efficient method to find the best arm of the N- arm bandit problem can be explained (Thathachar and Sastry [2003]).

Step 1 : Initialize $n=0$, $a = 0.1$

Step 2 : Initialize $Q^0(a) = 0, \forall\, a \in \mathcal{A}$

Step 3 : Select an action *"a"* using an action selection strategy[II]

Step 4 : Play the arm corresponding to action *"a"* and obtain the reward $r^n(a)$

Step 5 : Update the estimate of $Q(a)$,

$$Q^{n+1}(a) = Q^n(a) + \alpha\{r^n(a) - Q^n(a)\}$$

Step 6 : $n = n+1$

Step 7 : If $n <$ *max_iteration*, go to step 3

Step 8 : Stop.

To use the above algorithm, an efficient action selection strategy is required. One method would be to take an action with uniform probability. In this way one will play all the arms equal number of times. That is, throughout the learning the action space is explored.

[II] Action selection strategy is defined in the next paragraph

Instead of playing all the arms more number of times, it makes sense to play the arms which may be the best arm. One such efficient algorithm for action selection is e –greedy (Sutton and Barto [1998], Thathachar and Sastry [2003]). In this algorithm, the greedy arm is played with a probability (1- e) and one of the other arms with a probability e. Greedy arm (a_g) corresponds to the arm with the best estimate of Q value. That is,

$$a_g = \underset{a \in \mathcal{A}}{argmax}\, Q^n(a)$$

It may be noted that if e =1, the algorithm will select one of the actions with uniform probability and if e =0, the greedy action will be selected. Initially, the estimates $Q^n(a)$ may not be true value. However as n → ∞, $Q^n(a) \rightarrow Q(a)$, and then we may exploit the information contained in $Q^n(a)$. So in e greedy algorithm, initially e is chosen close to 1 and as n increases e is gradually reduced.

Proper balancing of exploration and exploitation of the action space ultimately reduces the number of trials needed to find out the best arm. For a variety of such algorithms refer (Thathachar and Sastry [2003]). A more detailed discussion on the parts of Reinforcement Learning problem is given in the following sections.

3.3 Parts of Reinforcement Learning problem

The earlier example discussed had only one state. In many practical situations, the problem may be to find the best action for different states. In order to make the characteristics of such general Reinforcement Learning problems clearer, and to identify the different parts of a Reinforcement Learning problem, a shortest path problem is considered in this section. Consider the grid world problem as given in Fig 3.1.

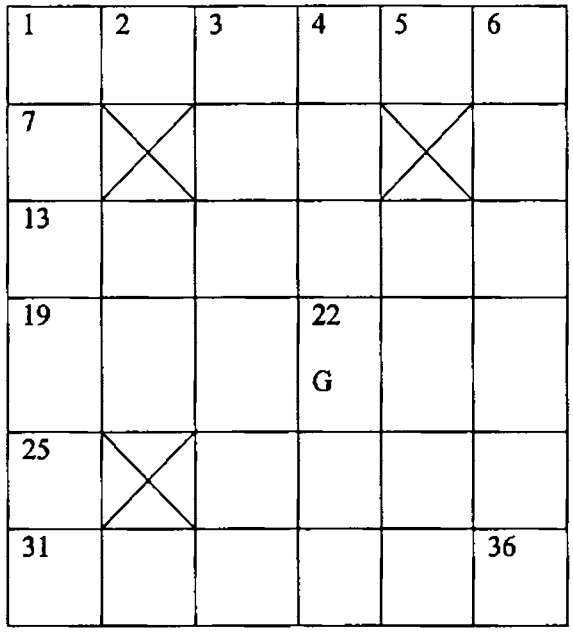


Fig 3.1 Grid world problem

The grid considered is having 36 cells arranged in 6 rows and 6 columns. A robot can be at any one of the possible cells at any instant. '*G*' denotes the goal state to which the robot aim to reach and the crossed cells denote cells with some sort of obstacles. There is a cost associated with each cell transition while the cost of passing through a cell with obstacle is much higher compared to other cells. Starting from any initial position in the grid, robot can reach the goal cell by following different paths and correspondingly cost incurred will also vary. The problem is to find an optimum path to reach the goal starting from any one of the initial cell position. With respect to this example, the parts of the Reinforcement Learning problem can now be defined.

3.3.1 State space

The cell number can be taken as state of the robot at any time. The possible state the robot can occupy at any instant is coming from the entire cell space. In Reinforcement Learning Terminology, it is termed as state space. State space in Reinforcement Learning problem is defined as the set of possible states the agent (learner) can occupy at different instants of time. At any instant, the agent will be at

any one of the state from the entire state space. The state of the robot at instant k can be denoted as x_k. The entire state space is then taken as χ, so that at any instant k, $x_k \in \chi$. In order to reach the goal state 'G' from the initial state x_0, the robot has to take a series of actions or cell transitions, $a_0, a_1, \ldots\ldots\ldots a_{N-1}$.

3.3.2 Action space

At any instant k, the robot can take any of the action (cell transition) a_k, from the set of permissible actions in the action set or action space $\mathcal{A}_k$. The permissible set of actions at each instant k depends on the current state x_k of the robot. If the Robot stays in any of the cells in the first column, 'move to Left' is not possible. Similarly for each cell in the grid world, there is a set of possible cell movements or state transitions. The set of possible actions or cell transitions at current state x_k is denoted as $\mathcal{A}_{x_k}$ which also depend on the current state x_k. For example if $x_k = 7$, $\mathcal{A}_{x_k}$ ={ right, up, down} and if $x_k = 1$, $\mathcal{A}_{x_k}$ ={ right, down}.

3.3.3 System model

Reinforcement Learning can be used to learn directly by interacting with the system. If that is not possible a model is required. It need not be a mathematical model. A simulation model would also be sufficient. In this simple example, a mathematical model can be obtained.

On taking an action the robot proceeds to the next cell position which is a function of the current state and action. In other words the state occupied by the robot in $k+1$, x_{k+1} depends on x_k and a_k. That is,

$$x_{k+1} = f(x_k, a_k) \tag{3.5}$$

For example, if $x_k = 7$ and a_k =down, then x_{k+1}=13 while when a_k = up ,$x_{k+1} = 1$. For this simple grid world, x_{k+1} is easily obtained by observation. For problems with larger state space, the state x_{k+1} can be found from the simulation model or studying the environment in which robot moves. The aim of a robot in the grid is to reach the goal state starting from its initial position or state at minimum cost. At each step it takes an

action which is followed by state transition or movement in the grid. The actions which make state transitions to reach the goal state at minimum cost points out the optimum solution. Therefore the shortest path problem can be stated as finding the sequence of actions $a_0, a_1, \ldots\ldots, a_{N-1}$ starting from any initial state such that the total cost for reaching goal state G is minimum.

3.3.4 Policy

As explained in the previous section, whenever an action a_k is taken in state x_k, state transition occurs governed by equation (3.5). Ultimate learning solution is to find out a rule by which an action is chosen at any of the possible states. In other words a good mapping from the state space χ to action space $\mathcal{A}$ is to be derived.

In Reinforcement Learning problems, any mapping from state space to action space is termed as policy and denoted as p. Then $p(x)$ denotes the action taken by the robot on reaching state x. At any state x, since there are different possible paths to reach the goal, they are treated as different policies: $p_1(x)$, $p_2(x)$,...etc. The optimum policy at any state x is denoted as $\pi^*(x)$. Reinforcement Learning methods go through iterative steps to evolve this optimal policy $\pi^*(x)$. In order to find out the optimum policy, some modes of comparison among policies are to be formulated. For the same, the reward function to be defined which give a quantitative measure of the goodness of an action at a particular state.

3.3.5 Reinforcement function

Designing a reinforcement function is an important issue in Reinforcement Learning. Reinforcement function should be able to catch the objective of the agent. In some cases, it is straight forward; in some other cases it is not. For example, in the case of N – arm bandit problem (which can be viewed as a Reinforcement Learning problem with just one state), the reinforcement function is the return obtained while the agent play an arm. In the case of the grid world problem, the objective is to find the shortest path. In this case, it can be assumed that the system will incur a cost of one unit when the agent moves from one cell to another normal cell and incur a cost of *"B"*

units when it moves to a cell with obstacle. The value *"B"* should be chosen depending on how bad the obstacle is.

More formally, at stage k the agent perform an action a_k at the state x_k and move to a new state x_{k+1}. The reinforcement function is denoted by $g(x_k, a_k, x_{k+1})$. The reinforcement obtained in each step is also known as reward and is denoted by r_k.The agent learns a sequence of action to minimize $\sum g(x_k, a_k, x_{k+1})$.

In the case of learning by animals, the reward is obtained from the environment. However in the case of algorithms, the reinforcement function is to be defined.

In this simple grid world, reinforcement function can be defined as,

$$g(x_k, a_k, x_{k+1}) = 1, if\ x_{k+1}\ is\ anormal\ cell$$

$$= B,\ if\ x_{k+1}\ is\ a\ cell\ with\ obstacles.$$

If cell with obstacle has to be avoided, choose B = 10,00,000. If the obstacle is having very smaller effect then B can be chosen as 10.

To find the total cost, cumulate the costs or rewards on each transition. Now the total cost for reaching the goal state can be taken as $\sum_{k=0}^{k=(N-1)} g(x_k, a_k, x_{k+1})$, x_0 being the initial state and N being the number of transitions to reach the goal state.

3.3.6 Value function

The issue is how the robot (in general, agent in Reinforcement Learning problem) can choose 'good' decisions in order to reach the goal state, starting from an initial state x, at minimum cost. Robot has to follow a good policy starting from the initial state in order to reach the goal at minimum cost. One measure to evaluate the goodness of a policy is the total expected discounted cost incurred while following a policy over N stages. Value function for any policy π, $V^{\pi} : \chi \rightarrow \mathcal{R}$ is defined to rate the goodness of the different policies. $V^{\pi}(x)$ represents the total cost incurred by starting in state x and following a policy π over N stages. Then,

$$V^{\pi}(x) = \sum_{k=0}^{N-1} \gamma^k g(x_k, a_k, x_{k+1}), \qquad | \; x_0 = x$$

(3.6)

Here γ is the discount factor. The reason for incorporating a discount factor is that, the real goodness of an action may not be reflected by its immediate reward. Value of γ is decided by the problem environment to account how much the future rewards to be discounted to rate the goodness of the policy at the present state. Discount factor can take a value between 0 and 1 based on the problem environment. A value 1 indicates that all the future rewards are having equal importance as the immediate reward. In this shortest path problem since all the costs are relevant to the same extent, γ is taken as1.

On formulating this objective function, a policy π_1 is said to be better than a policy π_2 when $V^{\pi_1}(x) \leq V^{\pi_2}(x), \forall x \in \chi$. The problem is to find an optimal policy π^* such that starting from an initial state x, the value function or expected total cost is lower when following policy π^* compared to any other policy $\pi \in \Pi$ That is, find π^* such that,

$$V^{\pi^*}(x) \leq V^{\pi}(x), \forall x \in \chi, \; \forall \pi \in \Pi \; , \Pi \text{ being the set of policies.}$$

The minimum cost or optimal cost thus obtained is also denoted as $V^*(x)$ and is called optimal value function.

There are various methods to find π^*. Here one method, Q- learning is explained. Q learning is based on learning Q- values which is defined as:

$$Q^{\pi}(x, a) = \sum_{k=0}^{N-1} \gamma^k r_k, \; x_0 = x, \; a_0 = a$$

(3.7)

$Q^{\pi}(x, a)$is the long term reinforcement when the robot start in state x, take an action a and thereafter follow policy p.

From equations (3.6) and (3.7), $Q^{\pi}(x, \pi(x)) = V^{\pi}(x), \forall x \in \chi$.

Therefore corresponding to optimum policy, we have

$$Q^{\pi^*}(x,\pi^*(x)) = V^{\pi^*}(x), \forall\, x \in \chi \tag{3.8}$$

Optimal Q value is denoted as $Q^*(x,a)$ or $Q(x,a)$ and optimal value function as $V^*(x)$ or $V(x)$. Once an optimal Q value is obtained,

$$\pi^*(x) = argmin_{a \in \mathcal{A}} Q^*(x,a) \tag{3.9}$$

Here, $argmin_{a \in \mathcal{A}} Q^*(x,a) = a^*, if\ Q^*(x,a^*) \leq Q^*(x,a), \forall a \in \mathcal{A}$.

Thus to obtain optimum policy, $Q^*(x,a)$ is to be obtained. How the Reinforcement Learning algorithm finds the optimum Q- value is explained in a more general frame work in section 3.6.

It may be noted that optimal Q- values are denoted by $Q^*(x,a)$ or $Q(x,a)$. Estimate of the Q- values are denoted by $\hat{Q}^n(x,a)$ *or* $Q^n(x,a)$.

In this section, the various parts of Reinforcement Learning are explained and the notations are introduced using a simple problem. But Reinforcement learning is capable of solving more general problems. In general, the environment will be non deterministic. That is, taking an action in the same state under two different situations may result in different final states and different values of reinforcement. In such cases the learning becomes more important. In the next section, a general multi stage decision making problem is considered and how it can be solved using Reinforcement Learning is explained.

3.4 Multistage Decision Problem (MDP)

In the last sections, Reinforcement Learning solutions for simple toy problems were discussed. Reinforcement Learning can be applied to any problem which can be modeled as Multi stage Decision Problem (MDP). These problems are concerned with situations in which a sequence of decisions is to be made to minimize some cost. The

reward received at each step of decision making may be stochastic. Reinforcement Learning solution for such a general class of problems is explained below.

At any time step, the agent observes the current state of the environment, $x \in \chi$ and executes an action $a \in \mathcal{A}$. As a result, the system moves to the new system state y with a transition probability p_{xy}^{a} where

$$\begin{aligned} p_{xy}^{a} &\geq 0 && \forall x, y \in \chi \text{ and } a \in \mathcal{A} \\ \textstyle\sum_{y \in \chi}(p_{xy}^{a}) &= 1 && \forall x \in \chi \text{ and } a \in \mathcal{A} \end{aligned} \tag{3.10}$$

Also, an immediate cost is incurred depending on the action and state transition. *ie*, payoff or reward '*g*' is defined as a function *g(x, a, y)*.

The agent's task is to determine a policy for selecting actions at various states of the environment such that the cumulative measure of payoffs received is optimum. Such a policy is called an optimal policy. The number of time steps over which the cumulative pay off is determined is called the horizon of MDP. There are two classes of MDPs.

(i) Finite horizon problem in which the number of stages of decision is finite and is known. The number of stages is usually denoted as *N*.

(ii) The infinite horizon problem in which the number of stages is indefinite

For a finite horizon problem with *N* stages like grid world problem discussed before, value function $V^{\pi}(x)$ is given by equation (3.6). To get a more insight of the same, first consider a one stage problem *(N = 1)*. Then at instant $k = 0$, from state x_0 an action prescribed by policy π, $\pi(x_0)$ is applied and state transition occurs to x_1, which is the terminal state. Then due to this state transition two types of reward are received. The immediate pay off $g(x_0, \pi(x_0), x_1)$ and reward $G(x_1)$ which is the terminal reward received from state x_1.

Then the value function,

$V_1^{\pi}(x_0) = E\,[g(x_0, \pi(x_0), x_1) + \gamma G(x_1)]$, $0 = \gamma = 1$ is the discount factor.

If N = 2 or for a two stage problem, from x_0, on taking action $\pi(x_0)$ reaches the state x_1; then an action $\pi(x_1)$ taken leads to state x_2. Then the state x_2 gives a reward $G(x_2)$, for the policy π. Now, the value function for the two stage problem with policy π is,

$$V_2^{\pi}(x_0)) = E[g(x_0, \pi(x_0), x_1) + \gamma G(x_1)]$$

$$= E[g(x_0, \pi(x_0), x_1) + \gamma (g(x_1, \pi(x_1), x_2) + \gamma G(x_2))]$$

$$= E[g(x_0, \pi(x_0), x_1) + \gamma g(x_1, \pi(x_1), x_2) + \gamma^2 G(x_2)]$$

Thus, In general for an N stage problem,

$$V_N^{\pi}(x_0) = E[\sum_{k=0}^{k=N-1} \gamma^k g(x_k, \pi(x_k), x_{k+1}) + \gamma^N G(x_N)]$$

The discount factor $0 = \gamma = 1$ allows the terminal rewards distant in time to be discounted or weighted less than immediate pay offs.

The policy π^* is also termed as a greedy policy since it gives the best action and hence the best reward at one particular state. The minimum cost or optimal cost for N stage problem corresponding to the greedy policy π^* is called optimal value $V_N^*(x)$. To find $V_N^*(x)$, recursive calculation is used.

Considering the case with $N = 1$ and assume a transition probability p_{xy}^a, for the expectation operator,

$$V_1^{\pi}(x) = \sum_{y \in \chi} p_{xy}^{\pi(x)}[g(x, \pi(x), y) + \gamma G(y)], \forall x \in \chi.$$

The optimal value function is,

$$V_1^*(x) = \min_{\pi \in \Pi} \sum_{y \in \chi} p_{xy}^{\pi(x)}[g(x, \pi(x), y) + \gamma G(y)], \forall x \in \chi$$

If $\pi(x)$ is a fixed one for any state x, then

$$V_1^*(x) = \min_{a \in \mathcal{A}} \sum_{y \in \chi} p_{xy}^a [\, g(x,a,y) + \gamma G(y) \,], \forall x \in \chi$$

The above equation implies that the optimal action and thus the optimal value function is implied by the minimization of the two terms $g(x,a,y)$ and $G(y)$. The first one is the immediate reward and the second term is the 'cost to go'. If a k stage problem is considered, the optimal value will be obtained only when the 'cost to go' from $k\text{-}1^{th}$ stage is also optimum. That is, $V_k^*(x)$ is obtained corresponding to $V_{k-1}^*(y)$.Thus, the optimal value function for k^{th} stage,

$$V_k^*(x) = \min_{a \in \mathcal{A}} \sum_{y \in \chi} p_{xy}^a [\, g(x,a,y) + \gamma V_{k-1}^*(y) \,], \forall x \in \chi$$

Therefore, the optimal value function for N stages can be calculated recursively starting from $V_0^*(x) = G(x)$, and searching the action space $\mathcal{A}$, N times. Thus the solution for a finite MDP is obtained.

Now the formulation can be extended to infinite horizon problems. In these problems, the number of stages is indefinite or very large in number. For obtaining a solution according to the previous procedure, a value function is to be defined. Since the number of stages is very large, there is no terminal cost. Then the value function under policy π,

$$V^\pi(x) = \lim_{N \to \infty} E\,[\sum_{k=0}^{N} \gamma^k g\,(x_k, \pi(x_k), x_{k+1}) \mid x_0 = x\,], \forall x \in \chi \tag{3.11}$$

Since the immediate cost g (., ., .)is considered as finite or bounded , $V^\pi(x)$ given by equation (3.11) is defined if $0 < \gamma < 1$. Problems with $\gamma < 1$ are called discounted problems.

Next, the definition of value function can be extended to infinite horizon problems considering the initial transition from x_0 to x_1,

$$V^{\pi}(x) = E[\,(\, g(x_0, \pi(x_0), x_1) + \gamma \lim_{N\to\infty} \sum_{k=1}^{N} \gamma^{k-1}\, g\,(x_k, \pi(x_k), x_{k+1}))|$$

$$x_0 = x],\ \forall x \in \chi \tag{3.12}$$

It can be again simplified as,

$$V^{\pi}(x) = E[\, g\,(x_0, \pi(x_0), x_1) + \gamma V^{\pi}(x_1)],\quad x_0 = x$$

Since the expectation operator is with respect to the transition probabilities,

$$V^{\pi}(x) = \sum_{y\in\chi} p_{xy}^{\pi(x)}\,[\, g(x, \pi(x), y) + \gamma V^{\pi}(y)] \tag{3.13}$$

Equation (3.13) gives a set of linear equations which will give $V^{\pi}(x)$, if the transition probabilities $p_{xy}^{\pi(x)}$ are known.

Then, the optimal policy π^* can be defined to be the one for which

$$V^{\pi^*}(x) \le V^{\pi}(x),\ \forall x \in \chi,\ \forall \pi \in \Pi$$

For an N stage problem, optimal value function is then defined as in Dynamic Programming steps as,

$$V^*(x) = \min_{a\in\mathcal{A}} \sum_{y\in\chi} p_{xy}^{a}\,[\, g(x, a, y) + \gamma\, V_{k-1}^*(y)],\ \forall x \in \chi; \tag{3.14}$$

starting from the initial state or initial condition $V_0^*(x) = 0$.

If the number of stages $N \to \infty$, it gives general infinite horizon problem. Then putting the limit $k \to \infty$, the optimum value of the value function,

$$V^*(x) = \min_{a\in\mathcal{A}} \sum_{y\in\chi} p_{xy}^{a}\,[\, g(x, a, y) + \gamma\, V^*(y)],\ \forall x \in \chi \tag{3.15}$$

If χ and $\mathcal{A}$ are finite and if the transition probabilities are known, iterative methods can be used to solve the unknowns. When the value function is obtained, optimum policy can be retrieved as

$$\pi^*(x) = argmin_{a \epsilon \mathcal{A}} \sum_{y \in \chi} p_{xy}^a \, [g(x,a,y) + \gamma V^*(y)], \forall x \in \chi \tag{3.16}$$

Some methods for finding $V^*(x)$ are explained in the next section.

Now, Multi stage decision making problems are formulated mathematically. Also the steps to reach an optimum policy or decision sequence in the various states to get the optimum net reward or cost are described. In the next section the different methods for reaching the optimum policy are explained.

3.5 Methods for solving MDP

For solving Markov Decision Problems, classical solutions based on Bellman's optimality principle are widely used. Reinforcement Learning Based solutions are developed keeping the basic principle of optimality itself. Value iteration and Policy iteration are the two basic methods based on optimality.

3.5.1 Value iteration

Value iteration is an iterative method for obtaining the optimal value function $V^*(x)$. First start with an initial guess of value $V^0(x_i)$, $i = 1,2,....n$. At each iteration of the learning phase, an estimate of the value is obtained. The algorithm is obtained by using V^{n-1} instead of V^* in the Bellman equation (3.15). Then, at n^{th} iteration of learning the estimate V^n is obtained from V^{n-1} using

$$V^n(x) = \min_{a \epsilon \mathcal{A}} \sum_{y \epsilon X} p_{xy}^a \, [g(x,a,y) + \gamma V^{n-1}(y)] \tag{3.17}$$

For the infinite horizon problems, if finite and bounded values of pay off or 'g' function are available, then the sequence of value estimates V^0, V^1,..... will converge to V^*. When the optimal value V^* is reached, the optimal policy π^* is obtained as

$$\pi^*(x) = argmin_{a\epsilon\mathcal{A}} \sum_{y\epsilon\mathcal{X}} p_{xy}^a [\, g(x,a,y) + \gamma V^*(y)], \quad \forall x \in \chi \tag{3.18}$$

3.5.2 Policy iteration

Another iterative method to obtain optimal policy is policy iteration. In this a policy is first evaluated and then improved. Policy evaluation consists of working out the value of every state x under policy π. That is, expected long term reward starting from the given initial state and following policy π. Algorithm starts with an arbitrary policy, say π^0, and improves it on each iteration or generates a sequence of policies π^0, π^1,.....such a way that the policy, π^{k+1} is better than the previous policy π^k.

Each iteration involves two phases; a policy evaluation step and a policy improvement step. In the policy evaluation step of the k^{th} iteration, the value function corresponding to policy π^k is evaluated by solving the set of equations given by,

$$V^{\pi^k}(x) = \sum_{y\epsilon\mathcal{X}} p_{xy}^{\pi^k(x)} \left[g\left(x,\pi^k(x),y\right) + \gamma V^{\pi^k}(y) \right], \quad \forall x \in \chi \tag{3.19}$$

In the policy improvement phase, improved policy π^{k+1} is obtained as

$$\pi^{k+1} = \underset{a\epsilon\mathcal{A}}{\text{argmin}} \{ \sum_{y\epsilon\mathcal{X}} p_{xy}^a \left[g(x,a,y) + \gamma V^{\pi^k}(y) \right] \}, \quad \forall x \in \chi \tag{3.20}$$

Implementing either policy or value iteration requires the agent to know the expected reward and transition probabilities. In most applications, this may not be available. If the agent does not know these, but it can learn interacting with the environment, Reinforcement Learning based solutions are more promising.

3.6 Reinforcement Learning approach for solution

As seen in the previous section, value iteration and policy iteration can be applied, when the state transition probabilities p_{xy}^a are known. If it is unknown, just like in practical stochastic situations, probabilities can be estimated using Monte Carlo

simulation (Bertsekas and Tsitsikilis [1996]).Starting from some initial state, choice of action is made based on some strategy; obtain the next state using the simulation model. That is a sequence of samples of the form (x_k, a_k, x_{k+1}) is used to learn and obtain the optimal policy.

Reinforcement Learning techniques provide one such method to obtain the optimal policy, using training samples of the form (x_k, a_k, x_{k+1}). After training using these samples sufficient number of times, the optimum value and optimum policy are reached. In the next section Q – learning is discussed for a general multi stage problem.

3.6.1 Q learning

Q learning is a Reinforcement Learning algorithm that learns the values of the function $Q(x, a)$ to find an optimal policy. The value of the function $Q(x, a)$ indicate how good is to perform action *'a'* at the given state *'x'*. When Q-value without any qualifier is used, it means the optimal Q- value. Q – value under a policy π is defined as,

$$Q^{\pi}(x,a) = \sum_{y \in X} p_{xy}^{a} [\, g(x,a,y) + \gamma V^{\pi}(y)].$$

(3.21)

Comparing with equation (3.13),

$$Q^{\pi}(x, \pi(x)) = V^{\pi}(x), \qquad \forall x \in X$$

(3.22)

Considering the optimal policy π^*,

$Q^{\pi^*}(x, \pi^*(x)) = V^{\pi^*}(x) = V^*(x), x \in X$ will be the optimum Q value for the state action pair $(x, \pi^*(x))$.

Now the optimal Q- value for a minimization problem is defined.

$$Q^*(x,a) = \min_{\pi} Q^{\pi}(x,a)$$

it implies that,

$$Q^*(x,a) = Q^{\pi^*}(x,a), \forall x \in X, \qquad \forall a \in A$$

Then, $$\pi^*(x) = argmin_{a \in \mathcal{A}} Q^*(x,a) \tag{3.23}$$

From the definition of Q^* and V^*,

$$Q^*(x,a) = \sum_{y \in X} p_{xy}^a [\, (g(x,a,y) + \gamma V^*(y)], \qquad \forall x \in X, \qquad \forall a \in \mathcal{A} \tag{3.24}$$

Since $V^*(x)$ is the minimum of $Q^*(x,a)$ over the action set $\mathcal{A}$,

$$V^*(x) = \min_{a \in \mathcal{A}} Q^*(x,a) \tag{3.25}$$

Using equations (3.24) and (3.25),

$$Q^*(x,a) = \sum_{y \in X} p_{xy}^a [\, g(x,a,y) + \gamma \min_{a' \in \mathcal{A}} Q^*(y,a')], \qquad \forall x \in X, \qquad \forall a \in \mathcal{A}$$

Thus, if the transition probabilities are known, the optimal Q values can be computed iteratively.

$$Q^{n+1}(x,a) = \sum_{y \in X} p_{xy}^a [\, g(x,a,y) + \gamma \min_{a' \in \mathcal{A}} Q^n(y,a')], \forall x \in X, \forall a \in \mathcal{A} \tag{3.26}$$

When the transition probabilities are unknown the Q learning method can be employed by generating a sequence of samples. At each and every iteration of the algorithm, from the current state x, it chooses an action a based on some strategy and reaches the new state y and obtains reward $g(x, a, y)$ which is used for updating the Q value of the state – action pair as,

$$Q^{n+1}(x,a) = Q^n(x,a) + \alpha[g(x,a,y) + \gamma \min_{a' \in \mathcal{A}} Q^n(y,a') - Q^n(x,a)] \tag{3.27}$$

$a \in (0, 1)$ is the learning parameter and determines the extent of modification of the Q value at each iteration of the learning phase.

When the learning parameter α is sufficiently small and if all possible (x, a) combinations of state and action occur sufficiently often then the above iteration given by equation (3.27) will result Q^n converging to Q^* (Bertsekas and Tsitsikilis [1996], Sutton and Barto [1998]).

A complete and general algorithm for Q learning is described below:

For all states $x \in \chi$ and for all action $a \in \mathcal{A}$,

Initialize $Q^0(x, a)$ to zero

Repeat for each iteration or trial

Initialize or get the current state x_0

Repeat for each stage

Select an action 'a_k' using action selection strategy

Execute the action a_k and obtain the next state x_{k+1}

Receive the immediate reward

Update $Q^n(x_k, a_k)$

Update x_k to x_{k+1}.

Until, the terminal stage is reached.

If the environment is a stable MDP with finite and bounded rewards, the estimated Q values can be stored in a look up table. Each action is executed in each state a number of times and finally the estimated Q values are found to converge to true Q values. The discount factor γ is taken a suitable value in the range (0, 1) and the learning parameter a is also a value in the range (0, 1). For choosing an action from the action set at each step, different exploration strategies are employed. In the next section the action selection methods are explained.

3.7 Action selection

If the true Q values are known, the optimal action is found by finding the greedy action, having the minimum Q value. However, during the initial part of the learning, true Q values are unknown. But there is a set of estimated Q values, $Q^n(x, a)$, where n is the iteration number. During the initial phase of learning $Q^n(x, a)$ will not be close to $Q^*(x, a)$. But as the learning proceeds, $Q^n(x, a)$ approach to $Q^*(x, a)$. Hence, while learning, initially the action space is to be explored and as the learning proceeds, the information available in $Q^n(x, a)$ should be exploited. There are various methods for striking a balance between exploration and exploitation (Thathachar and Sastry [2003]). Two of them are discussed here:

3.7.1 ε - greedy method

The action which has been found good or having highest estimated Q value is termed as greedy action. But, there is a possibility that one among the remaining actions being as good or even better than the greedy action.

In ε - greedy strategy of action selection, the greedy action is selected with a probability of (1- ε) and one of the other actions in the action set in random is selected with a probability of ε. Value of ε decides the balancing between exploration and exploitation. Value of ε is normally chosen as close to 1 at the initial stages and then reduced in steps as the learning proceeds. As it reaches the final stages of learning greedy action will turn to be the best action and therefore ε is reduced to a very small value.

3.7.2 Pursuit Method

The ε - greedy method discussed above provides a good method of action selection, for providing better exploration in the initial phases of learning while exploiting the goodness of greedy action during the later phases. However e -greedy requires a gradual reduction of e. That is, a proper cooling schedule is to be designed which gradually updates the value of e as the learning proceeds so that proper

convergence and correctness of the result are assured. The length of learning phase mainly depends on this cooling schedule and therefore it is one significant part of e- greedy method. It is a difficult task to develop a good cooling schedule so as to ensure minimum time for convergence.

Another stochastic policy followed for selection of action in the Reinforcement Learning task is Pursuit algorithm. In this method along with maintaining estimates of Q values as measure of goodness of actions, some preference is also associated with actions. Each action a_k at any state x_k is having a probability $p_{x_k}(a_k)$ of being chosen. These probability values will be same for all actions and all states initially assuring sufficient exploration of the action space. Then on performing an action a_k at any state x_k during learning, the numerical reward is used to update the estimate of Q value associated with the state – action pair. Along with that, based on the current estimates of Q values, probability values associated with actions are also modified as.

$$p_{x_k}^{n+1}(a_k) = p_{x_k}^{n}(a_k) + \beta[1 - p_{xk}^{n}(a_k)], \quad when\ a_k = a_g$$
$$p_{x_k}^{n+1}(a_k) = p_{x_k}^{n}(a_k) - \beta p_{xk}^{n}(a_k), when\ a_k \neq a_g \tag{3.28}$$

where $0 < ß < 1$ is a constant. Thus at each iteration n of the learning phase, algorithm will slightly increase the probability of choosing the greedy action a_g in state x_k and proportionally decrease the probability associated with all other possible actions. Initially since all probabilities are made equal, sufficient exploration of action space is assured. When the algorithm proceeds a number of iterations, with high probability $Q^n(x,a)$ will approach to $Q^*(x,a)$ corresponding to all states. This is because, when the parameter ß is properly chosen, after sufficient number of iterations, the greedy action in state x, with respect to Q^n would be the same as greedy action in state x with respect Q^* which gives the optimal action. In other words, through the iterative updating of probabilities by equation (3.28), probability of optimal action increases successively. This in turn indicates an increase in probability of selecting the optimum

action in the succeeding steps. If α and β are sufficiently small, $p_x^n(\pi^*(x))$ would converge with high probability to unity.

3.8 Reinforcement Learning with Function Approximation

The Reinforcement Learning described above involves the estimating of value functions that indicate how good an action is, in a particular state. Q values of the different state action pairs are stored as a look up table. Q value of a state action pair $Q(x, a)$ indicate how good action a is, at the particular state x. But such look up table storage of Q values is having two major limitations:

(i) The state and action should have discretised values.

(ii) The number of state action pairs is to be finite.

In cases with very large number of state action pairs and with continuous state values, the look up table approach cannot be directly used for Q learning.

For large state space or continuous state space, some kind of function approximation is needed. In this case the approximating function is used to store the Q values. That is, the state space χ is treated as continuous and the Q values are represented using a parameterized class of functions, $\{Q(x, a, \theta) : \theta \in \Re^d; Q : \chi \times \mathcal{A} \times \Re^d \rightarrow \Re\}$ where ? is the parameter vector. When such a parameterized class of function is used, learning the optimal Q values involves learning the optimum parameter vector θ^* such that $Q(x, a, \theta^*)$ is a good approximation of $Q^*(x, a)$, $x \in \chi$ and $a \in \mathcal{A}$.

The main tasks in obtaining such a function approximator for $Q^*(x, a)$are: (i) selection of proper parameterized class of functions Q (x, a, θ) that suits the problem and (ii) suitable algorithm to learn the optimal parameter vector θ^* (Bertsekas and Tsitsikilis [1996], Sutton and Barto [1998]).

There are many parameterized classes of functions that can be used as approximating functions. Due to the ability to represent and learn non linear functions, Neural Networks are used as function approximators (Haykin [2002]). Two of the most popular Neural Networks used for function approximation task are Multi Layer

Perceptrons (MLP) and Radial Basis Function (RBF) networks. These networks can be used for approximating the continuous functions (Van Roy [1996], [2001]).

While used with Q learning task or getting the approximated parameterized function for obtaining the optimal Q values, the network should capture the characteristics of Q learning. Since the action space is discretised and the optimal action in a small neighbourhood varies very little, the function approximation for Q^* can be constructed through a set of local approximations. It is verified that Gaussian RBF networks with the exponentially decaying nonlinearities provide nonlinear mapping in an efficient manner (Haykin [2002]).Therefore RBF networks is a good choice for using in approximating the Q values. In the next section, a description of RBF network and the learning parameters are given.

3.8.1 Radial Basis Function Networks

Radial Basis Function networks are one class of function approximators that can be used in Reinforcement Learning. In this case the output function is represented as the sum of many local functions. A simple RBF network with n input nodes, m hidden nodes and one output node is shown in Fig 3.2.

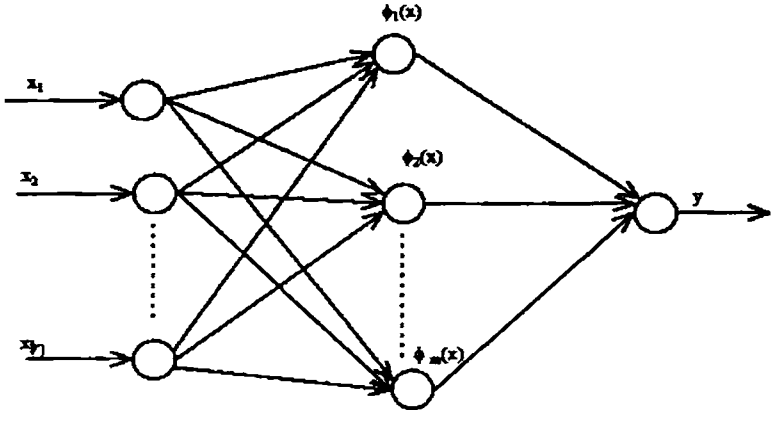


Fig 3.2 Radial Basis Function network

The output of the network is given as,

$y = \sum_{i=1}^{i=m} W_i \emptyset_i(x), W_i, i = 1, \ldots\ldots m$, are the weights of the connections into the linear output node and $\emptyset_i(x)$, $i = 1, \ldots\ldots m$ represent the m radial basis function

networks. These m radial basis functions represent the m hidden nodes in the network structure. Gaussian function is the commonly used function in RBF networks. The output of a Gaussian RBF network with m hidden nodes is given by

$$y = \sum_{i=1}^{m} W_i \exp\left(\frac{-\sum_{j=1}^{n}(x_j - c_j^i)^2}{2(\sigma^i)^2}\right) \tag{3.29}$$

where $c^i = [c_1^i, \ldots\ldots\ldots\ldots\ldots\ldots c_n^i], i = 1, \ldots\ldots m$ are called the centres of the RBF network and $\sigma^i, i = 1, \ldots\ldots\ldots m$ are called their widths. Such an RBF network can be described by the parameter vector ? = [c, σ, W], where

$c = \{c^1, \ldots\ldots\ldots\ldots, c^m\}, \sigma = \{\sigma^1, \ldots\ldots\ldots\ldots\ldots, \sigma^m\}$ *and*

$W = \{W_1, \ldots\ldots\ldots\ldots W_m\}$

Therefore, finding a good approximating function using such an RBF network is to find an optimum parameter vector $\theta^* = [c^*, \sigma^*, W^*]$.

In these networks, adjusting the weight associated with a given basis function, W_i which is the weight associated with $\emptyset_i(x) = \exp\left(\frac{-\sum_{j=1}^{n}(x_j - c_j^i)^2}{2(\sigma^i)^2}\right)$ will effect the value of the function only in a small region around the center of the i^{th} RBF, $c^i \in \Re^n$. For any x away from c^i, $\emptyset_i(x) = \exp\left(\frac{-\sum_{j=1}^{n}(x_j - c_j^i)^2}{2(\sigma^i)^2}\right)$ will be close to zero. In a straight forward solution of this optimum parameter vector θ^*, the centers c^* are placed on a uniform grid and width σ^* are fixed as a function of grid spacing, based on the problem environment. This reduces equation (3.29) to a linear one in W. Then the approximating task is to find W^* which can be done by the learning procedures.

3.9 Advantages of Reinforcement Learning

While most of the optimization and soft computing techniques provide solution for static optimization tasks, Dynamic Programming and Reinforcement Learning based strategies can easily provide solution for dynamic optimization problems. This makes Reinforcement Learning a good learning strategy suitable for real time control tasks and many optimization problems. In case of RL based solution strategies, the environment need not be a mathematically well defined one. It can acquire the

knowledge or learn in a model free environment. Acquiring the knowledge of rewards or punishments to an action taken in the environment or state of the system, the learning strategy improves the performance step by step. Through a simple learning procedure with sufficient number of iterative steps, the agent can learn the best actions at any situation or state of the system. Also the reward or return function need not be a deterministic one, since at each action step the agent can accept the reward from a dynamic environment.

3.10 Reinforcement Learning Application to Power system

In the field of Power system, only a few applications have been found till now. Automatic Generation Control problem for a two area system is solved using Reinforcement Learning strategy (Imthias *et al.* [2002]). The input state space is constituted by the Area Control Error (ACE) and the action space is the different discretised values in the reference input to the controller. Pursuit method of action selection is used and through Q learning an efficient control policy is learned.

Application of Adaptive Design for handling the damping problems in large power system is addressed by Venayagamoorthy *et al.* [2002]. They proposed an efficient heuristic controller for turbo generators in an integrated power system using Adpative Dyanamic Programming. Feed forward neural networks are used to implement the Adaptive Critic Design based adaptive controllers for turbo generators which is adaptive to even larger disturbances in the integrated power system. The adaptation starts with an optimal arbitrarily chosen control by the action network and the critic network guides towards the optimal action. The technique of using critic network avoids the need of learning process of the control network. The critic network learns to approximate the 'cost to go' or strategic ability function and uses the output of the action network as one of its inputs directly or indirectly.

The optimal bidding for Genco in a deregulated power market is an involved task. Gajjar *et al.* [2003] have formulated the problem in the framework of Markov decision process. The cumulative profit over the span is the objective function

optimized. The temporal difference technique and actor-critic learning algorithm are employed.

Vlachogiannis and Nikos [2004] solved the optimal load flow problem using Reinforcement Learning. The RL method formulates the constrained load flow problem as a multistage decision problem. More specifically, the model-free learning algorithm through Q learning learns by experience how to adjust a closed-loop control rule, mapping states (load flow solutions) to control actions (offline control settings) by means of reward values. Rewards are chosen to express how well control actions cause satisfaction of operating constraints.

Power system stability problem is solved through RL by Ernest and Glavic [2004] .They proposed the method of finding the control variables in a power system [2005]. Two Reinforcement Learning modes are considered: the online mode in which the interaction occurs with the real power system and the offline mode in which the interaction occurs with a simulation model of the real power system. They developed algorithm for learning control policy and showed how the methodology can be applied to control some devices aimed to damp electrical power oscillations. The control problem is formalized as a discrete-time optimal control problem and the information acquired from interaction with the system as a set of samples.

In the deregulated power system, pricing mechanism is one important part. Auction pricing is one method used for the same. A Reinforcement Learning model to assess the power to be used in the auction pricing is developed by Nanduri and Das [2007].

Lu *et al.* [2008] have also employed the adaptive design concepts in implementing a power system stability controller for a large scale power system having non linear disturbances. The actor and critic parts are realized using Multi layer perceptrons and using the reinforcement or cost function as the feed back signal to the controller, learning is carried out. The proposed controller is found to be efficient in handling large scale real power system examples.

3.11 Conclusion

In this chapter, an introduction and discussion on the Reinforcement Learning frame work has been carried out. The mathematical description of the optimum policy and the learning strategies to reach the optimum policy has been explained. The different action selection strategies are also discussed. Also the various recent applications of Reinforcement Learning have been discussed. In the field of power system a few applications have been developed using Reinforcement Learning methodology. Active power scheduling problem has not been solved till now through this efficient learning method. Therefore, the development of solution for active power scheduling is proposed in the following chapters.

CHAPTER 4

REINFORCEMENT LEARNING APPROACHES FOR SOLUTION OF UNIT COMMITMENT PROBLEM

4.1 Introduction

Unit Commitment Problem (UCP) in power system refers to the problem of determining the on/ off status of generating units that minimize the operating cost during a given time horizon. Formulation of exact mathematical model for the same is difficult in practical situations. Cost associated with the different generating units is also different and random. Most often it is difficult to obtain a precise cost function for solving UCP. Also availability of the different generating units is different during each time slot due to the numerous operating constraints.

The time period considered for this short term scheduling task varies from 24 hours to one week. Due to the large number of ON /OFF combinations possible, even for small number of generating units and short period of time, UCP is a complex optimization problem. Unit Commitment has been formulated as a non linear, large – scale, mixed integer combinational optimization problem (Wood and Wollenberg [2002]).

From the review of the existing strategies, mainly two points can be concluded:

(i) Conventional methods like Lagrange Relaxation, Dynamic Programming etc. find limitation for higher order problems.

(ii) Stochastic methods like Genetic Algorithm, Evolutionary Programming etc. have limited computational efficiency when a large number of units involved.

Since Reinforcement Learning has been found to be a good tool for many of the optimization problems, it appeared to be very much promising to solve this scheduling problem using Reinforcement Learning.

In this chapter, a stochastic solution strategy based on Reinforcement Learning is proposed. The class of algorithms is termed as RL_UCP. Two varieties of exploration methods are used: ε greedy and pursuit method. The power generation constraints of the units, minimum up time and minimum down time are also considered in the formulation of RL solution. A number of case studies are made to illustrate the reliability and flexibility of the algorithms.

In the next section, a mathematical formulation of the Unit Commitment Problem is given. For developing a Reinforcement Learning solution to Unit Commitment problem, it is formulated as a multi stage decision making task. The Reinforcement solution to simple Unit Commitment problem is reviewed (RL_UCP1). An efficient solution using pursuit method without considering minimum up time and minimum down time constraints is suggested (RL_UCP2). Then the minimum up time and down time constraints are incorporated and a third algorithm (RL_UCP3) is developed to solve the same. To make the solution more efficient one, an algorithm with state aggregation strategy is developed (RL_UCP4).

4.2 Problem Formulation

Unit Commitment Problem is to decide which of the available units has to be turned on for the next period of time. The decision is subject to the minimization of fuel cost and to the various system and unit constraints. At the system level, the forecasted load demand should be satisfied by the units in service. In an interconnected system, the load demand should also include the interchange power required due to the contractual obligation between the different connected areas. Spinning reserve is the other system requirement to be satisfied while selecting the generating units. In addition, individual units are likely to have status restrictions during any given time period. The problem becomes more complicated when minimum up time and down

time requirements are considered, since they couple commitment decisions of successive hours.

The main objective of this optimization task is to minimize the total operating cost over the scheduled time horizon, while satisfying the different operational constraints. The operating cost includes start up cost, shut down cost, running cost, maintenance cost etc. The UCP can be formulated as:

Minimize Operational cost

Subject to

- Generation constraints
- Reserve constraints
- Unit capacity limits
- Minimum Up time constraints
- Minimum Down time constraints
- Ramp rate constraints
- Unit status restrictions

4.2.1 Objective

As explained above, the objective of UCP is the minimization of total operating cost over the complete scheduling horizon. The major component of the operating cost for thermal units is the fuel cost. This is represented by an input / output characteristics which is normally approximated as polynomial curve (quadratic or higher order) or as a piecewise linear curve. For quadratic cost, the cost function is of the form

$$C_i(P_{i\,k}) = a_i + b_i P_{i\,k} + c_i P_{i\,k}^2, \qquad where\ a_i, b_i\ and\ c_i\ are\ cost\ coefficients,$$

$P_{i\,k}$ – Power generated by i^{th} unit during hour k

If a unit is down for a time slot, it can be brought back to operation by incurring an extra cost, which is due to the fuel wastage, additional feed water and energy needed

for heating. Accordingly, the total fuel cost F_T which is the objective function of UCP is:

$$F_T = \sum_{k=1}^{T} \sum_{i=1}^{N} [C_i (P_{i\,k}) u_{i\,k} + ST_i (u_{i\,k})(1 - u_{i\,k-1})]$$

where T is the time period (number of hours) considered, $C_i(P_{i\,k})$ is the cost of generating power P_i during k^{th} hour by i^{th} unit, ST_i is the start up cost of the i^{th} unit, u_{ik} is the status of the i^{th} unit during k^{th} hour and $u_{i\,k-1}$ is the status of the i^{th} unit during the previous hour.

4.2.2. The constraints

The variety of constraints to UCP can be broadly classified as System constraints and Unit constraints

System Constraints:

- *Load demand constraint*: The generated power from all the committed or on line units must satisfy the load balance equation

$$\sum_{i=1}^{N} P_{i\,k} u_{i\,k} = l_k; \quad 1 \le k \le T,$$

where l_k is the load demand at hour k.

Unit Constraints:

- *Generation capacity constraints*: Each generating unit is having the minimum and maximum capacity limit due to the different operational restriction on the associated boiler and other accessories

$$P_{\min(i)} \le P_{i\,k} \le P_{\max(i)}, \quad 0 \le i \le N-1,\ 1 \le k \le T$$

- *Minimum up time and down time constraint*: Minimum up time is the number of hours unit i must be ON before it can be turned OFF. Similarly, minimum down time restrict it to turn ON, when it is DOWN. If $t_{off\,i}$ represents the number of hours i^{th} unit has been shut down, $t_{on\,i}$ the number of hours i^{th} unit has been on line, U_i the minimum up time and D_i the minimum down time corresponding to i^{th} unit, then these constraints can be expressed as:

$$t_{off\,i} \ge D_i; \qquad t_{on\,i} \ge U_i, \qquad 0 \le i \le N-1$$

- *Ramp rate limits*: The ramp rate limits restrict the amount of change of generation of a unit between two successive hours.

$$P_{i\,k} - P_{i\,(k-1)} \leq UR_i$$

$$P_{i\,(k-1)} - P_{i\,k} \leq DR_i$$

where UR_i and DR_i are the ramp up and ramp down rates of unit i.

- *Unit status restrictions*: Some of the units will be given the status of 'Must Run' or ' Not available' due to the restrictions on the availability of fuel, maintenance schedule etc.

4.3 Mathematical model of the problem

The mathematical description of the problem considered can be summarized as:
Minimize the objective function,

$$F_T = \sum_{k=1}^{T}\sum_{i=1}^{N}[C_i(P_{i\,k})u_{i\,k} + ST_i(u_{i\,k})(1-u_{i\,k-1})] \tag{4.1}$$

subject to the constraints,

$$\sum_{i=1}^{N} P_{i\,k}u_{i\,k} = l_k; \quad 1 \leq k \leq T \tag{4.2}$$

$$P_{\min(i)} \leq P_{i\,k} \leq P_{\max(i)}, \quad 0 \leq i \leq N-1,\ 1 \leq k \leq T \tag{4.3}$$

$$t_{off\,i} \geq D_i; \quad t_{on\,i} \geq U_i, \quad 0 \leq i \leq N-1 \tag{4.4}$$

In order to formulate a Reinforcement Learning approach, in the next section UCP is formulated as a multi stage decision task.

4.4 Unit Commitment as a Multi Stage decision making task

Consider a Power system having N generating units intended to meet the load profile forecasted for T hours, $(l_0, l_1, l_2, \ldots\ldots\ldots\ldots l_{T-1})$. The Unit Commitment Problem is to find which all units are to be committed in each of the slots of time. Objective is to select units so as to minimize the cost of generation, at the same time meeting the load demand and satisfying the constraints. That is to find a decision or commitment schedule $a_0, a_1, a_2, \ldots\ldots\ldots\ldots a_{T-1}$, where a_k is a vector representing the status of the N generating units during k^{th} hour.

$$a_k = [\, a_k^0, a_k^1, \ldots\ldots\ldots\ldots, a_k^{N-1} \,]$$

$a_k^i = 0$ indicates the OFF status of i^{th} unit during k^{th} time slot while $a_k^i = 1$ indicates the ON status.

For finding the schedule of T hour load forecast, it can be modeled as a T stage problem. While defining an MDP or Reinforcement Learning problem, state, action, transition function and reward function are to be identified with respect to the scheduling problem.

In the case of Unit Commitment Problem, the state of the system at any time slot (hour) k can represent the status of each of the N units. That is, the state x_k can be represented as a tuple (k, p_k) where p_k is a string of integers, $[\, p_k^0, p_k^1, \ldots\ldots\ldots\ldots p_k^{N-1}]$, p_k^i being the integer representing the status of i^{th} unit. When the minimum up time and down time constraints are neglected the ON / OFF status of each unit can be used to represent p_k^i. Then the integer p_k^i will be binary; ON status represented by *'1'* and OFF status by *'0'*. Consideration of the minimum up time and minimum down time constraints force to include the number of time units each unit has been ON /OFF in the state representation. Then the variable p_k^i can take positive or negative value ranging from $-D_i$ to $+U_i$.

The part of the state space at time slot or stage k can be denoted by

$\chi_k = \{(\, k, [\, p_k^0, p_k^1, \ldots\ldots p_k^{N-1}])\}$ and the entire state space can be defined as

,

$$\chi = \chi_0 \cup \chi_1 \cup \ldots\ldots\ldots \chi_{T-1}$$

Next is to identify the actions or decisions at each stage of the multi stage problem. In case of UCP, the action or decision on each unit is either to commit or not the particular unit during that particular hour or time slot. Therefore action set at each stage k can be defined as $\mathcal{A}_k = \{[a_k^0, a_k^1, \ldots\ldots\ldots\ldots, a_k^{N-1}], a_k^i = 0 \text{ or } 1\}$. When certain generating units are committed during particular hour k, ie, $a_k^i = 1$ for certain values of i, then the load demand or power to be generated by these committed units is to be decided. This is done through an Economic Dispatch solution.

The next part to be defined in this MDP is the transition function. Transition function defines the transition from the current state to the next state on applying an action. That is, from the current state x_k , taking an action a_k, it reaches the next state x_{k+1}. Since the action is to make the units ON /OFF, the next state x_{k+1} is decided by the present state x_k and action a_k. Transition function $f(x_k, a_k)$ depends on the state representation.

Last part to be defined is the reinforcement function. It should reflect the objectives of the Unit Commitment Problem. Unit Commitment Problem can have multiple objectives like minimization of cost, minimizing emissions from the thermal plants etc. Here, the minimization of total cost of production is taken as the objective of the problem. The total reward for the T stages should be the total cost of production. Therefore, the reinforcement function at k^{th} stage is defined as the cost of production of the required amount of generation during the k^{th} period.

That is,

$$g(x_k, a_k, x_{k+1}) = \sum_{i=0}^{N-1}[C_i(P_{i\,k})u_{i\,k} + ST_i(u_{i\,k})(1 - u_{i\,k-1})],$$

Here, P_{ik} is the power generation by i^{th} unit during k^{th} time slot and $u_{i\,k}$ is the status of i^{th} unit during k^{th} time slot.

In short, Unit Commitment Problem is now formulated as a Multi Stage decision making problem, which passes through T stages. At each stage k, from one of the states $x_k = (k, p_k)$ an action or allocation a_k is chosen depending on some exploration strategy. Then a state transition occurs to x_{k+1} based on the transition

function. Each state transition results in a reward corresponding to power allocation to the committed units. Then the problem reduces to finding the optimum action a_k at each state x_k and corresponding to each time slot k.

In the next sections a class of Reinforcement Learning solutions is proposed. In all these algorithms the action space and the reinforcement function are the same. The definition of state space, transition function and the update strategy are different.

4.5 Reinforcement Learning Approach to Unit Commitment Problem

Having formulated as a Multistage Decision Problem, implementable solutions are developed using Reinforcement Learning approach. First a review of the basic algorithm is given. Neglecting the minimum up time and minimum down time constraints and using exploration through e – greedy strategy, solution is presented (RL_UCP1). Then employing pursuit method for action selection, algorithm for solution is proposed (RL_UCP2).

Next, Minimum up time and down time constraints are incorporated which needs the state of the system (status of the units) to be represented as integer instead of binary representation in the previous solutions. To handle the large state space, an indexing method is proposed while developing solution (RL_UCP3). A more efficient solution is then proposed using state aggregation strategy. In the next sections, the solution methods and algorithms are presented in detail.

4.6 ε - greedy algorithm for Unit Commitment Problem neglecting minimum up time and minimum down time (RL_UCP1)

In the previous section, a T hour allocation problem is modeled as a T stage problem. In this section, an algorithm based on Reinforcement Learning and using ε- greedy exploration strategy is presented. For the same, different parts of Reinforcement Learning solution are first defined precisely.

When the minimum up time and minimum down time are neglected, the state of the system at any hour k can be represented by the ON /OFF status of the units.

Hence, state can be represented by the tuple, $x_k = (k, p_k)$, *where* $p_k = [p_k^0, p_k^1, \ldots\ldots\ldots\ldots p_k^{N-1}]$ *and* $p_k^i = 1$ if the i^{th} unit is ON, $p_k^i = 0$ if the i^{th} unit is OFF.

The part of the state space at time slot or stage k can be denoted by

$$\chi_k = \{(k, [p_k^0, p_k^1, \ldots\ldots p_k^{N-1}]),\ p_k^i = 0 \text{ or } 1\}$$

The state space can be defined as ,

$$\chi = \chi_0 \cup \chi_1 \cup \ldots\ldots\ldots \chi_{T-1}$$

Action or decision at any stage of the problem is the decision of making ON / OFF of a unit. Therefore the action set at stage k is represented by,

$$\mathcal{A}_k = \{[a_k^0, a_k^1, \ldots\ldots\ldots\ldots, a_k^{N-1}], a_k^i = 0 \text{ or } 1\}.$$

The transition function defines the change of state from x_k to x_{k+1}. In this case, the next state (in RL terminology) is just the status of units after the present action or decision. Therefore the transition function $f(x_k, a_k)$ is defined as,

$$x_{k+1} = a_k$$

Lastly, the reward is the cost of allocating the committed units with power P_{ik} $i = 0,\ldots N\text{-}1$ and status of the unit $u_{i\,k}=1$. Thus the reward function,

$$g(x_k, a_k, x_{k+1}) = \sum_{i=0}^{N-1} [C_i(P_{i\,k})u_{i\,k} + ST_i(u_{i\,k})(1 - u_{i\,k-1})] \tag{4.5}$$

For easiness of representation, the binary string in the state as well as action can be represented by the equivalent decimal value. The state at any stage can be represented as a tuple *(k, d)* where *k* represents the stage or time slot and *d* represents the decimal equivalent of the binary string representing the status. For example (2, 4) represent the state (2, [0100]) which indicate the status 0100 during 2nd hour for a four unit system. Or in other words it indicates only unit 1 is ON during 2nd hour.

Now a straight forward solution using Q learning is suggested for solving this MDP. Estimated Q values of each state – action pairs are stored in a look up table as $Q(x_k, a_k)$, x_k having the information on the time slot and present status of the different

units. At each step of the learning phase, the algorithm updates the Q value of the corresponding state – action pair. The algorithm (RL_UCP1) for the learning phase is described below:

The initial status of the different generating units is read from the unit data. Then the different possible states and actions possible are identified. Q value corresponding to different state – action pairs are initialized to zero.

The generating units are having their minimum and maximum generation limits. At each slot of time, the unit combinations or actions should be in such a way as to satisfy the load requirement. Therefore, using the forecasted load profile and the unit generation constraints, the set of feasible actions $\mathcal{A}_k$ is identified for each stage k of the multi stage decision problem. Using the ε- greedy strategy one of the actions a_k from the permissible action set $\mathcal{A}_k$ is selected. Depending on the action selected, state transition occurs to next stage $k+1$ as $x_{k+1} = a_k$. The reward of state transition or action is calculated using the power allocation to each unit $P_{i\,k}$ through dispatch algorithm and using the equation (4.5).

The cost function can be non convex in nature and can be represented either in piece wise quadratic form or higher order polynomial form. While finding the dispatch among the committed units, for simplicity, linear cost function is taken. This method gives only tolerable error. After that, cost of generation is obtained using the given cost functions. In this approach of solution a defined mathematical cost function is not at all necessary. The net cost of generation is taken as the reward $g(x_k, a_k, x_{k+1})$. Using the reward, estimated Q value of the corresponding state – action pair is updated at each of the stages until the last stage using the equation:

$$Q^{n+1}(x_k, a_k) = Q^n(x_k, a_k) + \alpha\,[\,g(x_k, a_k, x_{k+1}) + \gamma \min_{a' \in \mathcal{A}_{k+1}} Q^n(x_{k+1}, a') - Q^n(x_k, a_k)] \tag{4.6}$$

here, a is the step size of learning and γ is the discount factor.

During the last stage *(k = T)*, since there is no more future stages the second term in the update equation will turn to be zero, the updating is carried out as

$$Q^{n+1}(x_k, a_k) = Q^n(x_k, a_k) + \alpha\,[\,g(x_k, a_k, x_{k+1}) - Q^n(x_k, a_k)]$$

(4.7)

This constitutes one episode. In each episode the algorithm passes through all the T stages. Then the algorithm is executed again from the initial state x_0. These episodes are repeated a large number of times. If α is sufficiently small and if all possible (x_k, a_k) combinations of state and action occur sufficiently often then the above iteration will result in Q^n converging to Q^* (Bertsekas and Tsitsikilis [1996], Sutton and Barto [1998]).

In the initial phases of learning the estimated Q values, $Q^n(x_k, a_k)$ may not be closer to the optimum value $Q^*(x_k, a_k)$. As the learning proceeds, the estimated Q values turn to be better. When the estimated Q values approach to optimum, change in the value in two successive iterations will be negligibly small. In other words, $Q^{n+1}(x_k, a_k)$ will be the same as $Q^n(x_k, a_k)$.

In order to apply the proposed Reinforcement Learning algorithms, first suitable values of the learning parameters are to be selected. Value of ε balances the rate of exploration and exploitation. A small fixed value result in premature convergence, while a large fixed value may make the system oscillatory. For balancing exploration and exploitation, a reasonable value between 0 and 1 is taken for the learning parameter e initially and is decreased by a small factor successively.

In the learning procedure, a block of consecutive iterations are examined for modification in the estimated Q values. If the change is negligibly small in all these iterations, the estimated Q values are regarded as optimum corresponding to a particular state – action pair. The iteration number thus obtained can be taken as

maximum number of iterations in the learning algorithm. The learning steps are described as RL_UCP1.

Algorithm for Unit Commitment solution using ε - greedy (RL_UCP1)

Read the unit data

Read the initial status x_0

Read the forecast for the next T hours

Identify the feasible states and actions

Initialize $Q^0(x, a) = 0 \quad \forall x \in \chi, \ \forall a \in \mathcal{A}$

Initialize $k = 0$

Initialize $\epsilon = 0.5$, $a = 0.1$ and $\gamma = 1$

For $n = 0$ to max_iteration

Begin

For ($k = 0$ to T-1)

Do

Choose an action using ϵ - greedy algorithm

Find the next state x_{k+1}

Calculate the reward using equation (4.5)

If ($k < T-1$) Update the Q^n to Q^{n+1} using equation (4.6)

Else update Q^n to Q^{n+1} using equation (4.7)

End do

Update the value of ϵ

End

Save Q values.

4.7 Pursuit algorithm for Unit Commitment without considering minimum up time and minimum down time (RL_UCP2)

As explained before, in case of pursuit algorithm, actions are selected based on a probability distribution function $p_{x_k}()$. This probability distribution function is updated as the algorithm proceeds.

In the solution of Unit Commitment problem, initially the probability associated with each action a_k in the action set $\mathcal{A}_k$ corresponding to x_k are initialized with equal values as

$$p_{x_k}(a_k) = 1/n_k$$

n_k - Total number of permissible actions in state x_k.

As in the previous algorithm, Q values of all state – action pairs are initialized to zero. Then at each iteration step, an action a_k is selected based on the probability distribution. On Performing action a_k, state transition occurs as $x_{k+1} = a_k$.

The cost incurred in each step of learning is calculated as the sum of cost of producing power l_k with the generating units given by the binary string 's' in a_k and the cost associated with 's' as given in the equation (4.5). Q values are then updated using the equation (4.6). At each of the iteration of learning, the greedy action as $a_g = \text{argmin}_{a \in \mathcal{A}_k} Q(x_k, a)$ is found. Then the corresponding probabilities of actions in the action set are also updated as :

$$p_{x_k}^{n+1}(a_k) = p_{x_k}^{n}(a_k) + \beta\left[1 - p_{x_k}^{n}(a_k)\right], when\ a_k = a_g$$

$$p_{x_k}^{n+1}(a_k) = p_{x_k}^{n}(a_k) - \beta\left[p_{x_k}^{n}(a_k)\right], when\ a_k \neq a_g \quad (4.8)$$

The algorithm proceeds through several iterations when ultimately the probability of best action in each hour is increased sufficiently which indicate convergence of the algorithm. As in the previous solution, learning steps can be stopped when the change of Q values in a set of successive iterations are tolerably small, which gives the maximum number of iterations required for the learning procedure. The entire algorithm is given in RL _UCP2:

Algorithm for Unit Commitment using Pursuit method (RL_UCP2)

Read the Unit data and Load data for T hours

Find out set of possible states (χ) and actions($\mathcal{A}$)

Read the learning parameters

Read the initial status of units x_0

Initialise $Q^0(x,a) = 0$, $\forall x \in \chi$ *and* $\forall a \in \mathcal{A}$

Identify the feasible action set in each hour k as $\mathcal{A}_k$

Initialize $p^0_{x_k}(a_k)$ *to* $1/n_k$, n_k *the number of actions in* $\mathcal{A}_k$

For n = 0 to max_iteration

Begin

For k = 0 to T-1

Do

Choose action a_k *based on the current probability distribution* $p_{x_k}()$

Find the next state x_{k+1}

Calculate $g(x_k, a_k, x_{k+1})$

Update Q^n *to* Q^{n+1} *using equation (4. 6) and (4.7)*

Update probability $p^n_{x_k}(a_k)$ *to* $p^{n+1}_{x_k}(a_k)$ *using equation (4.8)*

End do

End.

Save Q values.

Since the exploration is based on probability distribution and the probability is updated each and every time an action is selected, the speed of reaching the optimum is improved by this strategy. In the simulation section the performance of this algorithm is compared with the ε - greedy method using several standard systems.

4.8 Policy Retrieval

Once the learning phase is completed, the schedule of the generating units corresponding to the given load profile can be retrieved. During the learning phase Q values of the state – action pairs will be modified and will approach to optimum. Once the optimum Q values are reached, the best action will be the greedy action at each stage *k*.

$$a_k^* = argmin_{a_k \in A_k} \{ Q(x_k, a_k) \}, k = 0, \ldots . T-1. \quad (4.9)$$

Algorithmic steps for finding the optimum schedule $[a_0^*, a_1^*, \ldots\ldots\ldots\ldots, a_{T-1}^*]$ are detailed below:

Policy Retrieval steps:

Read the Q values

Get the initial status of the units, x_0

For (k = 0 to T-1)

Do

Find the greedy action a_k^* using equation (4.9)

Find the next state, $x_{k+1} = a_k$

End do.

For the above two algorithms, the unit and system constraints are considered except the minimum up time and minimum down time. Now, to incorporate the minimum up time and minimum down time, algorithms are extended in the next sections.

4.9 Reinforcement Learning algorithm for UCP, considering minimum up time and minimum down time (RL_UCP3)

In case of Unit Commitment Problem, one important constraint comes from the minimum up time and minimum down time limitation of the units. Therefore the 'state' of the system should essentially indicate the number of hours the unit has been UP or DOWN. Then only the decision to turn on or turn off will be valid. Therefore the state representation used in the previous sections cannot be used further.

For resolving this issue, the state representation is modified. Status of each unit is represented by a positive or negative number indicating the number of hours it has been ON or OFF. Thus, at each stage or hour, system state will be of the form, $x_k = (k, p_k), where\ p_k = [\ p_k^0, p_k^1, \ldots\ldots p_k^{N-1}]$. Each p_k^i has positive or negative value corresponding to the number of hours the unit has been UP or DOWN. For example, if the state of a four generating unit system during 2nd hour is given as $x_2 = (2,\ [-2,\ 1,\ 2, -1])$, it gives the information that first and fourth units have been DOWN for two hours and one hour respectively and second and third units have been UP for one hour and two hours respectively.

In principle, for a T stage problem p_k^i can take any value between –T to +T. That is,

$$\chi_k = \{(k, [\ p_k^0, p_k^1, \ldots\ldots p_k^{N-1}\ ]) \mid p_k^i \in \{-T, -T+1, -T+2, \ldots\ldots +T\}.$$

For such a choice state space will be huge. It may be mentioned here that x_k is the state of the system as viewed by the learning agent and it need not contain all the information regarding the system. Or in other words, only sufficient information need to be included in the state. For example, in the previous formulations it does not matter how many hours the unit was on, what matters to the learner is whether the unit is ON or OFF. Hence in that case $p_k^i \in \{0, 1\}$.

Here, when considering the minimum up time and down time, it is immaterial whether the unit has been ON for U_i hours or U_i + L hours (where U_i is the minimum

up time). Therefore, if a unit is ON for more than U_i hours p_k^i is taken as U_i. Similar is the case with D_i. Hence, $p_k^i \in \{-D_i, -D_i + 1, \ldots\ldots\ldots, U_i\}$.

Thus the sub space corresponding to stage k,

$$\chi_k = \{ k, [p_k^0, p_k^1, \ldots\ldots p_k^{N-1}] \mid p_k^i \in \{-D_i, -D_i + 1, \ldots\ldots\ldots, U_i\}\}$$

The number of elements in $\{-D_i, -D_i + 1, \ldots\ldots\ldots, U_i\}$ is $D_i + U_i$.

Therefore, the number of elements in $\chi = T\,(D_0 + U_0)\,(D_1 + U_1)\ldots\ldots(D_{N-1} + U_{N-1})$.

For a six generating unit system with minimum up time and down time of 5 hours for each of the units, the number of states in the state space will be 10^6 x T which is a large number. Therefore storing Q- values for all the possible state action pairs is a cumbersome task. To resolve the same a novel method is proposed in the next section. Regarding the action space, as in the previous solution, each action represents the ON/ OFF status of the units. For an N generating unit system due to the different combinations of ON – OFF status, there will be 2^{N-1} actions possible. At each stage depending on the generation constraints enforced by the generating units and the load demand to be met there exists a permissible set of actions,

$$\mathcal{A}_k = \{ [\, a_k^0, a_k^1, \ldots\ldots\ldots\ldots, a_k^{N-1} \,], a_k^i = 0 \text{ or } 1 \}$$

For making the new algorithm simpler, an action is selected based on ε - greedy exploration strategy. Each action selection is accompanied by a state transition. In this case, it should account the number of hours one unit has been UP or DOWN. Therefore, the transition function is to transform the state $x_k = (k, [\, p_k^0, p_k^1, \ldots\ldots p_k^{N-1}])$ to $x_{k+1} = (k+1, [\, p_{k+1}^0, p_{k+1}^1, \ldots\ldots p_{k+1}^{N-1}])$ and is defined as:

$$
\begin{aligned}
p_{k+1}^i &= p_k^i + 1, \quad if\ p_k^i\ positive, a_k^i = 1 \\
p_{k+1}^i &= -1, \quad if\ p_k^i\ positive, a_k^i = 0 \\
p_{k+1}^i &= p_k^i - 1, \quad if\ p_k^i\ negtive, a_k^i = 0 \\
p_{k+1}^i &= +1, \quad if\ p_k^i\ negative, a_k^i = 1 \\
p_{k+1}^i &= U_i, \quad if\ p_k^i > U_i \\
p_{k+1}^i &= D_i, \quad if\ p_k^i < D_i
\end{aligned}
\tag{4.10}
$$

Since each action corresponds to a particular unit combination of generating units to be on-line, the cost of generation or reward will be the function $g(x_k, a_k, x_{k+1})$ as given in equation(4.5).

Q learning described previously is used for solution of this MDP. Q values of each state – action pairs are to be stored to find the good action at a particular state. In this Unit Commitment Problem, when the minimum up time and down time constraints are taken, the possible states come from a very large state space. Straight forward method of storing the $Q(x_k, a_k)$ values is using a look up table. But all the states in this huge state space are not relevant. Therefore a novel method of storing Q values is suggested.

Q values of only those states which are encountered at least once in the course of learning are stored. Since the learning process allows sufficient large number of iterations, this seems to be a valid direction. The states are represented by an index number *(ind* $\_x_k$*)*, which is an integer and initialized at the first time of encountering the state. For example the tuple, (5, (2,[-2,1,1,2])) denote the state (2, [-2,1,1,2]) with an index number '5'.

Similarly, the actions in the action space can also be represented by an integer, which is the decimal equivalent of the binary string representing the status of the different units. The index value of action 0011 is '3'. Using these indices for the state and action strings, the Q values of the different state action pairs can be stored very easily. Q (5, 3) indicate the Q value corresponding to the state (2, [-2, 1, 1, 2]), which is having index value 5 and action [0 0 1 1].

The possible number of states *nstates* is initialized depending on the number of units N and the minimum down time and minimum up time of the units, since it depends on number of combinations possible with *N* units as well as the given values of minimum up time and down time. Since some of the states will not be visited at all, the value of *nstates* is initialized to 70% of the total number states. The number of actions '*naction*' is initialized to 2^N -1. Then the permissible action set corresponding to each hour based on the load demand at that particular hour are identified. The algorithm during the learning phase proceeds as follows.

At each hour *k*, the state x_k depending on the previous state and action is found as explained previously. The state x_k is added to the set of states χ_k if not already present and find the index of the state x_k. From the permissible action set, one of the actions is chosen based on ε-greedy method. Then the next state x_{k+1} can be found corresponding to stage $k+1$. On taking action a_k, the state of the system proceeds from x_k to x_{k+1} as given in (4.10). The reward, $g(x_k, a_k, x_{k+1})$ is given by equation (4.5).

The Q value corresponding to the particular hour '*k*', action 'a_k' (decimal value of the binary string) and index no (*ind_xk*) is then updated using the equation:

$$Q^{n+1}(ind\_x_k, a_k) = Q^n(ind\_x_k, a_k) + \alpha\,[\,g(x_k, a_k, x_{k+1}) + \gamma \min_{a' \in \mathcal{A}_{k+1}} Q^n(ind\_x_{k+1}, a') - Q^n(ind\_x_k, a_k)]$$

(4.11)

If the stage is the last one ($k = T$), corresponding to the last hour to be scheduled, there is no more succeeding stages and the updating equation reduces as,

$$Q^{n+1}(ind\_x_k, a_k) = Q^n(ind\_x_k, a_k) + \alpha\,[\,g(x_k, a_k, x_{k+1}) - Q^n(ind\_x_k, a_k)]$$

(4.12)

At each episode of the learning phase, the algorithm passes through all the '*T*' stages. As the algorithm completes several iterations, the estimated Q values will reach nearer to the optimum values and then the optimum schedule or allocation can be easily retrieved for each stage *k* as, $a_k^* = arg\,min_{a_k \in \mathcal{A}_k}(Q(ind\_x_k, a_k))$

The entire algorithm is illustrated as RL_UCP3.

Algorithm for Unit Commitment using state indexing (RL_UCP3)

Read Unit Data

Read the initial status of the units, x_0

Read the Load forecast for next T hours

Initialize 'nstates' (number of states) and 'nactions' (number of actions)

Initialize Q^0 *[ind_*x_k*,* a_k*] =0 ,* $0 < ind\_x_k <= nstates, 0 < a_k <= nactions$

Find the set of permissible actions corresponding to each hour k

Initialize $\epsilon = 0.5$ *and* $a = 0.1$

For n=1 to max _ iteration

Begin

Read the initial status of the units x_0

Add the state x_0 *to set* χ_0

For k=0 to T-1

Do

Find the feasible set of actions $\mathcal{A}_k$ *corresponding to state* x_k *considering up and down times.*

Choose an action using ε*- greedy strategy from the feasible set of actions*

Find the next state x_{k+1}

If x_{k+1} *is present in* χ_{k+1} *Get the index ind_* x_{k+1}

Else Add x_{k+1} *in* χ_{k+1} *and obtain index ind_* x_{k+1}

Calculate cost as $g(x_k, a_k, x_{k+1})$

If (k != T-1) Update Q value using equation (4.11)

Else Update Q value using equation (4.12)

$ind\_x_k = ind\_x_{k+1}$.

End do

Update the value of ε

End

Save Q values.

This algorithm can accommodate the minimum up time and down time constraints easily, when the number of generating units is small. Up to 5 hours of minimum up time and minimum down time the algorithm is found to work efficiently. But when the minimum up time and minimum down time increase beyond 5 hours and the number of generating units is beyond six, the number of states visited increases. Then the number of Q values stored and updated becomes enormously larger. This demands more computer memory. In order to solve this issue and make an efficient solution, in the next section a state aggregation method is discussed which needs much less computer memory than the above formulated algorithm.

4.10 Reinforcement Learning algorithm for UCP, through State Aggregation (RL_UCP4)

While looking into the Unit Commitment Problem with minimum up time and minimum down time constraints, the state space become very huge. The huge state space is difficult to handle in a straight forward manner when the minimum up time / minimum down time increases or the number of generating unit increases. Storing of Q value corresponding to each state – action pair becomes computationally expensive. Some method is to be thought of to reduce the number of Q values to be handled. In the perspective of Unit Commitment problem one can group the different states having the same characteristics so that the goodness of the different groups is stored instead of goodness of the different states corresponding to an action. The grouping of states can be done based on the number of hours a unit has been UP or DOWN.

(i) A machine which has been already UP for duration equal to or greater than the minimum up time can be considered as to occupy a state 'can be shut down'.

(ii) A unit which is already UP but not have covered minimum up time can be considered as to represent a state 'cannot be shut down'.

(iii) An already offline unit which has been DOWN for number of hours equal to or more than its minimum down time can be represented as a state 'can be committed'.

(iv) A unit which has been DOWN but has not covered the minimum down time so that cannot be committed in the next immediate slot of time can be represented as a state 'cannot be committed'.

Thus, at any slot of time, each of the generating unit will be in any of the above mentioned four representative states. If these four conditions are denoted as decimal integers (0, 1, 2, 3), regardless of the UP time and DOWN time of a generating unit, the state is represented by one of this integer value. By aggregating the numerous states visited in the previous algorithm to a limited number of states, number of Q values to be stored and updated in the look up table is greatly reduced.

With the decimal numbers 0,1,2,3 representing the aggregated states of a unit, for an N generating unit system the state x_k is represented as a string of integers having length N and with each integer having any of these four values. Then the state can be represented as a number with base value 4. For an N generating unit problem, there will be 4^N -1 possible states, regardless of minimum up time and down time of the different units. (In the previous algorithm RL_UCP3, the number of states increases with increase in the minimum up time and / or down time). This reduction in the number of states drastically reduces the size of look up table for storing the Q values. Now an algorithm is formulated making use of state aggregation technique for handling the up/ down constraints of the units.

The number of states, *nstates* is initialized to 4^N-1 and the number of actions *naction* to 2^N-1 for an N generating unit system. At any stage k of MDP, the state of the system is represented as a string of integers as in the previous algorithm, integer value representing the number of hours the unit has been up or down.

In order to store the Q values, the state x_k is mapped into set of aggregate states. Each aggregate state,

$$ag\_x_k = \{(k, [\, ag\_p_k^0, ag\_p_k^1, \ldots\ldots ag\_p_k^{N-1}\,]),\ ag\_p_k^i \in \{0,1,2,3\}.$$

From any state x_k an action is selected using one of the exploration strategies. On selecting an action a_k, the status of the units will change as, $x_{k+1} = f(x_k, a_k)$ given by equation (4.10). From the above explained categorization of states, $ag\_p_k^i$ can be found corresponding to any $x_k = (k, [\, p_k^0, p_k^1, \ldots\ldots p_k^{N-1}\,])$ as:

p_k^i positive and $p_k^i \geq U_i$, $ag\_p_k^i = 0$;

p_k^i positive and $p_k^i < U_i$, $ag\_p_k^i = 1$;

p_k^i negative and $p_k^i \leq D_i$, $ag\_p_k^i = 2$;

p_k^i negative and $p_k^i > -D_i$, $ag\_p_k^i = 3$.

The reward function for the state transition is found using the cost evaluations of the different generating units using equation (4.5). For each of the states x_k and x_{k+1}, the corresponding aggregate state representation is found as ag_x_k and ag_x_{k+1}. Each action in the action space is represented as the decimal equivalent of the binary string. At each state k, estimated Q value corresponding to the state – action pair (ag_x_k, a_k) is updated using the equation,

$$Q^{n+1}(ag\_x_k, a_k) = Q^n(ag\_x_k, a_k) + \alpha\,[\, g(x_k, a_k, x_{k+1}) + \gamma \min_{a' \in \mathcal{A}_{k+1}} Q^n(ag\_x_{k+1}, a') - Q^n(ag\_x_k, a_k)]$$

(4.13)

During the last hour, omitting the term to account future pay –off Q value is updated using the equation,

$$Q^{n+1}(ag\_x_k, a_k) = Q^n(ag\_x_k, a_k) + \alpha\,[\,g(x_k, a_k, x_{k+1}) - Q^n(ag\_x_k, a_k)] \quad (4.14)$$

After a number of iterations, learning converges and the optimum schedule or allocation for each state x_k can be easily retrieved after finding the corresponding aggregate state as,

$$a_k^* = argmin_{a_{k\in\mathcal{A}_k}}\,\{\,Q(ag\_x_k, a_k)\,\}, k = 0, \ldots . T-1,$$

The entire algorithm using state aggregation method is given below:

Algorithm for Unit Commitment through state aggregation (RL_UCP4)

Read Unit Data
Read the Load forecast for next T hours.
Initialize nstates (number of states) and nactions (number of actions)
Initialize $Q^0\,[ag\_x_k, a_k] = 0$, $\forall\, ag\_x_k$ $\forall\, a_k$
Find the set of permissible actions corresponding to each hour k
Initialize the learning parameters
For n=1 to max _ episode
Begin
    Read the initial status of the units x_0
    For k=0 to T-1
    Do
        Find aggregate state ag_x_k *corresponding to* x_k

        Find the feasible set of actions $\mathcal{A}_k$ *corresponding to state* x_k *considering up and down times.*
        Choose an action using ε- greedy strategy from the feasible set of actions

Contd...

Find the next state x_{k+1}

Find the corresponding aggregate state ag_x_{k+1} *of* x_{k+1}

Calculate the reward $g(x_k, a_k, x_{k+1})$

If (k != T-1) Update Q value using equation (4.13)

Else Update Q value using equation (4.14)

End do

Update the value of ε.

End

Save Q values.

The optimal schedule $[a_0^*, a_1^*, \ldots\ldots a_{T-1}^*]$ is obtained using policy retrieval steps similar to the algorithm given in section 4.8.

4.11 Performance Evaluation

Solution to Unit Commitment Problem has now been proposed by various Reinforcement Learning approaches. Now, one can validate and test the efficacy of the proposed methods by choosing standard test cases. The high level programming code for the algorithms is written in C language in Linux environment. The execution times correspond to Pentium IV, 2.9 GHz, 512 MB RAM personal computer.

In order to compare the ε greedy and pursuit solutions (RL_UCP1 and RL_UCP2) a four generating unit system and an eight generating unit system are considered. The generation limits, incremental and start up cost of the units are specified. Performance of the two algorithms is compared in terms of number of iterations required in the learning phase and the computation time required for getting the commitment schedule.

In order to validate and compare the last two algorithms (RL_UCP3 and RL_UCP4), four generating unit system with different minimum up time and down time are considered. The schedule obtained is validated and the performance comparison is made in terms of execution time of the entire algorithm, including the learning and policy retrieval. In order to prove the scalability of the algorithms, an

eight generating unit system with given minimum up time and down time limits is also taken for case study.

For comparing with the recently developed stochastic strategies a ten generating unit system with different minimum up time and down time limits are taken for case study. The schedule obtained and the computation time is compared with two hybrid methodologies: Simulated Annealing with Local Search (SA LS) and Lagrange Relaxation with Genetic Algorithm (LRGA).

In order to apply the proposed Reinforcement Learning algorithms, first suitable values of the learning parameters are to be selected. Value of ε balances the rate of exploration and exploitation. For balancing exploration and exploitation, a value of 0.5 is taken for the learning parameter e initially. In every (max_iteraion/10) iterations, ε is reduced by 0.04 so that in the final phases, ε will be 0.1.

Discount parameter γ accounts for the discount to be made in the present state in order to account of future reinforcements and since in this problem, the cost of future stages has the same implication as the cost of the current stage, value of γ is taken as 1. The step size of learning is given by the parameter α and it affects the rate of modification of the estimate of Q value at each iteration step. By trial and error α is taken as 0.1 in order to achieve sufficiently good convergence of the learning system. The RL parameters used in the problem are also tabulated in Table 4.1.

Table 4.1 – RL Parameters

ε	0.5
α	0.1
γ	1

Now the different sample systems and load profile are considered, for evaluating the performance of the algorithms.

Case I – A four generating unit system

Consider a simple power system with four thermal units (Wood and Wollenberg [2002]). For testing the efficacy of the first two algorithms and to compare them, minimum up and down times are neglected. Load profile for duration of 8 hours is considered and is given in Table 4.2

Table 4.2 – Load profile for eight hours

Hour	0	1	2	3	4	5	6	7
Load(MW)	450	530	600	540	400	280	290	500

The cost characteristics of the different units are taken to follow a linear incremental cost curve. That is, cost of generating a power P_i by the i^{th} unit is given as,

$$C_i(P_i) = NL_i + IC_i * P_i$$

where NL_i represents the No Load cost of i^{th} unit and IC_i is the Incremental cost of the same unit. The values P_{min} and P_{max} represent the minimum and maximum values of power generation possible for each of the units. The different unit characteristics and the generation limits are given in Table 4.3.

Table 4.3 – Generating Unit Characteristics

Unit	Pmin(MW)	Pmax(MW)	Incremental cost Rs.	No Load Cost Rs.	Startup Cost Rs.
1	75	300	17.46	684.74	1100
2	60	250	18	585.62	400
3	25	80	20.88	213	350
4	20	60	23.8	252	0.02

When the learning is carried out using the first two algorithms, learning is first carried to find the maximum number of iterations required for the learning procedure.

In the learning procedure, 100 consecutive iterations are examined for modification in the estimated Q values. If the change is negligibly small in all these 100 iterations, the estimated Q values are regarded as optimum corresponding to a particular state – action pair. The iteration number thus obtained is approximated to nearest multiple of 100 is taken as 'maximum iteration (max_iteration)' and used in next trials. Different successive executions of the algorithm with max_iteration provided with almost the same results with tolerable variation.

RL_UCP1 indicated the convergence after 5000 iterations. While using RL_UCP2 the optimum is reached in 2000 iterations. The schedule obtained is given in Table 4.4 which is same as given in Wood and Wollenberg [2002].

Table 4.4 – Commitment schedule obtained

Hour	0	1	2	3	4	5	6	7
State	0011	0011	1011	0011	0011	0001	0001	0011

The computation time taken by RL_UCP 1 was 15.62 sec while that taken by RL_UCP2 was only 9.45sec. From this, it can be inferred that, the pursuit method is faster.

Case II – Eight generating unit system

Now an eight generating unit system is considered and a load profile of 24 hours is taken into account in order to prove the scalability of the algorithms. The load profile is given in Table 4.5

Table 4.5 – Load profile for 24 hours

Hour	0	1	2	3	4	5	6	7
Load(MW)	450	530	600	540	400	280	290	500
Hour	8	9	10	11	12	13	14	15
Load(MW)	450	530	600	540	400	280	290	500
Hour	16	17	18	19	20	21	22	23
Load(MW)	450	530	600	540	400	280	290	500

The cost characteristics are assumed to be linear as in previous case. The generation limit and the cost characteristics are given in Table 4.6

Table 4.6 – Gen. Unit characteristics for Eight generator system

Unit	P min (MW)	P max (MW)	Incremental Cost Rs.	No. Load Cost Rs.	Startup Cost Rs.
1	75	300	17.46	684.74	1100
2	75	300	17.46	684.74	1100
3	60	250	18	585.62	400
4	60	250	18	585.62	400
5	25	80	20.88	213	350
6	25	80	20.88	213	350
7	20	60	23.8	252	0.02
8	20	60	23.8	252	0.02

The optimal cost obtained for 24 hour period is Rs. 219,596/- and the solution obtained is given in Table 4.7. The status of the different units is expressed by the decimal equivalent of the binary string. For example during the first hour, the scheduled status is '3', which indicate 0000 0011.

Table 4.7 Commitment schedule for 24 hours

Hour	0	1	2	3	4	5	6	7	8	9	10	11
Status	3	3	131	3	3	2	2	6	6	6	134	6
Hour	12	13	14	15	16	17	18	19	20	21	22	23
Status	6	2	2	6	6	6	70	6	6	2	2	6

Comparison of two algorithms RL_UCP1 and RL_UCP2 are given in Table 4.8. The number of iterations as well as computation time is again found to be less for the pursuit method when compared with e- greedy method.

Table 4.8- Comparison of algorithms RL_UCP1 and RL_UCP2

		RL_UCP1	RL_UCP2
4Unit system	No: of iterations	5000	2000
	Time(sec.)	15.62	9.45
8 Unit system	No: of iterations	10^6	5×10^5
	Time(sec.)	34	17

Scalabillity of the proposed algorithms are now proved for simple Unit Commitment Problem.

Case III (Four unit system with minimum up time and minimum down time considered)

In order to validate the algorithms RL_UCP3 and RL_UCP4, first consider the four generator system (Wood and Wollenberg [2002]) with the given minimum up time and minimum down time. The unit characteristics and load profile are the same as given Table 4.2 and 4.3. The different units require different number of hours as minimum up time and minimum down time. The minimum up time, min. down time and the initial status of the units are given in Table 4.9.

Table 4.9 – Minimum up time and minimum down time, initial status

Unit	Min. Up ime(Hr.)	Min.Down time(Hr.)	Initial Status
1	4	2	-2
2	5	3	1
3	5	4	-4
4	1	1	-1

The initial status -1 indicate that the particular unit has been DOWN for 1 hour and the initial status 1 represent that the unit has been UP for 1 hour.

The learning of the system is carried out using RL_UCP3 and RL_UCP4. A number of states are visited and after 10^5 iterations, the Q values approach optimum. RL_UCP3 enumerates and stores all the visited states. The goodness of each state action pair is stored as Q value. On employing state aggregation in RL_UCP4, the number of entries in the stored look up table is reduced prominently. This is reflected by the lesser computation time. The optimum schedule obtained is tabulated in Table 4.10 which is consistent with that given through Dynamic Programming (Wood and Wollenberg [2002])

Table 4.10 – Optimum schedule obtained

Hour	1	2	3	4	5	6	7	8
Status	0110	0110	0111	0110	0110	0110	0110	0110

In RL_UCP3, since the number of states and hence the number of Q values manipulated are more, the execution time is more. In case of RL_UCP4, the number of states is drastically reduced due to the aggregation of states and hence the schedule is obtained in much lesser time. Time of execution of the algorithms RL_UCP3 and RL_UCP4 are tabulated for comparison in Table 4.11

Table 4.11 –Comparison of RL_UCP3 and RL_UCP4

Algorithm	Execution Time (Sec.)
RL_UCP3	9.68
RL_UCP4	3.89

From the comparison of execution time, it can be seen that state aggregation has improved the performance very much.

Case IV – Ten generating unit system

In order to prove the flexibility of RL_UCP4 and to compare with other methods, next a ten generating unit with different initial status given is considered (Cheng *et al.*[2000]).

In this case minimum up time and minimum down time are also different for different units. Minimum up time of certain units is 8 hours, which is difficult to be handled by RL_UCP3. The cost functions are given in quadratic cost form, $C(P) = a + bP + cP^2$, *where a, b and c are cost coefficients* and P the power generated. The values of the cost coefficients a, b and c for the different generating units are given in Table 4.12. For a load profile of eight hours given in Table 4.13, the algorithm gave an optimum result in 2 x 10^5 iterations. The obtained commitment schedule is given in Table 4.14

Table 4.12 – Generating Unit characteristics of 10 generator system

Unit	P min (MW)	P max (MW)	Cost coefficients			Start up cost (Rs.)	Min.Up (hrs.)	Min. Down (hrs.)	Initial status
			a	b	c				
1	150	455	1000	16.19	0.00048	4500	8	8	8
2	150	455	970	17.26	0.00031	4000	8	8	8
3	20	130	700	16.6	0.00211	550	5	5	-5
4	20	130	700	16.6	0.002	360	5	5	-5
5	25	160	450	19.7	0.00031	300	6	6	-6
6	20	85	370	22.26	0.0072	340	3	3	-3
7	25	85	480	27.74	0.00079	520	3	3	-3
8	10	55	660	25.92	0.00413	60	1	1	-1
9	10	55	665	27.37	0.00222	60	1	1	-1
10	10	55	670	27.79	0.00173	60	1	1	-1

Table 4.13 – Load profile for 24 hour

Hour	P_{Load} (MW)	Hour	P_{Load} (MW)
1	700	13	1400
2	750	14	1300
3	850	15	1200
4	950	16	1050
5	1000	17	1000
6	1100	18	1100
7	1150	19	1200
8	1200	20	1400
9	1300	21	1300
10	1400	22	1100
11	1450	23	900
12	1500	24	800

Table 4.14 – Unit Commitment schedule

Hr	Load(MW)	1	2	3	4	5	6	7	8	9	10
1	700	1	1	0	0	0	0	0	0	0	0
2	750	1	1	0	0	0	0	0	0	0	0
3	850	1	1	0	0	1	0	0	0	0	0
4	950	1	1	0	0	1	0	0	0	0	0
5	1000	1	1	0	1	1	0	0	0	0	0
6	1100	1	1	1	1	1	0	0	0	0	0
7	1150	1	1	1	1	1	0	0	0	0	0
8	1200	1	1	1	1	1	0	0	0	0	0
9	1300	1	1	1	1	1	1	1	0	0	0
10	1400	1	1	1	1	1	1	1	1	0	0
11	1450	1	1	1	1	1	1	1	1	1	0
12	1500	1	1	1	1	1	1	1	1	1	1
13	1400	1	1	1	1	1	1	1	1	0	0
14	1300	1	1	1	1	1	1	1	0	0	0
15	1200	1	1	1	1	1	0	0	0	0	0
16	1050	1	1	1	1	1	0	0	0	0	0
17	1000	1	1	1	1	1	0	0	0	0	0
18	1100	1	1	1	1	1	0	0	0	0	0
19	1200	1	1	1	1	1	0	0	0	0	0
20	1400	1	1	1	1	1	1	1	1	0	0
21	1300	1	1	1	1	1	1	1	0	0	0
22	1100	1	1	0	0	1	1	1	0	0	0
23	900	1	1	0	0	1	0	0	0	0	0
24	800	1	1	0	0	0	0	0	0	0	0

By executing RL_UCP4 for the above characteristics, the commitment schedule is obtained in 268 sec. The obtained schedule is given in Table 4.14. The cost obtained and the computation time are compared with that obtained through hybrid methods using Lagrange Relaxation and Genetic Algortihm (LRGA) proposed by Cheng *et al.* [2000] and Simulated Annealing and Local search (SA LS) suggested by Purushothama and Lawrence Jenkins.[2003]. Comparison of the cost and time are given 4.15.

Table 4.15 – Comparison of cost and time

Algorithm	Cost(Rs.)	Execution Time(sec.)
LRGA	564800	518
SA LS	535258	393
RL_UCP4	545280	268

A graphical representation of Table 4.15 is given in 4.1

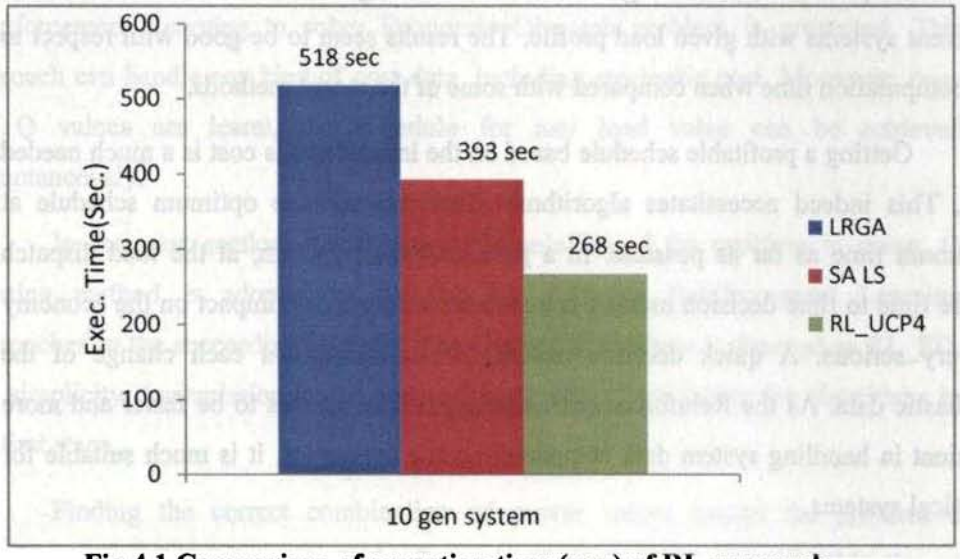


Fig 4.1 Comparison of execution time (sec.) of RL approach with other methods

The comparison revealed that the proposed method gave comparable cost with other methods and takes less computation time. Quick decision making is advantageous in a practical power system scheduling since the economy of power generation directly rely on the same. When a practical system is considered the cost is not at all constant and it changes from time to time. Reinforcement Learning provides with a solution for handling the same.

4.12 Conclusion

Unit commitment has now been formulated as a multi stage decision making task and then Reinforcement Learning based solution strategies are developed for solving the same. First the minimum up time and minimum down time limitations are neglected and the scheduling policy is arrived using ε greedy and pursuit methods for action selection. Then the minimum up time and minimum down time of the generating units are considered to find the optimum commitment schedule. An index based approach has been formulated to reduce the size of the search space in RL_UCP3 and state aggregation method is implemented to make the solution more efficient and reduce computation time in RL_UCP4. All the four algorithms have been verified for different systems with given load profile. The results seem to be good with respect to the computation time when compared with some of the recent methods.

Getting a profitable schedule based on the instantaneous cost is a much needed task. This indeed necessitates algorithms which provide the optimum schedule at minimum time as far as possible. In a practical power system, at the load dispatch centre time to time decision making is a serious task since the impact on the economy is very serious. A quick decision making is necessitated at each change of the stochastic data. As the Reinforcement Learning method proves to be faster and more efficient in handling system data compared to other strategies, it is much suitable for practical systems.

CHAPTER 5

REINFORCEMENT LEARNING APPROACHES FOR SOLUTION TO ECONOMIC DISPATCH

5.1 Introduction

In the previous chapter, Unit Commitment Problem has been solved using Reinforcement Learning approach. Next loop in power scheduling is Economic Dispatch. Economic Dispatch problem is challenging because of the large varieties of cost functions. Cost function in some cases may be non convex, discontinuous. In some other cases it is not well defined and may be stochastic.

Classical methods fail to handle the non convexity of the cost data. The soft computing methods efficiently handle the non convex cost functions. But most of them fail to handle the stochastic nature of the cost. In this thesis, an efficient approach using Reinforcement Learning to solve Economic Dispatch problem is presented. This approach can handle any kind of cost data, including stochastic cost. Moreover, once the Q values are learnt, the schedule for any load value can be retrieved instantaneously.

In the next section, mathematical formulation of the problem is given. Q learning method is adopted to develop the different Reinforcement Learning approaches in the succeeding sections. The class of algorithms is denoted as RL_ED. For simplicity, transmission losses are neglected while formulating the algorithms in the first stage.

Finding the correct combination of power values makes the problem a combinatorial optimization task. In the first step of solution, the power combination or optimum dispatch is obtained for each load demand independently. In this case, every load dispatch is considered as a separate problem as in methods like Genetic

Algorithm. The solution based on an adaptive decision making strategy (Thathachar and Sastry [2003]) is proposed, termed as Learning Automata algorithm (RL_ED1). In this case, the optimum dispatch is obtained by trying a sequence of possible power combinations or actions. The action selection is done in a more scientific manner. At each step of trying an action, value of a performance index associated with that action is updated. Performance index stores the goodness of an action for further consideration in the next steps.

When the number of generating units increases, the number of possible combinations of power allocation will increase beyond a manageable limit. Finding the allocation independently for each load demand from the huge action space is a difficult task. This motivates the formulation of Economic Dispatch as a multi stage decision making task.

In the second stage of solution, Reinforcement Learning solutions are developed for this multi stage decision making problem. Learning is carried out using Q- learning. Two types of action selection strategies, ε - greedy and pursuit method are used to develop the solution steps as RL_ED2 and RL_ED3 respectively.

The transmission losses occurring in a system are not considered in the previous two approaches of solution. As the third step of putting forward a solution suitable for practical power system, the transmission losses are also considered. This extended algorithm is given as RL_ED4.

In order to make the solution more efficient in handling the continuous nature of input at each stage of the problem, a function approximation approach is also suggested as the fourth step of solution. Radial Basis Function networks are used as the function approximating network and the learning is carried out through Reinforcement Learning. The algorithm is described as RL_ED5.

The performances of the developed algorithms are evaluated using several IEEE standard test systems. To assess the efficacy of the proposed methods, comparison is also made with some of the latest solution methods including Simulated Annealing and Partition Approach Algorithm.

5.2 Problem Description

Economy of operation, in particular, is more significant in the case of thermal stations, as the variable costs are much higher compared to the other type of generators. The cost of fuel is the major portion of the variable cost and the purpose of optimal operation is to reduce the cost of fuel used. A number of constraints also have to be considered while trying to minimize the operating cost. These include generation limits of the units, prohibited operating zones, ramp rate limits, valve point loading etc.

5.2.1 Generation limits

Each generating unit is having its minimum and maximum generation limit specified as

$$P_{\min(i)} \leq P_i \leq P_{\max(i)}$$

$P_{\min(i)}$: Min. Power generation of i^{th} unit

$P_{\max(i)}$: Max. Power generation of i^{th} unit

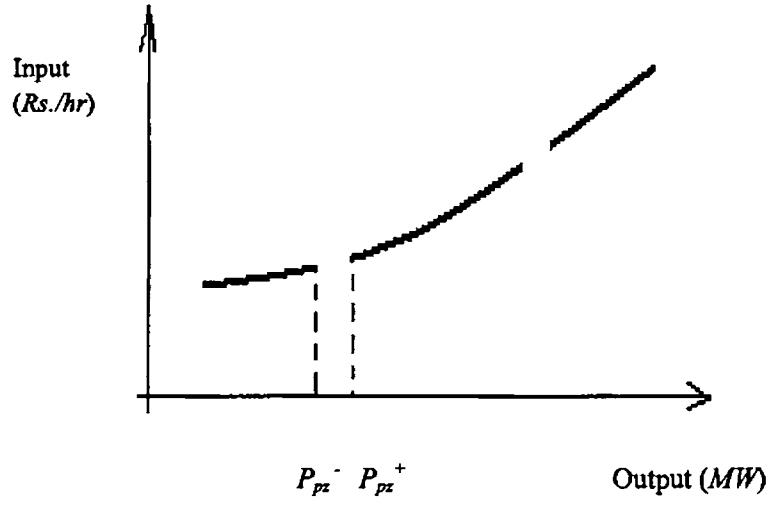
But the assumption of adjusting the unit generation output instantaneously over this entire range is not valid at all situations. Some of the practical systems will be having prohibited operating zones and ramp rate limits which also force constraint to limit their operation in the entire range of possible generation.

5.2.2 Prohibited Operating Zones

A thermal generating unit may have prohibited operating zone(s) due to the physical limitations of power plant components (e.g. vibrations in a shaft bearing are amplified in a certain operating region). As a result, in practice, the whole of the unit's operating range is not always available for load allocation. For a prohibited zone, the unit can only operate above or below the zone. For example, a 500 MW generator, with a minimum generation limit (P_{min}) of 100 MW and a maximum generation limit (P_{max})

of 500 MW, may have a prohibited operating zone, say, between 250 MW and 350 *MW.* This prohibited zone results in two disjoint convex regions -the region between 100 MW and 250 MW (i.e. [100 MW, 250 MW]) and the region between 350 MW and 500 *MW* (i.e. [350 MW, 500 MW]). These two disjoint regions form a non-convex set.

Fig. 5.1 shows the input-output performance curve for a typical thermal unit. Several cases available in the literature discuss the effects of the prohibited zone in the Economic Dispatch problem. In practice, the shape of the input-output curve in the neighborhood of the prohibited zone is difficult to determine by actual performance testing or operating records. In actual operation, the best economy is achieved by avoiding operation in these areas. As such, heuristic algorithms are developed to adjust the generation output of a unit in order to avoid unit operation in the prohibited zones.



(P_{pz}^-, P_{pz}^+ are bounds of a prohibited zone)

Fig.5.1 Typical input-output curve of a thermal unit.

5.2.3 Valve point effects

The unit input-output curve establishes the relationship between the energy input to the driving system and the net energy output from the electric generator. The input to thermal equipment is generally measured in Btu's per hour and the output is measured in megawatts.

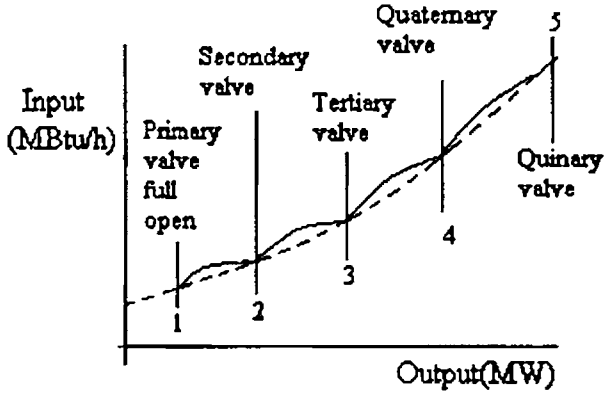


Fig.5.2 Thermal unit-input versus output with valve point effect

Fig. 5.2 shows a thermal unit input-output curve showing the valve point effects. The ripples in the input-output curve are the result of sharp increase in losses due to wire drawing effects, which occur as each steam admission valve starts to open, producing a rippling effect. As each steam valve opens, instantaneous output also increases sharply and then it settles. Smooth quadratic function approximations are used for solution in classical Economic Dispatch methods. Heuristic methods can avoid this approximation and provide better solution.

5.2.4 Multiple fuel options

Some of the thermal plants may take different types of fuels at different regions of power output, for efficient operation. In such cases the fuel cost function will not be following the same relation with the power output for the entire range of operation. It is better to represent the cost functions as piecewise polynomial functions corresponding to the different regions of operation.

5.2.5 Transmission Losses

Since the power stations are usually spread out geographically, transmission network losses must be taken into account to achieve true economic dispatch. Network loss is a function of power injection at each node. To calculate network losses, two methods are in use. One is the load flow computation method and the other is the *B* coefficients method. The latter is commonly used by the power utility industry.

Considering the operating characteristics and constraints of the thermal generating units, Economic Dispatch can be modeled as a constrained optimization problem.

5.3. Mathematical formulation

Consider a power system having N generating units. Let P_D be the power demand to be satisfied with these N units at any slot of time and let P_L be the total transmission loss in the system.

The objective function of Economic Dispatch problem C_T is equal to the total cost for supplying the load power P_D. The problem is to minimize C_T subject to the constraints that the total generated power and the load demand equals and the power constraints on all units are being met. Mathematically the objective function which is the total cost of generation (C_T) can be expressed as

$$C_T = C_1(P_1)+C_2(P_2)+C_3(P_3)+.....C_N(P_N)$$

$$= \sum_{i=1}^{i=N} C_i(P_i) \qquad (5.1)$$

where C_i denotes the cost function corresponding to i^{th} unit and P_i the electrical power generated by that particular unit.

The fuel cost function can be expressed in a variety of forms including quadratic cost functions, piecewise quadratic cost functions, higher order polynomials, tabular form etc.

(i) **Quadratic cost functions:**

In this representation, the fuel cost of each unit is expressed as a quadratic expression,

$$C_i(P_i) = a_i + b_i P_i + c_i P_i^2$$

Including the effect of valve point, the quadraric cost function is added with a recurring sinusoidal term:

$$C_i(P_i) = a_i + b_i P_i + c_i P_i^2 + e_i \sin(f_i P_{min\,(i)} - P_i)$$

Where a_i, b_i, c_i, e_i and f_i are the cost coefficients correponding to i^{th} generating unit.

(ii) **Higher order Polynomials:**

One of the commonly used model is the third order polynomial form as given by:

$$C_i(P_i) = a_i + b_i P_i + c_i P_i^2 + d_i P_i^3$$

Where a_i, b_i, c_i and d_i are the cost coefficients correponding to i^{th} generating unit.

(iii) **Piecewise Quadratic functions:**

For making the cost functions accurate, piecewise quadratic functions are also used. In this, Cost is represented by different quadratic cost functions in the different regions as,

$$\begin{aligned} C_i(P_i) \quad &= a_{i(1)} + b_{i(1)} P_i + c_{i(1)} P_i^2 \quad (P_{min(i)} \le P_i \ge P_{i(1)}) \\ &= a_{i(2)} + b_{i(2)} P_i + c_{i(2)} P_i^2 \quad (P_{i(1)} \le P_i \ge P_{i(2)}) \\ &= a_{i(3)} + b_{i(3)} P_i + c_{i(3)} P_i^2 \quad (P_{i(2)} \le P_i \ge P_{max\,(i)}) \end{aligned}$$

(iv) **Tabular form:**

When a mathematical expression is difficult to be arrived, from the experimental knowledge, the cost of a generating unit can be expressed in tabular form.

(v) **Stochastic cost data**

In the case of practical systems, the known details of the cost function may not be deterministic or may fit to any of the mathematical formulations exactly. Cost of generation of any power P may be a random variable.

The constraints for this optimization problem comes from the various aspects of generating unit characteristcs, transmission system effects, power demand etc. Since the generated power should meet the load demand and the transmission losses in the system, the most basic constratint is the power balance constraint expressed as,

$$\sum_{i=1}^{i=N} P_i - P_D - P_L = 0 \qquad (5.2)$$

Where P_D : Total load power demand

P_i : Power generated by i^{th} generating unit

P_L : Loss in the transmission system

Loss in the transmission system can be calculated by executing power flow algorithms or can be approximated by the B – Matrix loss formula. Due to simplicity, B-Coefficient formulation is widely used by the power utility industry. The B – Matrix Loss formula is given (Wood and Wollenberg [2002]) as

$$P_L = \sum_{i=1}^{i=N} \sum_{j=1}^{j=N} P_i B_{ij} P_j + \sum_{i=1}^{N} B_{i0} P_i + B_{00}$$

where B_{ij} is the ij^{th} element of the loss coefficient square matrix; B_{i0} is the i^{th} element of the loss coefficient vector and B_{00} is the loss coefficient constant.

The generation limit constraints are given as,

$$P_{\min(i)} \leq P_i \leq P_{\max(i)} \qquad (5.3)$$

$P_{\min(i)}$: Min. Power generation of i^{th} unit

$P_{\max(i)}$: Max. Power generation of i^{th} unit

Ramp rate limits are specified by the limits on the incremental rate of generation as,

$$P_{i\,t} - P_{i\,(t-1)} = UR_i \qquad and \; P_{i\,(t-1)} - P_{i\,t} = DR_i \qquad (5.4)$$

UR_i and DR_i are up ramp and down ramp limits of the i^{th} unit, which are in the units of MW/hr. In practice, DR_i is greater than UR_i.

In the next sections, some faster and efficient solution strategies to handle this allocation problem are proposed.

5.4 Learning Automata solution for Economic Dispatch

In Economic Dispatch problem, the Learner (Dispatcher) has to get the optimum generation of the N generating units so as to meet the power demand P_D. In order to develop a simple solution strategy, the transmission losses are neglected for the time being.

In this solution, optimum schedule is obtained for a single load demand in one learning procedure. This approach is similar to Genetic Algorithm, Simulated Annealing etc. The systematic approach suggested through Learning Automata seems to be better than Genetic Algorithm and Simulated Annealing. The solution procedure motivates the steps into Reinforcement Learning solution to Economic Dispatch.

Input to the decision making system is the amount of active power demand to be satisfied with the set of committed units. The different actions (decisions) possible can be treated as a set of vectors, where each action vector gives the loading of the different units (or in other words power combinations). This approach is similar to N arm bandit problem discussed previously.

The set of permissible actions (action set $\mathcal{A}$) is determined by taking into consideration the load demand and minimum and maximum limits of generation that can be met by each unit. A suitable discretization value for power increments is taken to generate the different power combinations or actions. For small values of discrete step, number of possible actions will increase.

Any action a_k is represented by a vector, $[P_{1k}, P_{2k} \ldots P_{Nk}]$, where $P_{1k}, P_{2k} \ldots P_{Nk}$ are the power allocation to the N units corresponding to action a_k such that,

$$\sum_{i=1}^{N} P_{i\,k} = P_D \text{ and}$$

$$P_{ik} \in \{P_{\min(i)}, P_{\min(i)} + S_a, P_{\min(i)} + 2S_a, \ldots\ldots\ldots P_{\max(i)}\}$$

Here, S_a is the discrete action step chosen.

Now the algorithm can be formulated to solve this learning automata problem. *ie,* to find the best action or optimum dispatch. The learning automata system learns through continuous taking up of actions and updating of the corresponding performance index. The values of the performance index associated with all the actions in the action set are first initialized with zero. One of the actions, $a_k \in \mathcal{A}$ is selected by the learning algorithm using any of the exploration strategies. In this case ε greedy selection strategy is used.

On applying the action a_k from the action set, the environment (the generating units) gives back a numerical value or reward equal to the cost of generation of power with the dispatch corresponding to a_k, $Cost(a_k)$.

$$Cost\,(a_k) = \sum_{i=1}^{N} C_i(P_{i\,k})$$

This numerical value can be used to update the performance index corresponding to action a_k, say $Q(a_k)$ as given by the equation:

$$Q^{n+1}(a_k) = Q^n(a_k) + \alpha\ [Cost(a_k) - Q^n(a_k)], \tag{5.5}$$

where α is the learning parameter

The learning parameter influences the convergence and correctness of the optimum values of the performance index. A large value of α will make the algorithm oscillatory. A very small value will slow down the convergence. By trial and error method, α is chosen as 0.1. The action selection and updating of performance index are repeated for sufficient number of times so that the values of the performance index will converge (change in the value become negligibly small) and afterwards the action with optimum (minimum) value of performance index will be chosen with highest probability. Therefore, once the learning system is converged, the optimum allocation (action) is found as:

$a^* = \text{argmin}_{a_k \in \mathcal{A}}\, Q(a_k)$, which is the greedy action itself.

The complete algorithm is given as RL_ED1.

Algorithm for Economic Dispatch using Learning Automata (RL_ED1)

Read the generating unit data

Initialize $\varepsilon = 0.5$ *and* $\alpha = 0.1$

Identify the demand to be met

Choose a suitable discretization step

Identify the max. no: of permissible actions 'm'

Generate the possible actions, $a_0 \ldots a_{m-1}$

Initialize $Q^0(a_k) = 0$, $0<k<m-1$

For (n=0 to max_iteration)

Begin

Select an action a_k *using* ε *greedy algorithm,*

using the current values of performance index

Calculate cost (a_k)

Update $Q^n(a_k)$ *to* $Q^{n+1}(a_k)$ *using eqn (5.5)*

End

Find the greedy action from the updated values of $Q(a_k)$, $0<k<m-1$

The Learning Automata method provides a very simple method of solving Economic Dispatch problem. When the number of generators increases, the action space becomes huge. This makes the computation difficult for finding the optimum dispatch even for a single load demand.

To handle the problem efficiently the Economic Dispatch is now formulated as a multi stage decision task. The states at each stage of the problem are discretised in terms of the demand to be met at each stage. Reinforcement Learning based solution strategies are proposed to find the best actions at each stage corresponding to the different states. Therefore as the next step, in the proposed method, Economic Dispatch is formulated as a multi stage decision making task.

5.5 Economic Dispatch as a multi stage decision problem

To view Economic Dispatch as a Multi stage decision making problem, the various stages of the problem are to be identified. Consider a system with N generating units committed for dispatch. Then Economic Dispatch problem involves deciding the amount of power to be dispatched by G_0, G_1, G_2,.....G_{N-1}.

In this formulation the amount of power to be dispatched by G_k is denoted as action a_k. Action a_k in Reinforcement Learning terminology corresponds to a power allocation P_k MW to generating unit G_k. P_k is numerically same as a_k. Therefore, the action set $\mathcal{A}_k$ consists of the different values of power dispatch possible to G_k. That is,

$\mathcal{A}_k = \{ Min_k, \ldots\ldots\ldots, Max_k \}$, Min_k being the minimum value of power that can be allotted to G_k and Max_k being the maximum power that can be allotted to G_k. Values of Min_k and Max_k depend on the minimum and maximum values of power generation possible with k^{th} unit and also maximum and minimum power that can be allotted among the remaining N - k units available. Therefore, action set $\mathcal{A}_k$ is a dynamically varying one depending on the power already allotted to the previously considered units.

The quantization step (in MW power) is chosen based on the accuracy needed. But a very small value is not necessitated due to the setting of the reference point setting in a plant. Therefore an optimum value is chosen based on the accuracy needed and the setting of the units. Also as number of generating units and hence the range of possible demand increases, the number of states in the state space increases. State space is also discretized to have definite number of states. For defining the same, an optimum value of step size is to be chosen so as to get the required accuracy keeping the number of states manageable.

Now the problem can be stated as follows: Initially there are N units and P_D MW of power to be dispatched. The initial state is denoted as $stage_0$. In $stage_0$, a decision is made on how much power is to be dispatched by G_0. This action is denoted as a_0 and corresponds to P_0MW allocation to G_0.

On making this decision, stage 1 is reached. Also $(P_D - a_0)$ MW of power remains to be allocated to the remaining $N-1$ units (G_1 , G_2, ...G_{N-1}). In $stage_1$, a decision a_1 is made on how much power is to be dispatched to G_1. Similarly at stage k, a decision is made on how much power is to be dispatched by G_k. Thus, the stage $N-1$ is reached where the amount of power to be dispatched by G_0, G_1, ...G_{N-2} are already decided as $(a_0, a_1, \ldots a_{N-2})$ which give directly the power allocations $(P_1, P_2, \ldots\ldots\ldots P_N)$.

From the power balance constraint (with $P_L = 0$), it follows that, $P_0+P_1+P_2+\ldots\ldots P_{N-1} = P_D$ which directly implies that

$$P_{N-1} = P_D - (P_0+P_1+P_2+\ldots\ldots\ldots P_{N-2})$$

Therefore, in $stage_{N-1}$, there is no choice but to allocate power P_{N-1} or take action a_{N-1}.

Each state at any $stage_k$ (k varies from 0 to $N-1$) can be defined as a tuple (k, D_k) where k is the number indicating the stage number and D_k , the power to be distributed among the remaining $N - k$ units.

That is, with $k = 0$, the state information is denoted as $(0, D_0)$ where D_0 is the load demand P_D for Economic Dispatch among the N generating units. The RL algorithm selects one among the permissible set of actions (between max. and min. power limits corresponding to one of the unit) and allocates to the particular machine considered so that it reaches the next stage $(k = 1)$ with the remaining power after allocation, and $N-1$ units for generation. Transition from $(0, D_0)$ on performing an action $a_0 \in \mathcal{A}_0$ results in the next state reached as $(1, D_1)$.

$$D_1 = D_0 - a_0$$

Or in general, in stage k, from state x_k on performing an action a_k reaches state x_{k+1}. ie, state transition is from (k, D_k) to $(k+1, D_{k+1})$, where

$$D_{k+1} = D_k - a_k \tag{5.6}$$

This proceeds until the last stage. Therefore, state transition can be denoted as,

$$x_{k+1} = f(x_k, a_k),$$

'f' being the function of state transition defined by equation (5.6).

Thus, Economic Dispatch algorithm can be treated as one of finding an optimum mapping from the state space χ to action space (possible discrete power allocation values) $\mathcal{A}$. The associative nature of the problem arises from the fact that each action denotes distribution of power to one unit so that the power to be distributed among the remaining units reduces by that much amount. Design of Economic Dispatch algorithm is finding or learning a good or optimal policy (allocation schedule) which is the optimum allocation at each stage. Such allocation can be treated as elements of an optimum policy π^*. For finding the net cost of generation, cumulate the costs at each of the N stages of the problem. These costs can be treated as reward of performance of an action in the perspective of Reinforcement Learning. The net cost of generation on following a policy π can be treated as a measure of goodness of that policy. Q learning technique is employed to cumulate costs and thus find out the optimum policy.

5.6 RL Algorithm for Economic Dispatch using ε- greedy strategy

In the previous section, Economic Dispatch is formulated as a multi stage decision making problem. To find the best policy or best action corresponding to each state, Reinforcement Learning strategy is used. Solution consists of two phases: learning phase and policy retrieval phase.

To carry out the learning task, one issue is regarding how to select an action from the action space. The two commonly used action selection methods are ε - greedy and pursuit. In this section, ε greedy strategy of exploring action space is used and the

developed solution is termed as RL_ED2. Pursuit action selection is used to develop the learning algorithm in the next section (RL_ED3).

For solving this multi stage problem using Reinforcement Learning, first step is fixing of state space χ and action space $\mathcal{A}$ precisely. The different units can be considered arbitrarily as corresponding to the different stages.

Fixing of state space χ primarily depends on number of generating units available on line and the possible values of power demand (which in turn directly depends on min. and max. values of power generation possible with each unit). Since there are N stages for solution of the problem, the state space is also divided into N subspaces. Thus, if there are N units to be dispatched,

$$\chi = \chi_0 \mathrm{U}\, \chi_1 \mathrm{U} \ldots\ldots\ldots \chi_{N-1}.$$

The dispatch problem should go through N (no: generating units) stages for making allocation to each of the N generating units. At any stage $(stage_k)$, the part of state space to be considered (χ_k) consists of the different tuples having the stage number as k and power values varying from $D_{min(k)}$ to $D_{max(k)}$, $D_{min(k)}$ being the minimum power possible to be met and $D_{max(k)}$ the maximum power possible at k^{th} stage (with N - k units).

That is, $\chi_k = \{(k, D_{min(k)}), \ldots\ldots\ldots (k, D_{max(k)})\}$

where $D_{min(k)}$ =Minimum power possible with N - k units

$$= \sum_{i=k}^{i=N-1} P_{\min(i)}$$

$D_{max(k)}$ = maximum power possible with N - k units

$$= \sum_{i=k}^{i=N-1} P_{\max(i)}$$

At each step, the Economic Dispatch algorithm will select an action from the permissible set of discretised values and forward the system to one among the next permissible states.

The action set $\mathcal{A}_k$ consists of different values of MW power that can be allotted to k^{th} unit. The action set $\mathcal{A}_k$ depends on the demand value D_k at the current state x_k and also on the minimum and maximum power generation possible with remaining $N - k$ units. Therefore action set $\mathcal{A}_k$ is dynamic in nature in the sense that it depends on the power already allotted up to that stage and also the minimum and maximum generation possible with the remaining N-k units. If D_k is the power to be allotted, minimum value and maximum value of action a_k are defined as

$$Min_k = max\ [(D_k - \sum_{i=k+1}^{i=N-1} P_{max\,(i)}),\ P_{min(k)}]$$

$$Max_k = min\ [(D_k - \sum_{i=k+1}^{i=N-1} P_{min\,(i)}),\ P_{max(k)}] \tag{5.7}$$

The number of elements in these sets χ and $\mathcal{A}$ depends on the minimum and maximum limits and also the sampling step.

For updating the Q value associated with the different state – action pairs, one should cumulate the cost at different stages of allocation in a proper way, by taking into account the associative nature of the problem. In Economic Dispatch problem, the reward function *(g)* can be chosen as the cost function itself. That is, Reward received or cost incurred on taking an action a_k or allocating a power P_k at k^{th} stage is the cost of generation of the power P_k. In the Reinforcement Learning terminology, the immediate reward,

$$r_k = g(x_k, a_k, x_{k+1}) = C_k(P_k) \tag{5.8}$$

Since the aim is to minimize the cost of generation estimated Q values of state-action pair are modified at each step of learning as,

$$Q^{n+1}(x_k, a_k) = Q^n(x_k, a_k) + \alpha\,[\,g(x_k, a_k, x_{k+1}) + \min_{a' \in \mathcal{A}_{k+1}} Q^n(x_{k+1}, a') - Q^n(x_k, a_k)] \tag{5.9}$$

Here, a is the learning parameter and γ is the discount factor.

When the system comes to the last stage of decision making, there is no need of accounting the future effects and then the estimate of Q value is updated using the equation,

$$Q^{n+1}(x_k, a_k) = Q^n(x_k, a_k) + \alpha\,[\,g(x_k, a_k, x_{k+1}) - Q^n(x_k, a_k)] \tag{5.10}$$

For finding an optimum policy, a learning algorithm is designed which will go through each of the N stages at each step of learning. As the learning steps are carried out sufficient number of times, estimated Q values of state-action pairs will approach to optimum so that we can easily retrieve the optimum policy (allocation) $\pi^*(x)$ corresponding to any state x.

The learning procedure can now be summarized. At each iteration of learning phase the algorithm will take the system initial condition (ie, for $k = 0$) which is the power demand, as one random value within permissible limits. Then an action is performed which will allocate power to one of the units and then pass to the next stage ($k = 1$) with the remaining power. This proceeds until all the N-1 units are allotted power. At each state transition step, the estimated Q value of the state – action pair is updated using equation (5.9).

As the learning reaches the last stage, since there is no choice of action, the remaining power to be allotted will be the power corresponding to the action ($a_{N-1} = D_{N-1}$). Then the Q value is updated using equation (5.10). The transition process is repeated a number of times (iterations) with random values of initial demand and each time the dispatch process goes through all the N-1 stages. Value of ε is taken closer to 0.5 in the initial phases of learning and is reduced in every max_iteration/10 iterations by 0.04.

The entire algorithm of Learning is given as RL_ED2:

Algorithm for Economic Dispatch using ε greedy (RL_ED2)

Get Unit parameters

Initialize the learning parameters

For all the stages Identify possible state vectors, χ_k

Evaluate minimum and maximum demands permissible at each stage

Initialize $Q^0(x, a)$ *to zero*

Initialize $\varepsilon = 0.5$

For (n = 0 to max_iteration)

Begin

$P_D = rand\ (Dmin_0, Dmax_0),\ D_0 = P_D$

For $k = 0$ *to N-2*

Do

State tuple $x_k = (k, D_k)$

Identify the action space $\mathcal{A}_k$ *using eqn. (5.7)*

Select an action a_k *from action set* A_k

using ε- greedy method.

Apply action a_k *and allot power to* k^{th} *unit,*

$$D_{k+1} = D_k - a_k$$

Calculate the reward function $g(x_k, a_k, x_{k+1})$

using eqn.(5.8)

Update Q^n *to* Q^{n+1} *using eqn. (5.9)*

End do

$a_{N-1} = D_{N-1}$

Calculate the reward using eqn. (5.8)

Update Q^n *to* Q^{n+1} *using eqn. (5.10)*

Update learning parameter ε.

End.

Save Q values.

The performance of the algorithm is evaluated for several standard test systems.

5.7 Pursuit algorithm for Economic Dispatch (RL_ED3)

As explained before, in case of pursuit algorithm, for any given state x_k, an action is selected based on the probability distribution function $p_{x_k}()$. In the case of Economic Dispatch, initially the probability associated with each action a_k in the action set $\mathcal{A}_k$ corresponding to x_k are initialized with equal values as

$$p_{x_k}(a_k) = \frac{1}{n_k}$$

where n_k is total number of permissible actions at stage k. As in the previous algorithm, initialize the Q values of all state – action pairs to zero. That is,

$$Q^0(x, a) = 0 \ \forall x \in \chi_k \text{ and } \forall a \in \mathcal{A}_k, \qquad 0 <= k <= N-1$$

Then at each iteration step, an action a_k is selected based on the probability distribution. On performing action a_k, it reaches the next stage with $D_{k+1}=D_k - a_k$. The cost incurred in each step of learning is calculated as the sum of cost of producing power $P_k(P_k = a_k)$ with the k^{th} generating unit. Q values are then updated using the equation (5.9). At each of the iteration of learning, we find the greedy action as $a_g = argmin_{a \in \mathcal{A}_k}(Q(x_k,a))$. Then accordingly the probabilities of actions in the action set are also updated as,

$$p_{x_k}^{n+1}(a_k) = p_{x_k}^{n}(a_k) + \beta\left[1 - p_{x_k}^{n}(a_k)\right], when\ a_k = a_g$$

$$p_{x_k}^{n+1}(a_k) = p_{x_k}^{n}(a_k) - \beta\left[p_{x_k}^{n}(a_k)\right], when\ a_k \neq a_g \qquad (5.11)$$

The algorithm proceeds through several iterations when ultimately the probability of best action in each hour is increased sufficiently which indicate convergence of the algorithm. First the learning is carried out to find the maximum number of iterations required, checking the updating of Q values in 100 successive iterations. The entire algorithm is given as RL_ED3.

Algorithm for Economic Dispatch using Pursuit method (RL_ED3)

Get Unit parameters

Initialize learning parameters

For all the stages Identify possible state vectors, χ_k

Evaluate minimum and maximum demands permissible

Initialize $Q^0(x_k, a_k)=0$

Initialize $p_{x_k}(a_k) = 1/n_k$, n_k *maximum number of actions possible in* $\mathcal{A}_k$

For (n=0 to max_iteration)

Begin

P_D = *rand* ($Dmin_0$, $Dmax_0$), $D_0 = P_D$

For $k = 0$ *to N-2*

Do

State tuple $x_k = (k, D_k)$

Identify the action space $\mathcal{A}_k$ *using eqn. (5.7)*

Select an action a_k *using* $p_{x_k}()$

Apply action a_k *and find the next state,* $D_{k+1} = D_k - a_k$

Calculate the reward function $g(x_k, a_k, x_{k+1})$ *using eqn.(5.8)*

Update Q^n *to* Q^{n+1} *using eqn. (5.9)*

Update probability $p^n_{x_k}(a_k)$ *to* $p^{n+1}_{x_k}(a_k)$ *using eqn.(5.11)*

End do

$a_{N-1} = D_{N-1}$

Calculate the reward using eqn (5.8)

Update Q^n *to* Q^{n+1} *using eqn (5.10)*

Update probability $p^n_{x_k}(a_k)$ *to* $p^{n+1}_{x_k}(a_k)$ *using eqn. (5.11)*

Update learning parameter ε

End.

Save Q values.

This exploration strategy updates the probability of selecting an action at each stage. As the learning proceeds the greedy action will turn to be having higher probability of selection compared to others. This leads to easy convergence compared to ε - greedy strategy.

5.8 Policy retrieval

As the learning proceeds and updating of Q values of state – action pairs are done sufficiently large number of times, Q' will be almost equal to Q^*. Then the optimum Q values are used to obtain the optimum dispatch. For any value of power demand P_D, initialize $D_0 = P_D$. Then the state of the system is $(0, D_0)$. Find the greedy action at this stage as a_g which is the best allocation for 0^{th} generating unit (P_0). The learning system reaches the next state as $(1, D_1)$ where $D_1 = D_0 - a_0$, find the greedy action corresponding to stage$_1$ as a_1. This proceeds up to $(N-1)^{th}$ stage. Then a set of actions (allocations) $a_0, a_1, a_2, \ldots\ldots a_{N-1}$ is obtained which is the optimum schedule P_0, $P_1, \ldots\ldots P_{N-1}$ of generation corresponding to power P_D. The algorithm for getting the schedule from the learnt system follows:

Policy retrieval algorithm:

Initialize P_D = Total power to be dispatched
$D_0 = P_D$
For (k=0 to N-1)
    Do
        State tuple $x_k = (k, D_k)$
        Find greedy action $a_g = \text{argmin}_a (Q(x_k, a))$
        Scheduled Power $P_k = a_g$
        $D_{k+1} = D_k - P_k$
    End do

Thus, on executing the learning algorithm and then retrieving the schedule by finding the greedy action corresponding to the input power to each stage of the

multi stage decision making task, optimum schedule is obtained for any value of load demand.

Till now, the transmission losses in the system are neglected. Now the Reinforcement Learning approach is extended in order to accommodate the transmission losses occurring in the system.

5.9 RL algorithm considering Transmission Losses

The loss in a transmission network can be estimated by executing power flow algorithm or can be approximated using B – Matrix Loss formula. In order to find the schedule accounting the transmission losses, one of the previous algorithms can be used to carry out the learning steps. For simplicity of introducing the extended method ε- greedy strategy is employed for learning the system, generating random values of initial demand. Once the learning phase is completed, the policy retrieval steps provide us with the optimum schedule for any load value. In order to incorporate the transmission losses, the learning is carried out first and policy retrieval is done successively for different values of load values, accounting the losses.

First learn the Q value for the different state action pairs. Schedule for the required load demand is retrieved by policy retrieval phase. For the schedule obtained, transmission losses are calculated by either finding the power flows or using B matrix loss formula. The input demand is then modified by adding the calculated loss MW. The learning algorithm proceeds to find the dispatch for the new demand value, giving out the new schedule of generation. This new power allocation will certainly give a new value of transmission loss, which is again used for updating the demand.

The iterative procedure is continued until the loss calculation converges (indicated by the change in loss in two successive iterations coming within tolerable limits). By following these steps iteratively for different load values ranging from $D_{min\,(0)}$ to $D_{max(0)}$, economic allocation schedule for the entire range of possible demand (with the given generating units) is obtained. Algorithm incorporating transmission

loss to find the schedule for all the possible values of load demand is presented in RL_ED4.

Algorithm for Economic Dispatch considering transmission losses (RL_ED4)

Get unit parameters including B- coefficient matrix of the system

Learn the Q values using RL_ED2

Calculate the range of load values possible $D_{min\ (0)}$ *to* $D_{max\ (0)}$

Initial load $P_D = D_{min\ (0)}$

Do

Initialize P_{loss} *and Prev_loss to zero*

Initialize final loss tolerance to a small value μ

Initialize change in loss (?) to zero

Do

Prev_loss = P_{loss}

Find the allocation corresponding to P_D *using the policy retrieval*

Find the loss using B coefficients as P_{loss}

Update $P_D = P_D + P_{loss}$

Compute change in loss ? = P_{loss} - *prev_loss*

while (? > μ*)*

Increment the load P_D *with suitable discrete step value.*

While (P_D <= $D_{max\ (0)}$)

The discrete step for load MW is taken as 10 MW so as to manage the number of states at each stage of the problem. Value of μ is taken as 1MW so that transmission loss, less than that can be neglected compared to the load power. Once the learning phase is completed, the economic allocation for all the possible load values can be obtained instantaneously. The main attraction of these algorithms comes from the fact that the learning is carried out only once and need not be repeated for each load demand as in other stochastic methods.

The learning algorithms discussed in the previous sections have one limitation. The input to each stage k of the multi stage problem is the amount of power to be dispatched among remaining N - k units. This input power is discretized in order to get definite number of states at each stage of the problem. If the discretization step is chosen to be a larger value, accuracy of the result will suffer while a smaller value needs longer computation time. In order to make the algorithm more efficient accounting the continuous value of input at each stage, a function approximation strategy is proposed in the next section

5.10 Neural Network based solution using Reinforcement Learning

The previous algorithms using Reinforcement Learning is based on finding a policy or mapping from finite set of states to finite set of actions. Learning is carried out as a multistage process, taking an action from the available action set when the learning system is in any of the possible states in the state space. Initially, the state of the system is represented by a tuple $(0, P_D)$, P_D being the power to be allocated among the N generating units. The learning proceeds by allocating certain amount of power to one of the units and proceeding to successive stages until all the units are allocated. At each step of learning, Q value corresponding to state –action pair is modified according to the reward (cost of generation) of the action. Finally the Q values approach to optimum and using the look up table of Q values, the optimum policy is retrieved as a mapping of generating unit to power allocation corresponding to an input load value.

One limitation of this algorithm is that the state and action spaces are discretised with certain value of step size. This may give some inaccurate result when the discretization step is to be made large in the case of larger ranges of demand values. Therefore one issue to be resolved is to somehow incorporate continuous nature for the power input values at each of the stages in the multi stage solution process so that solution is more efficient. One method that can be introduced is to use some form

of function approximation strategy in the learning process. In the next sections the method of solution using function approximation strategy is presented.

5.10.1 Q learning through Function Approximation

When a continuous state space is considered, the state variable can take any value in the continuous state space. Function approximation provides with a strategy in which quantization of state space is not necessary. When Q learning technique is used, Q values with respect to continuous state space are to be stored somehow. One important fact is, in such cases Q values cannot be stored in a look up table, since the values of state variable being of continuous nature. One solution is to construct a function which will approximate the Q values at different cases based on some parameters. That is, continuous state is denoted as x and represent Q values using a parameterized class of functions $Q(x, a, \theta)$, where θ is the parameter vector. With the parameterized function to approximate Q value, Q – learning or learning optimum Q values is to learn the optimum parameter vector θ^* so that $Q(x, a, \theta^*)$ is a good approximation of $Q^*(x, a)$, $\forall x \in \chi$, and $\forall a \in \mathcal{A}$ (Sutton and Barto [1998], Imthias *et al.*[2006]).

Therefore for making this learning through parameterized function possible, first a suitable architecture or class of functions $Q(x, a, \theta)$ that is well suited for our learning problem is to be decided. Secondly formulate a learning algorithm to get optimum value of the parameter vector θ^* which will give optimum Q value, $Q^*(x, a, \theta)$.

In the literature, a variety of parameterized functions are found which can be used for function approximation. Recently Neural Networks are being popularly used for function approximation due to their extensive learning capability even with non linear functions (Haykin [2002]).

Now, it is required to develop an algorithm to solve Economic Dispatch problem using Reinforcement Learning and making use of a function approximating network so that continuous nature of input variable can be accounted at each stage.

Then the algorithm will ultimately give a policy which is a mapping from the continuous state space to discrete action space. For the same, as told earlier, the Q values are represented using a parameterized class of functions $Q(x, a, \theta)$, where θ is the parameter vector. The class of functions used is the Radial Basis Function network, a category of Neural Network well suited for function approximation. The outputs of this network represent the Q – values.

When Neural Networks are used, mostly supervised learning is employed to train the network or adjust the weight vector elements. In such a case, a set of training samples are needed which can be used to adjust the weight vector values. In the case of Q learning, if supervised learning is employed one should be previously occupied with a set of N training samples of the form,

$\{(x_k, a_k): Q(x_k, a_k), k = 1, \ldots\ldots\ldots, N, x_k \in \chi, a_k \in \mathcal{A}\}$ in order to learn the optimal weight values. Then the learning will turn to be a gradient descent method such that $\{Q(x_k, a_k) - Q^*(x_k, a_k)\}$ is minimized. But in this case, such method is impractical, since the exact values for $Q^*(x_k, a_k)$ is not known for any (x_k, a_k) pair. Thus supervised mode of learning cannot be used to get the optimal weight vector of RBF network which is going to be used as a function approximating network in the Q learning method. A set of values of the form$\{(x_k, a_k, x_{k+1}), g(x_k, a_k, x_{k+1})\}$, where x_k is the current state, a_k is the current action , x_{k+1} is the succeeding state of applying action a_k and $g(x_k, a_k, x_{k+1})$ is the reward corresponding to the particular transition of state, are available. Now this information or set of examples can be used in some way to learn the neural network for optimum weight adjustment. For the same, Reinforcement Learning is used effectively so that optimum value of the parameter vector θ^* is obtained resulting in optimum Q values. For exploring the action space, just like in the previous algorithm ε - greedy method is employed for action selection.

In our problem of Economic Dispatch, demand at each stage can be considered as continuous. That is input power D_i to each of the stage is a continuous quantity and the action at each stage (allocation to one particular unit) a_i is discrete. The objective is to get a policy, which is a mapping from the continuous demand space to discrete

power allocation space. Learning optimal Q values involve learning the optimal parameter vector θ^* such that $Q(D, a, \theta^*)$ is a good approximation of $Q^*(D, a)$. Radial Basis Function (RBF) neural network is used to store the same.

5.10.2 Architecture of RBF Network

In this section, a novel architecture of the RBF network is proposed to store the Q – values in the context of Economic Dispatch. Q – values of each stage is stored in one RBF network. Thus for an N unit power system (N stage decision making problem), there are N RBF networks. RBF network of all stages consist of an input layer, hidden layer and an output layer. The input layer is made up of a single node for connecting the input variable to the network. The hidden layer consists of m_i hidden nodes. This layer applies a non linear transformation from the input space to the m dimensional hidden space, $\Re^m$. The output layer consists of n_i linear nodes which combine the outputs of hidden nodes (Haykin [2002]).

The architecture of the RBF network for the first stage is given in Fig 5.3

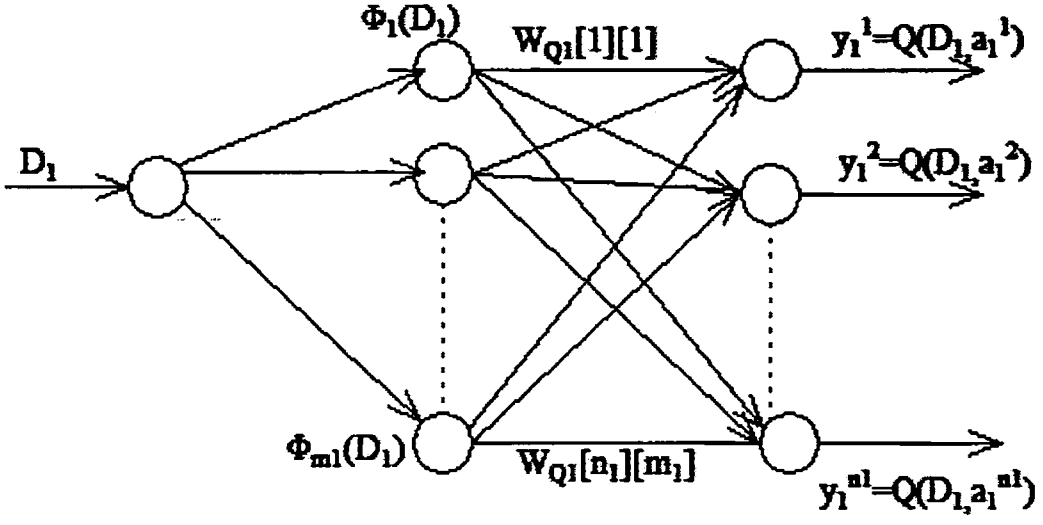


Fig 5.3 RBF network for Stage 1.

The input to this RBF network is D_1, the total power to be supplied by generators G_1, G_2, ...G_N and output of the RBF network after learning is $Q^*(D_1, a_1^1), Q^*(D_1, a_1^2), \ldots\ldots\ldots\ldots\ldots Q^*(D_1, a_1^{n_1})$, where a_1^1, a_1^2, ... $a_1^{n_1}$ are the different actions possible at stage 1.

Similarly, the input to the RBF network of k^{th} stage is the power to be allocated to generators G_k, G_{k+1},.....,G_N, which is denoted as the state of the system D_k. Also,

$$D_k = D_{k-1} - a_{k-1}^*$$

The output of this network is $Q(D_k, a_k^1), Q(D_k, a_k^2), \ldots\ldots\ldots\ldots, Q(D_k, a_k^{n_k})$ where n_k is the number of actions or power allocations possible at k^{th} stage. The i^{th} output of the RBF network at k^{th} stage is given by the expression:

$$y_k^i = \sum_{j=1}^{j=m_k} W_{Q_k}[i][j]\phi_j[D_k] \tag{5.12}$$

where W_{Q_k} is $n_k x\, m_k$ matrix of reals, and $W_{Q_k}[i][1], \ldots\ldots, W_{Q_k}[i][m_k]$ are the weights of the i^{th} output unit; and $\{\phi_j : \mathcal{R}^r \rightarrow \mathcal{R}, j = 1,.....m_k\}$ is a set of m_k radial basis functions which constitute the m_k hidden units at k^{th} stage.

One can use the Gaussian function as the RBF. Then the output of j^{th} RBF (ie, j^{th} hidden unit) at k^{th} stage is given by,

$$\phi_j(D_k) = \exp\left((D_k - c_k^j)^2\right)/2\sigma_k^2) \tag{5.13}$$

where c_k^j is the centre of j^{th} RBF at k^{th} stage and σ_k is the width of the RBF at k^{th} stage.

Substituting $\phi_j(D_k)$ from equation (5.13) to equation (5.12) we get,

$$Q(D_k, a_k, \theta) = y_k^i = \sum_{j=1}^{j=m_k} W_{Q_k}[i][j]\exp\left((D_k - c_k^j)^2\right)/2\sigma_k^2) \tag{5.14}$$

where $i = 1,....n_k$. The RBF network at k^{th} stage described above is thus completely specified by the parameter vector

$$\theta = [c_k, \sigma_k, W_{Q_k}]$$

where

$$c_k = [c_k^1, c_k^2, \ldots\ldots\ldots\ldots\ldots c_k^{m_k}]$$

$$\sigma_k = [\sigma_k^1, \sigma_k^2, \ldots\ldots\ldots\ldots\ldots \sigma_k^{m_k}]$$

$$W_{Q_k} = \{ W_Q[i][j], i = 1, \ldots\ldots, n_k, j = 1, \ldots\ldots\ldots, m_k\}$$

Thus, finding a good approximation of the Q value using the RBF network involves finding the optimum parameter vector $\theta^* = [c^*, \sigma^*, W^*]$.

5.10.3 Learning Algorithm for Economic Dispatch (RL_ED5)

From the previous section it is concluded that finding the optimum parameter vector, $\theta^* = [c^*, \sigma^*, W^*]$ is the task to be resolved in finding the good approximation of the Q value function. Next is, how to find the optimal parameters c^*, σ^* *and* W^*.

In the RBF network described above, adjusting the weights associated with a given basis function, say j^{th} basis function at k^{th} stage , will affect the value of the output only in a small region around the centre of j^{th} RBF, c_k^j . (For a value of input $D_k \in \mathcal{R}$, away from c_k^j, $\exp((D_k - c_k^j)^2/2\sigma_k^2)$ will be almost zero. This feature of RBF network structure which indicates that each hidden layer neuron can be viewed as approximating the target function over a small region around its centre makes it possible to place the centres on a uniform grid spacing in order to get a better interpolation of the input.

In the case of Economic Dispatch problem, first fix the number of hidden units based on the generation limit constraints. The input to this k^{th} RBF network is the fraction of the power demand D_k yet to be distributed among the remaining $N - k$ units. Therefore, number of hidden units in each RBF network basically depends upon

the maximum and minimum possible demand at that particular stage. i.e., for k^{th} stage, it depends on the values of $D_{min(k)}$ and $D_{max(k)}$.

For the first stage or first RBF network, the input will be equal to the power demand P_D. *i.e.*, $D_1 = P_D$.

Minimum and maximum ranges of power demand possible are calculated as discussed previously. The number of uniformly distributed centres (hidden nodes) m_1 at this stage is decided by the range of $D_{min(1)}$ *to* $D_{max(1)}$. Similarly for k^{th} stage, the number of hidden nodes is decided by $D_{min(k)}$ and $D_{max(k)}$.

Once the number of hidden nodes is fixed, find the distance between centres of Gaussian functions as,

$g_k = (D_{max(k)} - D_{min(k)}) / (m_k - 1)$

m_k – Number of RBF centres at k^{th} stage.

Then the optimal values for the m_k centres of the k^{th} RBF network (c_k^*) are chosen uniformly distributed between $D_{min(k)}$ and $D_{max(k)}$ as

$\{ D_{min(k)}, D_{min(k)} + g_k, \ldots\ldots\ldots\ldots\ldots\ldots D_{max(k)} \}$

Next is to find the optimum values for the width of the RBF networks at the different stages. Since the centres of the Gaussian functions form a uniform grid, width of the Gaussian function (σ) is taken as a suitable multiple of the distance between the centres. This multiplication factor decides the percentage overlapping between the successive functions. Thus width of the Gaussian distribution functions is calculated as:

σ = spread factor * distance between centres, where spread factor is the multiplication factor chosen to provide sufficient overlapping between successive Gaussian functions. The spread factor can be chosen in the range 0.5 - 1 based on the complexity of the problem.

Since the values for c_i^* and σ_i^* are fixed, the task of learning now reduced to finding the optimum value for the third element in the optimum parameterised vector θ^* or $W_{Q_k}^*$. In other words, problem reduces to learning the Neural Network for the optimum values of the weight matrix $W_{Q_k}[i][j], i = 1, \ldots\ldots, n_k, j = 1, \ldots\ldots\ldots\ldots, m_k$.

As mentioned earlier one can use of Q – learning strategy for getting the optimum values for the parameter $W_{Q_k}^*$.

The network has to learn for the optimal values of the weight elements $W_{Q_k}[i][j]$ such that y_k^i would be a good approximation of $Q^*(D_k, a_k^i)$. If the Q^* values are known for each stage corresponding to a large number of state action pairs, the learning of the network is an easier task since one can go for supervised learning of the weight matrix $W_{Q_k}^*$. But the Q values in the initial stage are unknown and therefore one cannot proceed in this direction. Q learning strategy is made use of to make the network learn for the optimum values of weight matrix.

In the standard Q learning method, updating of Q value at each iteration 'n' is given by the equation:

$$Q^{n+1}(x_k, a_k) = Q^n(x_k, a_k) + \alpha[(g(x_k, a_k, x_{k+1}) + \gamma \min_{a' \in \mathcal{A}_{k+1}} Q^{n+1}(x^{k+1}, a') - Q^n(x_k, a_k)] \quad (5.15)$$

In the problem of Economic Dispatch, the next state or input to the next stage is easily found out as,

$D_{k+1,} = D_{k,} - a_k^i$,where a_k^i is the power allocation denoted by the action performed at k^{th} stage. That is, on selecting an action a_k^i from the action space $\mathcal{A}_k$, input to the next RBF network is modified as the remaining power yet to be allocated.

In this context, for learning the weight vector elements, Q learning method is formulated for modification of the weights. In the network, if the current state is D_k and the action is a_k^i, the updating has to be localized to the output node,

$y_k^i = Q(D_k, a_k^i)$ or in other words the weight values connected to y_k^i need only be modified while keeping the remaining weight values unchanged.

Since $y_k^i = \sum_{j=1}^{j=m_k} W_{Q_k}[i][j]\, \emptyset_j(D_k)$, to change y_k^i, $W_{Q_k}[i][j]$, $j = 1, \ldots\ldots\ldots, m_k$ need to be modified. Therefore updating equations for Economic Dispatch problem for each of the *N-1* stages are summarised as,

$$W_{Q_k}^{n+1}[i][j] = W_{Q_k}^{n}[i][j] + \Delta W_{Q_k}^{n}[i][j], \qquad j = 1, \ldots\ldots\ldots, m_k$$

(5.16)

$$W_{Q_k}^{n+1}[i][j] = W_{Q_k}^{n}[i][j], \qquad j = 1, \ldots\ldots\ldots, m_k \text{ and } l = 1, \ldots\ldots, n_k, l \neq i$$

(5.17)

$\Delta W_{Q_k}^{n}[i][j]$ is given by the Q learning algorithm as:

$$\Delta W_{Qk}^{n}[i][j] = \alpha\Big(g(\mathrm{D_k}, a_k, \mathrm{D_{k+1}}) + \gamma\, min_{\mathrm{a'}\in\mathcal{A}_{k+1}} \mathrm{Q_{k+1}^{n}}(\mathrm{D_{k+1}}, \mathrm{a'}) - Q^{n}(\mathrm{D_k}, \mathrm{a_k})\Big)\emptyset_j(\mathrm{D_k})$$

The reward, $g(\mathrm{D_k}, a_k, \mathrm{D_{k+1}})$ is the cost of generation of power corresponding to action a_k. For the last stage *(k = N - 1)* since there is no choice of action but to allocate the power D_{N-1} itself, i.e, action $a_{N-1} = D_{N-1}$. Therefore update equation is expressed as:

$$W_{Q_k}^{n+1}[i][j] = W_{Q_k}^{n}[i][j] + \Delta W_{Q_k}^{n}[i][j], \; j = 1, \ldots\ldots\ldots, m_k$$

where, $$\Delta W_{Qk}^{n}[i][j] = \alpha[cost(a_k) - Q^{n}(\mathrm{D_k}, \mathrm{a_k})]\emptyset_j(D_k)$$

(5.18)

The weight values are updated iteratively during the learning phase. At the end of learning, Q values will be approaching to optimum. The selection of Gaussian distribution function as the functions defining the hidden nodes, make the updating a localized task which in turn improves the computational efficiency.

Once the learning is completed and the weight vector elements are converged, the allocation schedule is obtained by just retrieving the action element at each stage which corresponds to minimum Q values (greedy action). Thus the entire algorithm for finding the optimum allocation schedule is having two phases as in previous cases: learning phase and policy retrieval phase. Learning phase is given as RL_ED5.

Function Approximation algorithm for Economic Dispatch (RL_ED5)

Read the parameters of the RL algorithm

Read the Generating unit details

Read the demanded load power to be dispatched P_D

Fix suitable number of hidden nodes for each RBF network

Initialize input to the first RBF network $D_1 = P_D$

For each of the N stages

Do

Find the different centres of the RBF network

Find the set of actions at each stage

(number of output nodes for each network)

Initialize all the weight vector elements as zero

End do

For iteration =1 to max_iteration

Begin

For $k = 0$ *to N-2*

Do

Select an action a_k^i *from the action set* $\mathcal{A}_k$ *using e - greedy strategy and check the feasibility of action*

For a feasible action a_k^i, *Find the cost of generation Cost* (a_k^i)

Update the weight vector elements using eqn. (5.16)

Update the input parameter $D_{k+1} = D_k - a_k^i$

Enddo

$a_{N-1} = {}^{D}{}_{N-1}$

Find the cost of generation Cost (a_{N-1})

Update the weight vector elements connected to y_{N-1} *using eqn. (5.18)*

End.

Once the learning is completed, the allocation schedule corresponding to any load value can be found by the policy retrieval phase as explained before, by finding the greedy action at each stage.

5.11 Performance of the Algorithms

The proposed Economic Dispatch algorithms are assessed using different standard test cases. RL based Economic Dispatch can be applied for finding the schedule for generating units when the cost of generation is provided in any of the different forms like variable cost table, cost coefficient, non convex cost functions and actual cost data from a plant. This becomes useful when the cost of power varies in every block of time since the availability of power is practically a dynamic one.

Algorithms are coded in C language and compiled and executed in GNU Linux environment. Performance evaluation is done with Pentium IV, 2.9 GHz, 512 MB RAM personal computer.

In order to validate the proposed algorithms and make a comparison among them, first a three generator system with cost data given in a tabular form is considered (Wood and Wollenberg [2002]). The first three algorithms are executed to find the dispatch and a comparison of execution time is made.

Then IEEE 30 bus system with six generating units is taken in order to prove the efficacy of the proposed approaches. The suitability of the proposed algorithms for a system having generating units with piecewise cost functions is studied by considering a 10 generator system. In the case of Reinforcement Learning algorithms, there is no need of getting exact cost functions. It is evident from the execution results for the stochastic cost details.

The last two algorithms are validated and compared with the other recent methods like simulated annealing and partition approach algorithm by considering a standard test case, IEEE 6 bus system with three generators. The flexibility of the proposed approach is investigated for system with 20 generating unit having given cost functions.

In order to apply Reinforcement Learning algorithms, first the learning parameters are to be fixed based on the problem environment. The learning parameter ε accounts for rate of exploration and exploitation needed. Since it indicates a probability, it can take any positive value less than 1. A small fixed value may result in premature convergence of the learning algorithm while a large fixed value may make the system oscillatory. Therefore in these RL based algorithms, a value of 0.5 is assumed initially providing sufficient exploration of the search space and is decreased by a small factor successively.

Discount parameter γ accounts for the discount to be made in the present state for accounting of future reinforcements and since in the case of Economic Dispatch problem, the cost of future stages has the same implication as the cost of the current stage, value of γ is taken as 1.

The step size of learning is given by the parameter α and it affects the rate of modification of the estimate of Q-value at each iteration step. By trial and error α is taken as 0.1 for achieving sufficiently good convergence of the learning system. The RL parameters used in the dispatch problem are also tabulated in Table 5.1

Table 5.1 – RL Parameters

ε	*0.5*
α	*0.1*
γ	*1*

Case I – Three Generator system

First a simple example with three generating units (Wood and Wollenberg [2002]) is considered for validating and explaining the RL approach of solution. The transmission losses are neglected in this case. The cost details are given in tabular

form, which can be obtained from experience in case of a practical system. The unit characteristics are given in Table 5.2, where C_i stands for the cost of generating P MW by i^{th} unit.

Table5.2 – Cost Table for three generator system

P(MW)	C_1	C_2	C_3
0	100000	100000	100000
25	100000	100000	100000
50	810	750	806
75	1355	1155	1108.5
100	1460	1360	1411
125	1772.5	1655	11704.5
150	2085	1950	1998
175	2427.5	100000	2358
200	2760	100000	100000
225	100000	100000	100000

The three generating units are having the minimum and maximum power generation possible as (50,200), (50,150) and (50,175). The discretization step for state space and action space, S_s and S_a are taken as 25 MW for simplicity and fast computation.

Therefore, $Dmin_{(0)} = 150$ $Dmax_{(0)} = 525$

$Dmin_{(1)} = 100$ $Dmax_{(1)} = 325$

and $Dmin_{(2)} = 50$ $Dmax_{(2)} = 175$

The Learning Automata solution (RL_ED1) was run for a demand of 300 MW. After 1000 iterations the learning process converged (performance index values remain

unchanged). At this point the minimum value of performance index (Q_{a_k}) is found out as Rs. 4168 /- and the corresponding action a_k corresponds to the optimum allocation schedule.

In order to understand the performance of RL algorithms (RL_ED2 and RL_ED3), the different components of the multi stage decision process are to be identified. The state tuples is of the form (k, D_k), D_k being the power to be dispatched at k^{th} stage.

Then, State space $\chi = \chi_0 \cup \chi_1 \cup \chi_2$ *where*

$$\chi_0 = \{(0,150), (0,175), (0,200), \ldots\ldots\ldots\ldots (0,525)\}$$

$$\chi_1 = \{(1,100), (0,125), (0,150), \ldots\ldots\ldots\ldots (0,325)\}$$

$$and\ \chi_2 = \{(2,50), (2,75), (2,100), \ldots\ldots\ldots\ldots (0,175)\}$$

Now identify the action space, which is a dynamic one since it depends on the value of power D_k to be dispatched. The minimum and maximum values of actions are found out as

$Min_0 = (D_0 - D_{max(1)})$ or $P_{min(0)}$ whichever is greater

$Max_0 = (D_0 - D_{min(1)})$ or $P_{max(0)}$ whichever is smaller

$Min_1 = (D_1 - D_{max(1)})$ or $P_{min(1)}$ whichever is greater

$Max_2 = (D_1 - D_{min(1)})$ or $P_{max(1)}$ whichever is smaller

$Min_2 = P_{min(2)}$ $\qquad$ $Max_2 = P_{max(2)}$

For the purpose of explaining the algorithm, let the random value generated for the demand is 300 MW. Then the action space at stage$_0$ is

$\mathcal{A}_0 = \{50, 75, \ldots\ldots\ldots, 200\}$

One of these actions is selected and it passes to the next stage $k = 1$. Then the action space $\mathcal{A}_1$ is identified and action selection continued which brings out the remaining power as the allocation for the last machine. Each time cost corresponding to the power allotted is found out using the cost table given and Q value of the

corresponding state action pair is updated. Allocation to each unit is then found out as the action which gives the minimum Q value corresponding to state comprising the particular stage number (unit) and the power to be allotted. That is, $argmin_a(Q(x_k, a)$ gives the allocation for k^{th} unit for the power demanded D_k. Similarly the action (allocation) corresponding to each of the units ($k = 0$ *to* $N-1$) is found, calculating D_k at each stage of allocation.

The three algorithms RL_ED1, RL_ED2 and RL_ED3 are executed. The allocation schedule obtained is obtained as (50,100,150) and the cost of generation is Rs. 4168/-. The execution time for both the learning and retrieval algorithms is 2.034, 2.567sec. and 1.754sec. respectively. Once the learning is completed, using policy retrieval phase, power schedule for any value of possible input demand values can be retrieved.

The three algorithms are run for various the values of power demand $D_{min(0)} <= P_D <= D_{max(0)}$ ie, $150 <= P_D <= 525$. Part of the simulation result is tabulated in *Table 5.3* which is consistent with results given in (Wood and Wollenberg [2002]).

Table 5.3 – Allocation schedule for three generator system

D(MW)	P1(MW)	P2(MW)	P3(MW)	Cost(Rs.)
250	50	50	150	3558
275	50	150	75	3868.5
300	50	100	150	4168
325	50	125	150	4463
350	50	150	150	4758
375	100	125	150	5113
400	100	150	150	5408
425	125	150	150	5720.5
450	150	150	150	6033
475	175	150	150	6375.5
500	200	150	150	6708

For comparing the efficacy of the two algorithms, Simulation time for the three algorithms are compared in Table 5.4

Table 5.4 Comparison execution time for RL_ED1, RL_ED2and Rl_ED3

	RL_ED1	RL_ED2	RL_ED3
No: of iterations	10000	100000	50000
Computation time(sec.)	2.034	2.567	1.754

A graphical layout of the comparison is given in Fig 5.4.

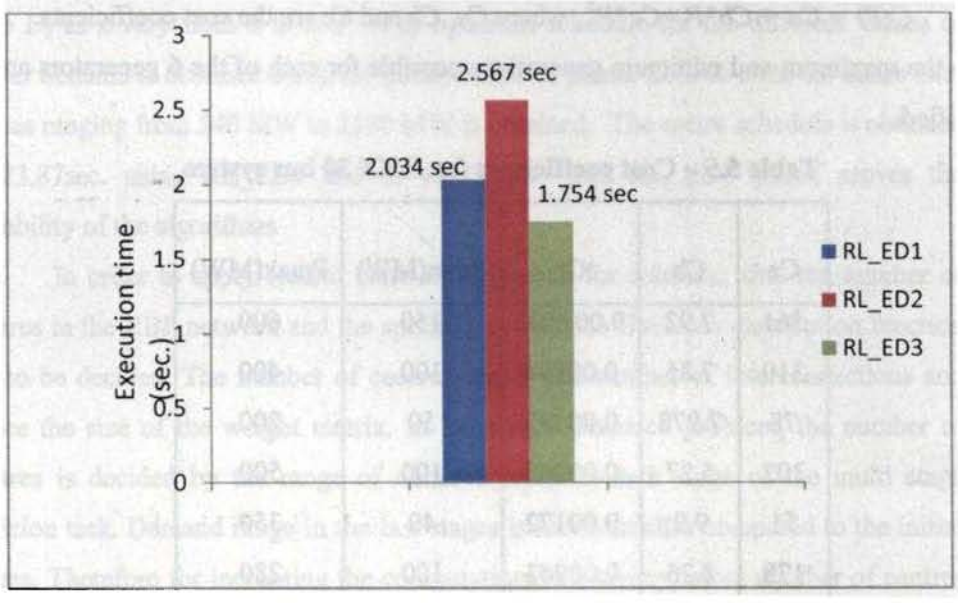


Fig 5.4 Comparison of execution time of RL approaches

(RL_ED1, RL_ED2 & RL_ED3)

On comparing the computation time of the algorithms, Learning Automata method gives lesser time compared to ε -greedy solution. ε -greedy provides a simple solution method compared to pursuit method. Pursuit strategy is faster compared to other two methods. Since execution time is less, all the three algorithms seem to be

suitable for such smaller systems. But on analyzing the algorithmic steps, it is found that for larger systems, Learning Automata is not preferable due to the large action space to be handled which increases the memory requirement. The other two algorithms are suitable for larger systems due to the multi stage formulation in the solution procedure.

Case II – IEEE 30 bus system

To prove the flexibility for larger systems and to make comparison, the proposed algorithms are now tested for IEEE 30 bus system consisting of six generators (Somasundaram and Kuppusamy [2005]), without considering the transmission losses. The system cost data is given in quadratic cost coefficient form as given in Table 5.5. ie, for any power P, cost of generation is given out by the equation

$C(P) = Ca + Cb*P + Cc*P^2$, where Ca, Cb and Cc are the cost coefficients. Also the maximum and minimum generations possible for each of the 6 generators are specified.

Table 5.5 – Cost coefficients for IEEE 30 bus system

Ca	Cb	Cc	Pmin(MW)	Pmax(MW)
561	7.92	0.001562	150	600
310	7.85	0.00194	100	400
78	7.978	0.00482	50	200
102	5.27	0.00269	100	500
51	9.9	0.00172	40	350
178	8.26	0.00963	100	280

The maximum generation possible with these 6 generators turns out to be 2330 MW while minimum generation is 540 MW. Since the number of action vectors increases to a very large value Learning Automata method is not preferable when the number of generators is increased. The RL algorithms (Rl_ED1, RL_ED2, RL_ED3 and RL_ED5) are now applied to get the economic allocation for the six units.

The discretization step for action and state space are taken as 10 MW as balance between the accuracy and size of the state and action spaces. At each step of iteration, action is selected according to the exploration method. The Q values of state-action pairs are updated for which cost of generation is calculated by evaluating the quadratic equation.

Even after two hours of execution, optimum schedule is not obtained for RL_ED1. This is because of the large number of combinations available in the action space.

In RL_ED2, after $5x10^5$ iterations the Q values approach optimum while RL_ED3 converged in $2x10^5$ iterations. The optimum dispatch is found out by tracing out the greedy action which give out minimum Q value corresponding to a particular state D_k as k vary from 0 to $N-1$. The optimum schedule for the different values of power demand is obtained using the policy retrieval phase. Schedule for the entire load values ranging from 540 MW to 2330 MW is obtained. The entire schedule is obtained in 23.87sec. using RL_ED2 and in 15.63 sec. with RL_ED3 which proves the suitability of the algorithms

In order to apply Neural Network approach for solution, first the number of centres in the RBF network and the spread factor of the Gaussian distribution function are to be decided. The number of centres decide the number of interconnections and hence the size of the weight matrix. In Economic Dispatch problem, the number of centres is decided by the range of demand input to each stage of the multi stage decision task. Demand range in the last stages is much smaller compared to the initial stages. Therefore for increasing the computational efficiency, more number of centres is selected at the initial stages compared to later ones. Here the number of centres is taken as 30, 30, 20, 20, 16 and 16. By trial and error spread factor of 0.7 is selected. The solution procedure RL_ED5 is executed for learning the network. The six RBF networks are made to adjust the weights and the learning converged in 5×10^6 iterations with 14.89sec.

The number of iterations required is more in the function approximation method. But since the number of weight values to be adjusted is less than the number of Q values, execution time is decreased.

The algorithms are executed in several trials and the cost and allocation schedule obtained are almost the same with negligible error in the different trials and with RL_ED2, RL_ED3 and RL_ED5.

A part of the allocation schedule corresponding to various values of power demand in steps of 100MW is tabulated in *Table 5.6.*

Table 5.6 - Allocation schedule for IEEE 30 bus system

D(MW)	P_1(MW)	P_2(MW)	P_3(MW)	P_4(MW)	P_5(MW)	P_6(MW)	Cost(Rs.)
600	150	100	50	160	40	100	5951.611
700	150	100	50	260	40	100	6591.591
800	150	100	50	360	40	100	7285.371
900	150	100	50	460	40	100	8032.951
1000	160	150	50	500	40	100	8847.839
1100	210	190	60	500	40	100	9698.202
1200	260	220	80	500	40	100	10563.33
1300	310	260	90	500	40	100	11443.07
1400	350	300	110	500	40	100	12337.4
1500	400	340	120	500	40	100	13246.5
1600	440	380	140	500	40	100	14170.28
1700	500	400	160	500	40	100	15109.32
1800	580	400	180	500	40	100	16070.22
1900	600	400	200	500	100	100	17070.12
2000	600	400	200	500	180	120	18108.22
2100	600	400	200	500	270	130	19175.55
2200	600	400	200	500	350	150	20272
2300	600	400	200	500	350	250	21483.2

CaseIII – 10 Generator system with piece wise quadratic cost functions

To verify the algorithms for non convex cost functions and compare with one of the recent techniques, 10 generator system having piecewise quadratic cost functions (Won and Park [2003]) is considered. The different generators are having two or three different operating regions. If the Cost function is C_i and the space interval is divided into three divisions, then it is represented as follows:

$$C_i(P) = a_{i(1)} + b_{i(1)}P_i + c_{i(1)}P_i^2 \quad (P_{min(i)} \le P_i \ge P_{i(1)})$$

$$= a_{i(2)} + b_{i(2)}P_i + c_{i(2)}P_i^2 \quad (P_{i(1)} \le P_i \ge P_{i(2)})$$

$$= a_{i(3)} + b_{i(3)}P_i + c_{i(3)}P_i^2 \quad (P_{i(2)} \le P_i \ge P_{max(i)})$$

The data $(a_i, b_i, c_i, P_{min}, P_{max})$ of generators are given in Table 5.7

Table 5.7 Generator data for 10 generator system

Gen.	P_{min}(MW)	P_{max}(MW)	a	b	c
1	100	196	26.97	-0.3975	0.002176
1	196	250	21.13	-0.3059	0.001861
2	50	114	1.865	-0.03988	0.001138
2	114	157	13.65	-0.198	0.00162
2	157	230	118.4	-1.269	0.004194
3	200	332	39.79	-0.3116	0.001457
3	332	388	-2.876	0.03389	0.000804
3	388	500	-59.14	0.4864	1.18E-05
4	99	138	1.983	-0.03114	0.001049
4	138	200	52.85	-0.6348	0.002758
4	200	265	266.8	-2.338	0.005935
					Contd....

Table 5.7 Contd...

5	190	338	13.92	-0.08733	0.001066
5	338	407	99.76	-0.5206	0.001597
5	407	490	53.99	0.4462	0.00015
6	85	138	1.983	-0.03114	0.001049
6	138	200	52.85	-0.6348	0.002758
6	200	265	266.8	-2.338	0.005935
7	200	331	18.93	-0.1325	0.001107
7	331	391	43.77	-0.2267	0.001165
7	391	500	43.35	0.3559	0.000245
8	99	138	1.983	-0.03114	0.001049
8	138	200	52.85	-0.6348	0.002758
8	200	265	266.8	-2.338	0.005935
9	130	213	14.23	-0.01817	0.000612
9	213	370	88.53	-0.5675	0.001554
10	362	407	46.71	-0.2024	0.001137
10	407	490	61.13	0.5084	4.16E-05
10	407	490	61.13	0.5084	4.16E-05

The system is made to learn using the algorithms given in *RL_ED2, RL_ED3* and *RL_ED5* and the Q values approach optimum in 10^7, 5 x 10^6 and 1.5 x 10^7 iterations respectively. The same values of learning parameters are taken as in previous cases. The discretization step for state and action spaces is taken as 10MW.

Allocation schedule corresponding to values of power demand ranging from 1400 MW to 3000 MW obtained are given in Table 5.8. The times of execution are 42.87sec., 38.69 sec. and 34.95 sec. respectively. The cost and allocation schedule obtained are comparable with that of improved genetic algorithm (Won and Park [2003]).

Table 5.8 – Part of Schedule – 10 generator system

Demand (MW)	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	P_{10}	Cost(Rs.)
1400	100	170	200	190	190	150	50	200	50	100	903.30
1500	100	190	200	210	210	150	90	200	50	100	948.3638
1600	100	200	200	220	230	150	150	200	50	100	996.4249
1700	100	210	200	240	240	150	210	200	50	100	1047.349
1800	100	220	200	260	270	150	250	200	50	100	1101.472
1900	100	220	200	310	320	150	250	200	50	100	1164.422
2000	100	220	200	360	370	150	250	200	50	100	1237.691
2100	110	220	200	400	420	150	250	200	50	100	1321.016
2200	120	220	210	430	450	150	250	220	50	100	1411.387
2300	140	220	230	450	470	150	250	240	50	100	1507.16
2400	150	220	250	480	490	150	250	260	50	100	1608.295
2500	170	220	280	500	500	150	250	280	50	100	1715.796
2600	190	220	310	500	500	150	250	320	50	110	1833.078
2700	210	220	350	500	500	150	250	350	50	120	1960.531
2800	230	220	380	500	500	150	250	380	60	130	2097.839
2900	250	220	410	500	500	160	250	400	70	140	2244.236
3000	250	220	440	500	500	170	250	440	80	150	2399.784

Case IV (IEEE 6 bus system Considering Transmission losses)

Next is to validate the solution approaches taking into account the transmission network losses occurring in the system. For testing the efficacy of solutions RL_ED4 and RL_ED5, considering the transmission losses, a three generating unit system with given loss coefficients is considered. While executing RL_ED5 the same procedure of updating of demand is carried out with the schedule obtained at each time from the Neural Network. Standard IEEE 6 bus system which is having three generating units and eight lines (Lin and Gow [2007]) is taken for case study. The fuel cost curve of the units is represented by a third order polynomial function:

$$C_i(P_i) = a_i + b_i P_i + c_i P_i^2 + d_i P_i^3$$

The associated fuel cost coefficients and B-matrix parameters are given in Table 5.9.

Table 5.9 Generator data and Loss Coefficients of IEEE 6 bus system

Generator data

Unit No	1	2	3
a_i	*11.2*	*-632*	*147.144*
b_i	*5.102*	*13.01*	*4.28997*
c_i	*-2.64E-03*	*-3.06E-02*	*3.08E-04*
d_i	*3.33E-06*	*3.33E-05*	*-1.77E-07*
$P_{min}(MW)$	*100*	*100*	*200*
$P_{max}(MW)$	*500*	*500*	*1000*

B Coefficients

1	7.50E-05	5.00E-06	7.50E-06
2	5.00E-06	1.50E-05	1.00E-05
3	7.50E-06	1.00E-05	4.50E-05

The learning is first carried out using RL_ED2. Then RL_ED4 is executed to find out the dispatch for all the possible load values ranging from 500MW to 1900MW. For getting accurate schedule, the discretization step taken is 2MW. The remaining power of the demanded value (< 2MW), which is negligibly small compared to the total demand is randomly assigned to one of the units without exceeding maximum limit. Number of iterations required is 9×10^4 and the time of execution is 14.87 sec for getting schedule for all the load values.

In order to apply the function approximation strategy using Radial Basis function networks (RL_ED5), Number of RBF centers is taken as 80, 60 and 40 and the action step is taken as low as 2MW for accounting the losses more effectively. RL_ED5 is executed to learn the Q values. The schedule is obtained for all the load values in suitable steps. The learning algorithm converged in 2×10^5 iterations and the total time taken is only 12.98 sec.

The obtained schedule and costs are tabulated in Table 5.10.

Table 5.10 Schedule and cost obtained for IEEE 6 bus system

P_D(MW)	P_{g1}(MW)	P_{g2}(MW)	P_{g3}(MW)	Cost	Loss(MW)
500	100	100	306	2383	6
600	100	100	409	2800	9
700	261	100	373	3246	14
800	298	100	420	3696	18
900	330	100	495	4140	25
1000	338	100	591	4737	29
1100	341	100	691	5200	32
1200	344	100	800	5679	44
					Contd...

Table 5.10 Contd....

1300	414	100	835	6002	49
1400	446	156	851	6474	53
1500	453	229	874	6896	56
1600	461	300	899	7438	59
1700	469	302	992	7772	64
1800	455	321	991	8320	67
1900	487	492	996	8801	75

Case V – IEEE 30 bus system with transmission system parameters

In the previous case, the transmission network loss is represented through B coefficients. For validating the algorithm while considering the entire transmission system representation, consider IEEE 30 bus system with entire transmission system parameters. The transmission line parameters are given in Table 5.11.

Table 5.11 Line data—IEEE 30-bus system

Branch no.	From	To	R (pu)	X (pu)	Y/2 (pu)
1	2	1	0.0192	0.0575	0.0264
2	1	3	0.0452	0.1852	0.0204
3	2	4	0.057	0.1737	0.0184
4	3	4	0.0132	0.0379	0.0042
5	2	5	0.0472	0.1983	0.0209
6	2	6	0.0581	0.1763	0.0187
7	4	6	0.0119	0.0414	0.0045
					Contd...

Table 5.11 Contd...

8	5	7	0.046	0.116	0.0102
9	6	7	0.0267	0.082	0.0085
10	6	8	0.012	0.042	0.0045
13	9	11	0	0.208	0
14	9	10	0	0.11	0
16	12	13	0	0.14	0
17	12	14	0.1231	0.2559	0
18	12	15	0.0662	0.1304	0
19	12	16	0.0945	0.1987	0
20	14	15	0.221	0.1997	0
21	16	17	0.0824	0.1932	0
22	15	18	0.107	0.2185	0
23	18	19	0.0639	0.1292	0
24	19	20	0.034	0.068	0
25	10	20	0.036	0.209	0
26	10	17	0.0324	0.0845	0
27	10	21	0.0348	0.0749	0
28	10	22	0.0727	0.1499	0
29	21	22	0.0116	0.0236	0
30	15	23	0.1	0.202	0
31	22	24	0.115	0.179	0
32	23	24	0.132	0.27	0
33	24	25	0.1885	0.3292	0
34	25	26	0.2544	0.38	0
35	25	27	0.1093	0.2087	0
38	27	30	0.3202	0.6027	0
39	29	30	0.2399	0.4533	0
40	8	28	0.0636	0.2	0.0214
41	6	28	0.0169	0.0599	0.0065

The six generators are located at buses: 1, 2, 5, 8, 11 and 13, and the cost coefficients are the same as given in Table 5.5. A total load of 283 MW is connected to the different buses as given in the Table 5.12.

Table 5.12 Load data—IEEE 30-bus system

Bus no.	P_D (MW)	Q_D (MW)
1	0	0
2	21.7	12.7
3	2.4	1.2
4	7.6	1.6
5	94.2	19
6	0	0
7	22.8	10.9
9	0	0
10	5.8	2
11	0	0
12	11.2	7.5
14	6.2	1.6
15	8.2	2.5
16	3.5	1.8
17	9	5.8
18	3.2	0.9
		Contd...

Table 5.12 Contd...

19	3.2	1.6
20	2.2	0.7
21	17.5	11.2
22	0	0
23	3.2	1.6
24	8.7	6.7
25	0	0
26	3.5	2.3
27	0	0
28	0	0
29	2.4	0.9
30	10.6	1.9

In this case, transmission losses are calculated by executing fast decoupled power flow solution. In this case since the connected load is given as 283MW, we fix the initial demand as the 283MW. First, the learning algorithm takes the total demand P_D = 283 MW. After sufficient number of iterations, the Q values approach optimum. Then by policy retrieval phase, an economic schedule is obtained. The power flow algorithm is executed to get the transmission losses in the system. The loss MW is used to update the initial demand to the solution algorithm and new schedule is obtained. The updating is continued until the iterative algorithm is converged, giving tolerable value of updating for the loss in two successive iterations. The results are given in Table 5.13.

Table 5.13 Economic Schedule for IEEE 6 bus system

P_D(MW)	P_{g1}(MW)	P_{g2}(MW)	P_{g3}(MW)	Cost(Rs.)	Loss(MW)
283	45	100	142	1576	4

Case VI – Three unit system with stochastic data

One important point to be considered while formulating the algorithm for Economic Dispatch is its flexibility for the different cost functions. In practical situation cost of generation for the same MW power may not be the same constant always. It exhibits randomness due to various factors. To prove that the proposed algorithms efficiently handle the randomness in cost values, next consider the cost given in terms of mean and variance. The cost values are given in Table 5.14 for a three generating unit system. C_i indicates the cost of generating power P *MW* by i^{th} unit.

Table 5.14 Cost details with given variance of three generator system

P(MW)	C_1		C_2		C_3	
	Mean	**variance**	**Mean**	**variance**	**Mean**	**variance**
0	100000		100000		100000	
25	100000		100000		100000	
50	810	60	750	100	806	60
75	1355	80	1155	100	1108.5	80
100	1460	100	1360	80	1411	100
125	1772.5	100	1655	100	11704.5	100
150	2085	100	1950	80	1998	80
175	2427.5	80	100000		2358	80
200	2760	60	100000		100000	
225	100000		100000		100000	

The three solution steps (RL_ED1, RL_ED2, RL_ED3 and RL_ED5) are executed to get the schedule for all the possible load values in steps of 25 MW. In case of RL_ED5, for simplicity the same number of RBF centers is taken in all the three networks. 12 centers are taken for this case. Spread factor of 0.7 is chosen by trial and error to get reduced computation time and sufficient accuracy for the result. The entire schedule is obtained in 2.03 sec., 2.70 sec., 2.05sec. and 1.82 sec respectively. The obtained allocation values are given in Table 5.15.

Table 5.15 Schedule obtained for stochastic data

D(MW)	P1(MW)	P2(MW)	P3(MW)	Cost(Rs.)
150	50	50	50	2353
175	50	50	75	2674
200	50	100	50	2989
225	50	100	75	3326
250	50	50	150	3592
275	50	150	75	3902
300	50	100	150	4150
325	50	125	150	4466
350	50	150	150	4742
375	100	125	150	5109
400	100	150	150	5394
425	125	150	150	5735
450	150	150	150	6067
475	175	150	150	6431
500	200	150	150	6745
525	50	50	125	13241

Case VII – 20 Generator system

For validating the efficacy of Reinforcement Learning based algorithms for large systems, next a 20 generator system is considered. The cost function is given in quadratic form. The unit details are given in Table 5.16.

Table 5.16– Generator Details of 20 generator system

Unit	C_a	C_b	C_c	P_{min}(MW)	P_{max}(MW)
1	1000	18.19	0.00068	150	600
2	970	19.26	0.00071	50	200
3	600	19.8	0.0065	50	200
4	700	19.1	0.005	50	200
5	420	18.1	0.00738	50	160
6	360	19.26	0.00612	20	100
7	490	17.14	0.0079	25	125
8	660	18.92	0.00813	50	150
9	765	18.97	0.00522	50	200
10	770	18.92	0.00573	30	150
11	800	16.69	0.0048	100	300
12	970	16.76	0.0031	150	500
13	900	17.36	0.0085	40	160
14	700	18.7	0.00511	20	130
15	450	18.7	0.00398	25	185
16	370	14.26	0.0712	20	80
17	480	19.14	0.0089	30	85
18	680	18.92	0.00713	30	120
19	700	18.47	0.00622	40	120
20	850	19.79	0.00773	30	100

The transmission loss is calculated using B coefficient matrix. Algorithm RL_ED4 is executed to give the schedule for the range of load from 1000MW to 3000MW. The execution time taken is 45.87sec. Part of the schedule and the loss are tabulated in Table 5.17.

Table 5.17 Schedule for 20 generator system

D(MW)	2000	2500	3000
P_1	421	498	530
P_2	140	159	167
P_3	105	120	140
P_4	94	118	135
P_5	81	92	97
P_6	51	74	87
P_7	89	115	141
P_8	81	106	162
P_9	84	103	155
P_{10}	70	98	108
P_{11}	236	290	358
P_{12}	89	120	136
P_{13}	82	119	124
P_{14}	90	115	147
P_{15}	23	30	70
P_{17}	64	87	111
P_{19}	72	100	106
P_{20}	45	54	75
Loss	39	64	81

5.12 Evaluation of Algorithms

The different Reinforcement Learning algorithms have been tested for their efficacy and performance. The computation time of the different RL algorithms for the different test cases are tabulated for comparison in Table 5.18.

Table 5.18 Comparison of Computation times of different RL algorithms

(Time in sec.)

	RL_ED1	RL_ED2	RL_ED3	RL_ED4	RL_ED5
Three gen system with given cost table, neglecting transmission loss	2.034	2.567	1.754		1.465
IEEE 30 bus system with 6 generators, neglecting transmission losses	Not giving optimum result	23.87	15.63		14.89
10 generator system with piecewise quadratic cost coefficients		42.87	38.69		34.95
IEEE 6 bus system with 3 generators, considering transmission losses				9.87	6.98
3 generator system with stochastic cost data	2.03	2.70	2.05		1.82

In order to highlight the efficacy and computational speed of the developed algorithms, the results of RL_ED4 and RL_ED5 are compared with other recently developed algorithms.

For comparing with other recent techniques, IEEE 6 bus system (Case IV) with a load power of 1200MW is considered. That is, the initial demand to the system is 1200MW and the corresponding schedule is obtained. The optimal cost is obtained as Rs.5679.2 and the power loss calculated is 44MW. The time taken by our proposed algorithm is only 9.87 sec and 6.98sec. for RL_ED4 and RL_ED5. The obtained schedule is tabulated and a comparison is made with other stochastic techniques (Wong *et al.*[1993] and Lin *et al.*[2007]) in Table 5.19. The dispatch schedule obtained is comparable. Transmission loss in all the case is nearly 43MW.

For getting the schedule for 10 different load values RL_ED4 took only 10.56 sec, while RL_ED5 was executed in 7.12sec. For other methods, the time needed is nearly 10 times the time for single load value. This directly highlights the efficiency of Reinforcement Learning approach for giving schedule for any forecasted load profile instantaneously.

Table 5.19 Comparison with SA and PAA

Method	PAA	SA	RL_ED4	RL_ED5
P_{g1}(MW)	362.2	342.8	344	343
P_{g2}(MW)	100	100	100	100
P_{g3}(MW)	781.4	801.4	800	800
Cost(Rs.)	5671.06	5682.32	5679.2	5676
Loss(MW)	43.68	43.8	44	43
Time (sec)	**16.82**	**27.253**	**9.87**	**6.98**

A graphical comparison is also given in Fig 5.5

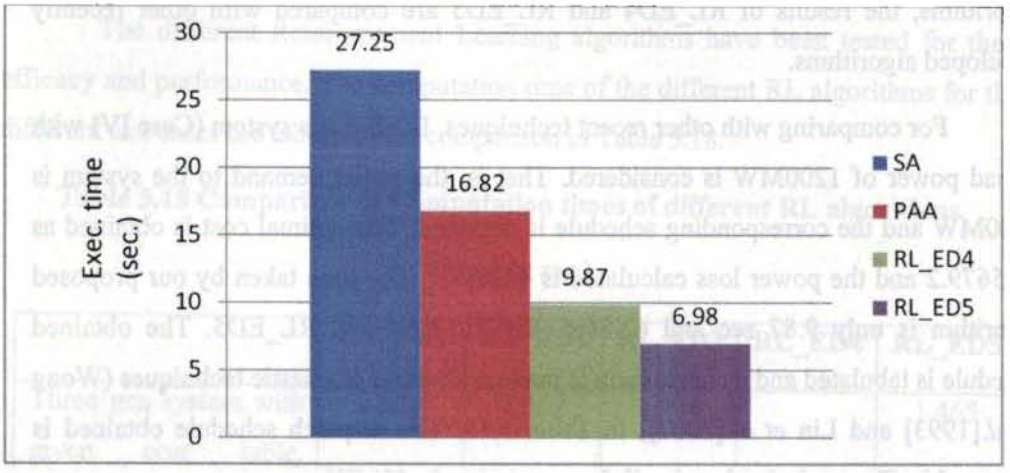


Fig 5.5 Comparison of execution time with other methods

The above comparison directly depicts the improved performance of Reinforcement Learning based solutions over other recent methods. This faster scheduling provided by Reinforcement Learning in effect helps to improve the economy of generation.

5.13 Conclusion

Even though many techniques are applied for the solution of Economic Dispatch problem, Reinforcement Learning provides a good methodology due to its faster computing speed and simplicity. Once the learning phase is completed, schedule for any load demand can be obtained instantaneously. Also it can effectively handle the stochastic cost functions associated with practical thermal units. The developed algorithms are applied on different test systems. In all these cases satisfactory performance is obtained. The result when compared with other stochastic techniques is found to be better. As a further step in this direction algorithm incorporating additional constraints such as ramp rate limits, valve point effects etc. existing in power systems can be developed.

CHAPTER 6

REINFORCEMENT LEARNING APPLIED TO AGC WITH COMMON SYSTEM FREQUENCY

6.1 Introduction

Automatic Generation Control (AGC) constitutes the on line dispatch part of generation control. Electrical energy is generated by the generators at the generating stations, transformed into suitable voltage level by the transformers and dispatched through various buses to the loads which consume the electric power. In an interconnected system, the overall power system is divided into several grids or pools, each comprising several subsystems. Through Tie lines the system is connected to the neighbouring systems belonging to the same grid (pool). The active power demand in the system is met by the combined generation of all the generating sources in the system. Considering the economic perspective of power generation, the forecasted load demand is distributed among the generating units in the system in the most economic manner by the pre dispatch control. It consists of Unit commitment and Economic Dispatch at each control area.

Once the pre dispatch or pre scheduling is over, the generating units will be entitled to generate the allotted power, (fraction of the forecasted load demand) for the specified duration of time. Instantaneous addition and removal of load in the system will be reflected by a change in the system frequency. Considerable drop in frequency result in high magnetizing currents in induction motors and transformers and decline their performance. Control of system frequency ensures constant speed for the frequency dependent load such as induction and synchronous motors and thus their efficient operation. Thus for satisfactory operation of a system, frequency should be maintained constant. The frequency of the system is dependent on active power

balance. A change in active power demand at one point is reflected by a change in frequency. Since there is more than one generator supplying power to the system the demand is allocated to the different generators.

In case of interconnected system with two or more independently controlled areas, in addition to the control of frequency, generation within each area is to be controlled so as to maintain scheduled power interchange. When the entire interconnected system is operating on a common system frequency, instantaneous load variations in any of the control area will affect the common system frequency. This makes the task more difficult to solve as the load is not predictable always. Also the generation capacities and the means by which generation can be changed are limited.

Even though primary control action is served by the speed governor associated with the generating units, supplementary control is needed to reallocate the generation so as to bring the frequency to exact scheduled value. Supplementary control can be done manually by setting the reference point so as to increase or decrease the generation. Automatic functioning of this supervisory or supplementary control action is referred to as Automatic Generation Control. Automatic Generation Control problem is discussed in the next section.

Reinforcement Learning approach for solving the AGC problem for an interconnected system (Imthias *et al.* [2002]) is extended in the next sections with an approach of common system frequency.

6.2 Automatic Generation Control problem

In a large interconnected power system with several pools having many number of generators, manual regulation is not feasible and therefore automatic generation and voltage regulation is essential.

Once a generating unit is tripped or a block of load is added to the system, the power mismatch is initially compensated by the extraction of kinetic energy from system inertial storage which causes a decline in system frequency. As the frequency decreases, power taken by loads decreases. Equilibrium for large systems is often

obtained when the frequency sensitive reduction of loads balances the output power of the tripped unit or that delivered to the added block of load at the resulting new frequency. If this effect halts the frequency decline, happens in less than 2 seconds.

If the frequency mismatch due to the addition of load ΔP_L is large enough to cause the frequency to deviate beyond the governor dead band of the generating units (generally in the range of 30-35mHz.), their output will be increased by the governor action. For such mismatches, equilibrium is obtained when the reduction in the power taken by the loads plus the increased generation due to governor action compensates for the mismatch. Such equilibrium is often obtained within 10-12 seconds. Typical speed droop are in the range of 5% and therefore at the expense of some frequency deviation, generation adjustment is carried out by governors.

On attaining the new equilibrium state after variation in the load ΔP_L,

$$\Delta P_L = D\,\Delta f$$

$$\Delta f = \Delta P_L / D,$$

where Δf is the change in frequency and D is the damping constant.

Lumped parameter model of the generation system is commonly used for the analysis of AGC systems (Elgerd [1982]). In such representation, the aggregate frequency sensitivity of all loads is represented by a damping constant. The perturbation model of a lumped parameter system is given in Fig 6.1.

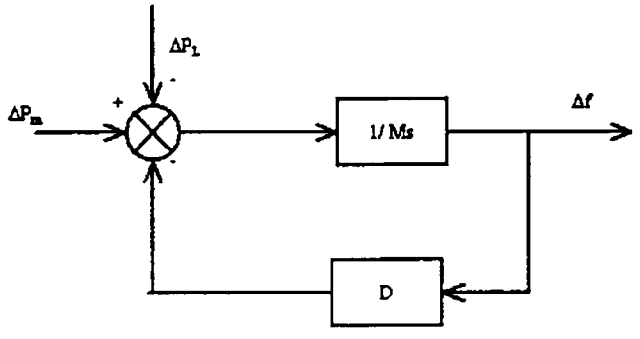


Fig 6.1 Perturbation model

In this model, M represents the aggregated inertia constant and D is the damping constant. If there is no additional frequency control, the change in the mechanical power output P_m is zero. Hence, the system response to load change ΔP_L is determined by the inertia constant and damping constant.

Each generating unit is equipped with a speed governor mechanism, which provides the function of primary frequency control. But for compensating the offset deviation and bringing back to the original scheduled frequency, a manual or automatic (through AGC) follow up and corresponding control are required.

Fig 6.2 represents the equivalent model including the governor and turbine.

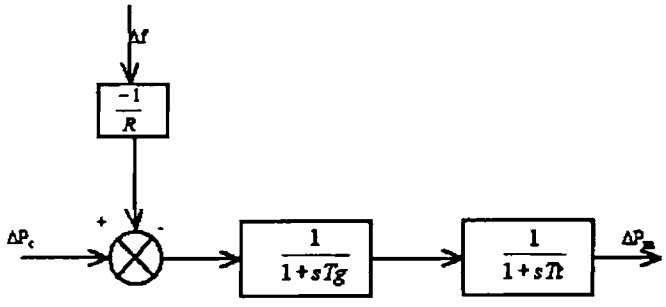


Fig 6.2 Equivalent model of Governor and Turbine

In this, R represents the speed regulation provided by the governor. It is usually expressed as $R = \Delta f / \Delta P_m$.

After addition of load ΔP_L and attaining steady state,

$$D\Delta f + (1/R)\,\Delta f = \Delta P_L$$

$$\Delta f = \Delta P_L / (D + 1/R).$$

$$= \Delta P_L / B$$

Thus the frequency of the area depends on the constant B or $(D + 1/R)$ value. Thus with the governor primary control alone, the frequency will be settled to a lower value compared to original system frequency. From the equivalent representation, it is evident that, the relationship between the frequency and power output can be varied by changing the load reference set point (ΔP_C). Bringing back the system frequency to the original value requires supplementary control. This can be done manually by increasing or decreasing the reference set point through some potentiometer arrangement. Since the system load is a continuously varying one, automatic changing of reference power setting is more preferable. Automatic Generation Control provides the automatic follow up and adjusting of power generation accordingly.

In an interconnected power system, according to contractual agreement between the different control areas, certain amount of power termed as Tie line power (P_{tie}) will be flowing through the interconnecting transmission lines. When a load is added in any part of the interconnected system, the frequency of the entire system will change causing a change in the tie line flow. In other words, by addition of a load in one area along with a frequency error, a tie line flow error will occur. Then the supplementary control should act in such a way as to bring the tie line flow error also to zero, in addition to bringing back the system frequency to original value.

The objectives of Generation Control can be summarized (Athay [1987]) as:

(i) Matching the total system generation to total system load

(ii) Regulating the frequency error to zero

(iii) Regulating the tie line flow error to zero

(iv) Distributing the area generation among the area generating resources so that the operating costs are minimized.

The first objective is met through the primary governor control and the last one is met through Economic Dispatch procedure. The second and third objectives are met through Automatic generation control associated with the system.

6.3 Automatic Generation Control – Models of Power system Network

AGC studies are carried out using simulation model proposed by Elgerd [1982]. In this approach, in each area, a group of generators are closely coupled internally and swing in unison. Also, the generator turbines tend to have the same response characteristics, ie, coherent. Then each control area is represented by a single AGC loop. The turbine, generator and load parameters represent the equivalent values considering all the generators in that area.

In an interconnected system, the different control areas are connected by loss less tie line. The power flowing through the tie line, tie line power flow appears as a load decrease/ increase in each area, depending on the direction of flow. A block diagram model is given in Fig 6.3.

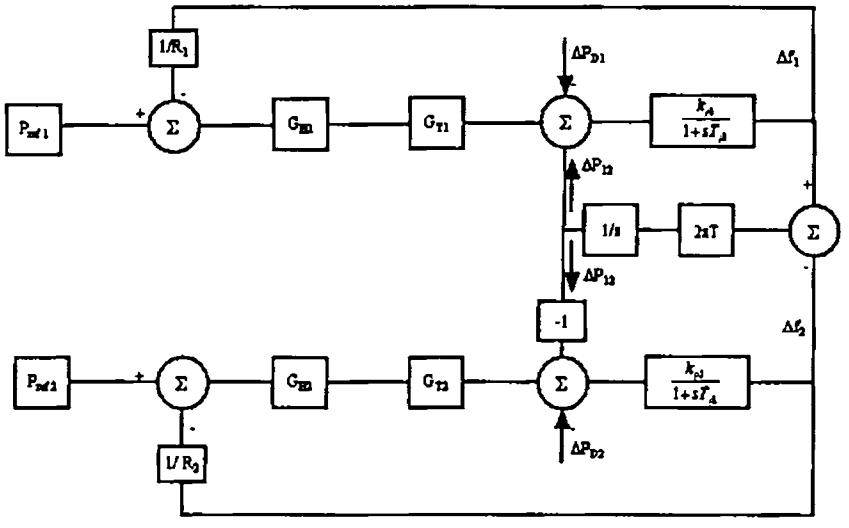


Fig 6.3 Two Area system model with two different frequencies

A change of power in one of the areas is met by a change in generation of all interconnected areas followed by a change in tie line power. Correspondingly the

frequency change will occur in all the interconnected areas. Conventional LFC of a multi area system is based on tie line bias control, where each area tends to reduce the Area Control Error (ACE) to zero. The control error for each area consists

$$ACE_i = \Sigma \Delta P_{tie} + B_i \Delta f_i$$

Δf_i is the change in frequency of i^{th} area and B_i represents the area frequency response characteristics. P_{tie} or tie line power is computed as the product of tie line constant and the angular difference between the two areas considered.

The limitation of the above model is that the different areas are assumed to be operating at different frequencies and tie line power is computed based on the frequency difference. But this is not true as far as practical power system network is considered. In a practical network, the interconnected power system operate at a single frequency and this common frequency (common to all areas) is determined by the net generated power and connected load of all the areas (Divya and Nagendra Rao [2005]). A model of such a system having two areas is given in Fig 6.4.

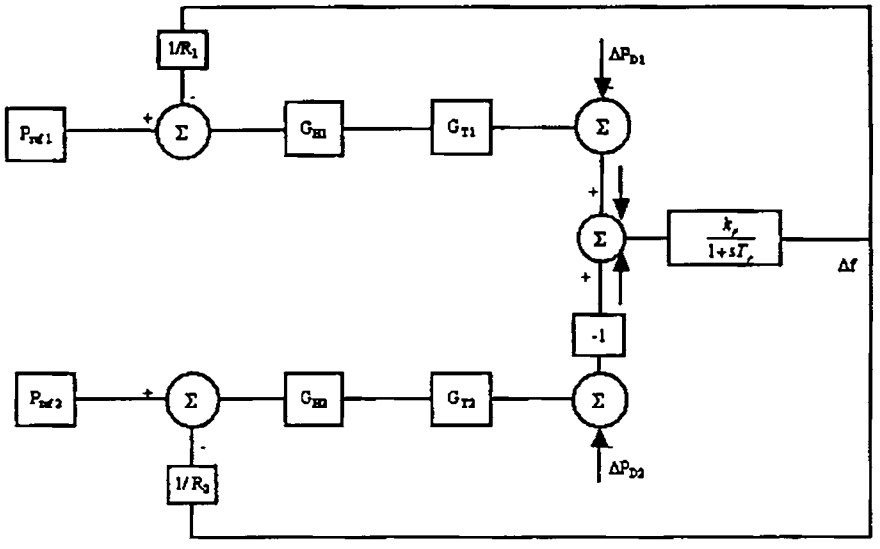


Fig 6.4 Two Area model with common system frequency

In such a system, the tie line power of each area is computed as the difference of generated power and load power of that area. $P_{tie} = P_{gen} - P_{Load}$. Accordingly the different areas will be associated with different values of P_{tie} based on the instantaneous values of power generated and consumed (Elgerd [1982]).

The control action is based on the parameter Area Control Error (ACE) which is calculated as

$ACE_i = P_{tie} + B_i * \Delta f$, *where* $\Delta f = f(actual) - f(scheduled)$ provided f denote the common frequency of the system which is determined by the total generated power and connected load of the entire system.

Advantages of such a system can be enumerated as

(i) The system model is closer to practical power system network.

(ii) It does not require the calculation of tie line constant (which depends on the nature and no: of lines of interconnection)

A Reinforcement solution to the AGC problem has already been developed by Imthias *et al.* [2002], using the first model described. In this thesis, the common frequency model is taken and the Reinforcement Learning solution is suggested for the same. In order to develop the solution strategy, AGC is viewed as a multi stage decision process in the following section.

6.4 AGC as a Multistage Decision Process

The function of AGC is to change the reference power setting so as to bring the frequency back to the original one. In a practical system, Automatic Generation Controller monitors the system frequency at different discrete instants of time and issues the control signal. With this view point AGC can be treated as a Multi stage Decision Process.

At each instant of time (every AGC cycle), system can take one of the possible system states which is described through a set of variables. The system variable normally considered include system frequency, change in frequency at two successive

time slots, ACE value etc. The controller observes the current state of the system through the set of variables. Then a decision or action is taken which corresponds to a change in the reference power setting. Accordingly the generator power will change which is reflected through a change in the system variables or state transition occurs. This state transition will not be always deterministic, since the load is a continuously varying quantity.

In the proposed formulation ACE is taken as the state variable describing the system state completely. The value of ACE will be averaged over the decision making period and this average value is the state of the system x_k at any discrete instant k. The set of possible states or possible values of ACE is taken as finite or having certain quantized values. Therefore the state space χ in the AGC problem is the quantized values of ACE.

Next is the action space. Action or decision in AGC solution is the command to increase or decrease the reference power setting. Therefore the various discrete values of ΔP constitute the action space $\mathcal{A}$.

Next is the reinforcement function. The immediate reward or reinforcement of any state transition is represented by $g(x_k\, a_k, x_{k+1})$. In this case, since the aim is to bring the error in ACE to a tolerable limit (approaching to zero discrete level), the g function can be taken as binary. Whenever the resulting state is good (tolerable error), $g(x_k\, a_k x_{k+1}) = 0$. Otherwise $g(x_k a_k x_{k+1}) = 1$.

On applying an action a_k to the system, the system moves to a new system state. The action selection is based on the current probability distribution, $p_{x_k}(a_k)$. The new state is indicated by the new frequency and the corresponding quantized ACE value. Since the load applied to the system is undergoing instantaneous variations, the next state or resulting state of an action at one current state is stochastic. Using the simulation model of the turbine generator system, the next state x_{k+1} can be observed for the action a_k taken at the current system state.

AGC algorithm is to decide what action or change in the reference power setting is to be taken for a current system state or ACE value so as to bring back the frequency error and tie line flow error to zero. AGC can be modeled as a mapping or policy from the state space χ to action space $\mathcal{A}$. To rate the goodness of policy, value function is to be defined. A policy π_1 can be treated as better than another policy π_2, if it leads to one desirable state faster. In this Reinforcement Solution approach, Q learning strategy is employed as the method of achieving the optimum policy.

6.5. Proposed system and control strategy

A Reinforcement Learning control scheme for AGC is proposed with a common frequency for the interconnected areas. The concept of common system frequency for a two area system is proposed by Divya and Nagendra Rao [2005].

Each of the two areas A and B is having two inputs, one the load disturbance in the area and the other reference power setting. Tie line flow is governed by the unbalance in the load power and the generation in the particular area. The controllers attached to area give out the decisions on the reference setting in each AGC decision time. Considering an integration time of 0.05 sec, 40 values of frequency and the P_{tie} are given to the pre processor.The preprocessor generates the corresponding discrete value of ACE and give it to the Reinforcement Learning Controller (RLC 1 and RLC 2). A block diagram of AGC control strategy used in the simulation is given in Fig 6.5

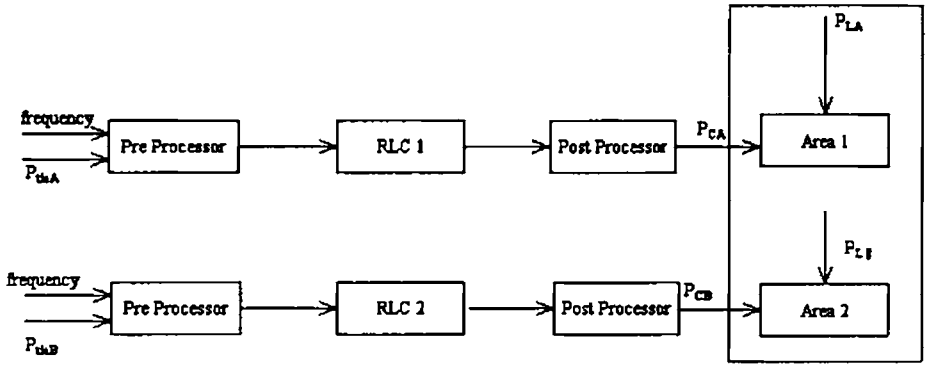


Fig 6.5 Simulation scheme for AGC

During the learning phase, the RL controller takes an action based on one of the exploration strategies. In this simulation, pursuit method is used for choosing an action from the available action space. On selecting an action, the post processor associated with the area generates the reference control signal. Each action is accompanied by a corresponding state transition and the resulting immediate reward. The Q leaning algorithm then updates the Q value corresponding to the state – action pair as:

$$Q^{n+1}(x_k, a_k) = Q^n(x_k, a_k) + \alpha\,[\,g(x_k, a_k, x_{k+1}) + \min_{a' \in A_{k+1}} Q^n(x_{k+1}, a') - Q^n(x_k, a_k)]$$

(6.1)

The new system state is represented by the new value of state variable or ACE. The learning is proceeded on updating of the Q values at each and every AGC decision time. At the same time, the probability of the different actions in the action space corresponding to the system state is updates according to the equation:

$$p_{x_k}^{n+1}(a_k) = p_{x_k}^n(a_k) + \beta[\,1 - p_{x_k}^n(a_k)], when\ a_k = a_g$$

$$p_{x_k}^{n+1}(a_k) = p_{x_k}^n(a_k) - \beta[\,p_{x_k}^n(a_k)], when\ a_k \neq a_g$$

(6.2)

Once learning is completed, the policy or optimum action at each of the system state is stored in a look up table by considering the greedy action.

6.6 Algorithm for AGC

In the context of Reinforcement Learning problem, state space, action space and reinforcement function are to be defined. The state of the system should capture the information on the current status of the system described by the different state variables. For the AGC problem since ACE is the signal based on which control action can be taken ΔACE (change in ACE signal between two discrete instants) is taken as the state variable. The range of values for this variable depends on the maximum values of ACE (on both sides) for which AGC control should respond.

Since AGC is to tackle the small load disturbances in the system, its action is to correct the ACE in a small limited range. A small value is chosen for L_A which is the maximum value for which the AGC should act. As the purpose is to maintain ACE within a very small value ε_{ACE}, ACE values whose values are less than ε_{ACE} are considered as zero discrete level. The range of ACE values between ε_{ACE} and L_A are divided into finite number of levels, M_A. Then $M_A = L_A / 2\varepsilon_{ACE}$ and the different discrete levels are uniformly distributed in the range. The finite quantized values are taken as the midpoint of each interval. All the values greater than L_A are aggregated to the maximum level. Similarly the negative values in the range $-\varepsilon_{ACE}$ and L_A are also discretised to M_A levels. Thus each value of ACE falls in one of the $(2M_A + 1)$ level. At instant k, $x_k \in \chi$, $\chi = \{-M_A(2\varepsilon_{ACE}), \ldots\ldots -2\varepsilon_{ACE}, 0, 2\varepsilon_{ACE}, \ldots\ldots M_A(2\varepsilon_{ACE})\}$.

The action or control action of AGC is to change the generation set point, ΔP. The discrete value of ΔP implies the generation change by a discrete amount. Since the range of generation change that can be made in the generators are limited and can be fixed as $-U_{MAX}$ and $+U_{MAX}$. The minimum change in the reference setting can be fixed as ΔP_{min} and then the action set is defined as,

$$\mathcal{A} = \{-U_{MAX}, \ldots\ldots -P_{min}, 0, +P_{min}, \ldots\ldots, U_{MAX}\}.$$

The total number of actions in the action space $M_P = U_{MAX} / P_{min}$.

Since the main objective of AGC is to maintain the ACE value at desirable limit, the immediate reinforcement function $g(x_k, x_{k+1}, a_k) = 0$ whenever $x_{k+1} = 0$ (desirable level) and otherwise $g = -1$. The algorithm proceeds as follows.

Q values of different state action pairs are initialized to zero. Also the probability of each action will be initialized to $1/(2M_p+1)$, giving the same chance for every action in the action space during the initial iteration of learning.

At each of the learning step, state x_k of the system is observed by the current value of Area Control Error. Taking a sampling time of 0.05 sec for the ACE signal, 40 observed values are averaged to find the current state of the system. Then an action $a_k \in \mathcal{A}$ is selected based on the current probability distribution. On applying an action

or applying the change in the reference power setting, the generated power will change which will make a change in system frequency.

Using the simulation model, the new value of frequency and ACE are calculated which represents the next state. On accounting the status of the next state as 'desirable' or not, immediate reward $g(x_k, x_{k+1}, a_k)$ can be manipulated. Then in the Q learning procedure, Q values are updated using equation (6.1). On taking any action, based on the present Q values, the probability of state –action pairs are also updated according to equation (6.2). As the learning proceeds the probability of optimum action will be increased successively at the same time the remaining actions will get the probability diminished. Thus after sufficient number of iterations, the action selection will be converged to the optimum one. The learning algorithm is summarized below:

Learning Algorithm

Initialize Q values (x, a) =0 for every $x \in \chi$ *and* $a \in \mathcal{A}$.
Initialize probability of choosing an action a at state x, $p_x(a) = 1/M_p + 1$
Repeat
  Start the system at some quiescent state, $x = x_k$
  Do
    Choose an action a_k *based on*
      the current probability distribution.
    Apply action a_k *to the system and find the next state* x_{k+1}
      (by integrating ACE over one AGC decision time)
    Find the discrete level of the state to get x_{k+1}.
    Calculate the $g(x_k, a_k, x_{k+1})$
    Update Q^n *to* Q^{n+1}
    Find the greedy action with respect to Q^{n+1}
    Update the probability values
  End Do
End

6.7 Simulation results

The performance of the AGC algorithm for the two area system with common frequency is evaluated through the simulation experiments. Simulation consists of two phases: Learning and Testing. During the learning phase, random load disturbances are given and the Q values are learnt to approach the optimum. During the testing phase, the learnt policy is used to control the power system.

In the two area model considered, each area is represented by an equivalent thermal unit, shown in Fig 6.4. The governor is represented by effective droop characteristics with $1/R$ and a single time constant T_g is considered. Also the turbine unit is represented by single equivalent time constant T_t. Power system dynamic is represented by $K_p / (1+sT_p)$, where $K_p = 1/D$ and $T_p = M/D$. D represents the load frequency characteristics and M represents the combined inertia of the system.

The values of the combined system parameters used are given in Table 6.1

Table 6.1 Generator system parameters

T_g	0.08s
T_t	0.3s
T_p	20s
R	2.4Hz/pu
K_p	120 Hz/pu
T_{12}	0.545

The two independent RL based AGC controllers used in the two areas. The parameters used for learning of these RL AGC controllers are listed in Table 6.2

Table 6.2 Learning Parameters for AGC

ε_{ACE}	0.002
L_A	0.02
U_{max}	0.0025
γ	0.9
α	0.01
β	0.01
AGC time	2.0 sec
Sampling time	0.05 sec
No: of states	11
No: of actions	11

The system derives the policies for the two RL controllers after running the system with different random loads at random intervals of time. The controller is trained successfully after suitable large number of iterations and the policy then derived will be an optimum one. The action corresponding to each state will then be the best action possible.

Using the learnt policy, the system is simulated for different load values to the two areas. The simulation results corresponding to a load of 0.02pu applied at t = 5sec. to area1 is given in Fig 6.6

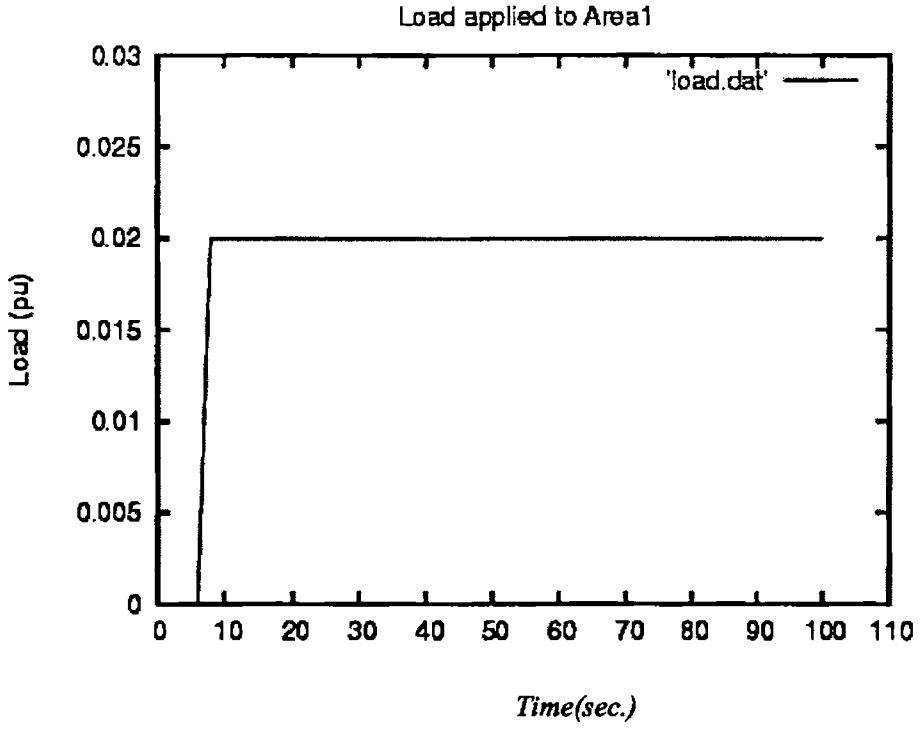


Fig 6.6 Load Disturbance

Load of 0.02pu remains connected in the system from 5sec. onwards. On addition of this load, frequency of the system drops. The controller begins to act and the reference setting is increased in discrete intervals so as nullify the frequency error. Fig 6.7 gives the variation of the base point setting when using an RL controller. Variation in ACE values with RL controller at the discrete instants is plotted in Fig 6.8.

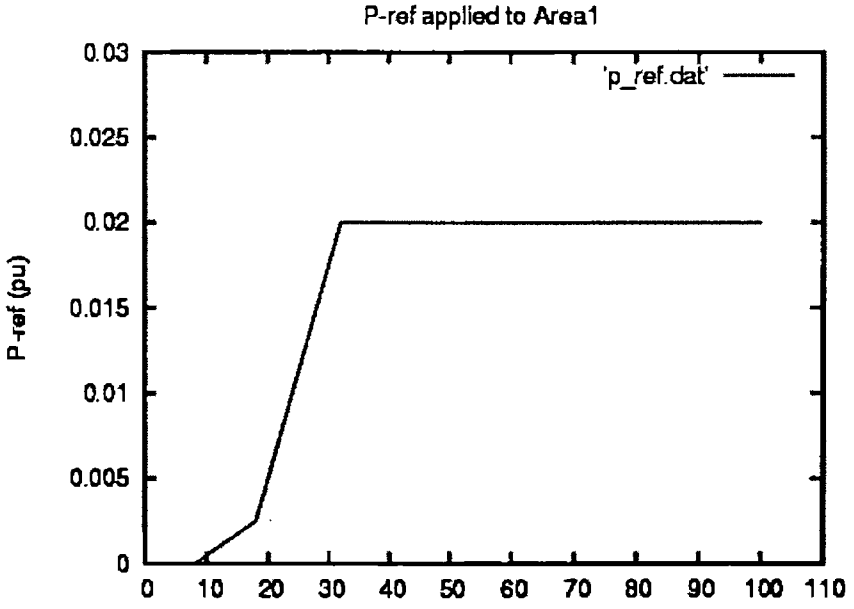


Fig 6.7 P_{ref} obtained using RL controller

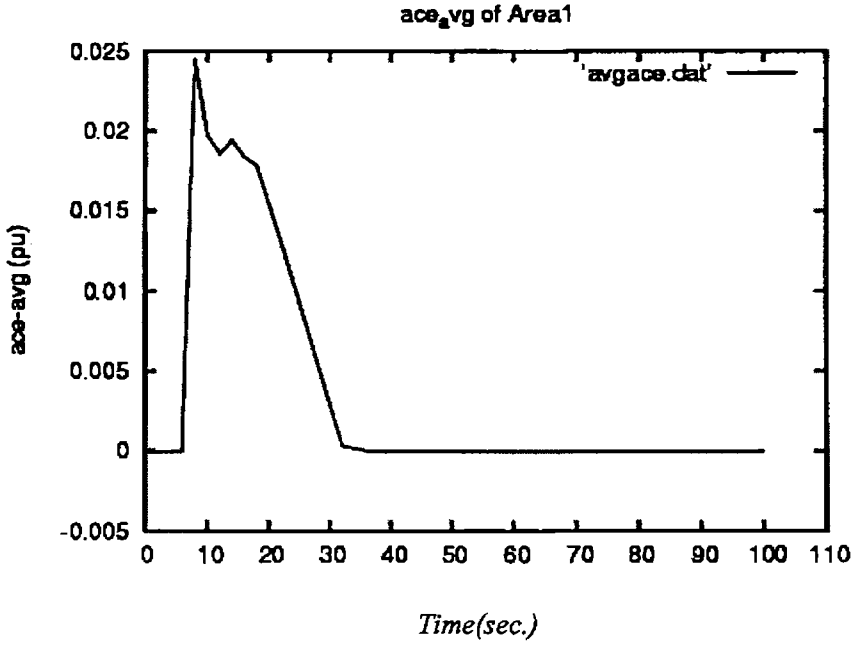


Fig 6.8 Variation of ACE of Area1

The controller makes use of the look up table of optimum Q values to get the best action corresponding to each value of Area Control Error. Correspondingly the reference power setting is changed and frequency error begins to decrease in successive discrete steps. Variation of frequency with an RL controller is shown in Fig 6.9. From the observation, it is evident that RL controller picks up the variation in ACE very quickly and settles the Area control error to zero in 30 sec. Also the reference power setting is changed in steps so that there is no oscillation in the power setting.

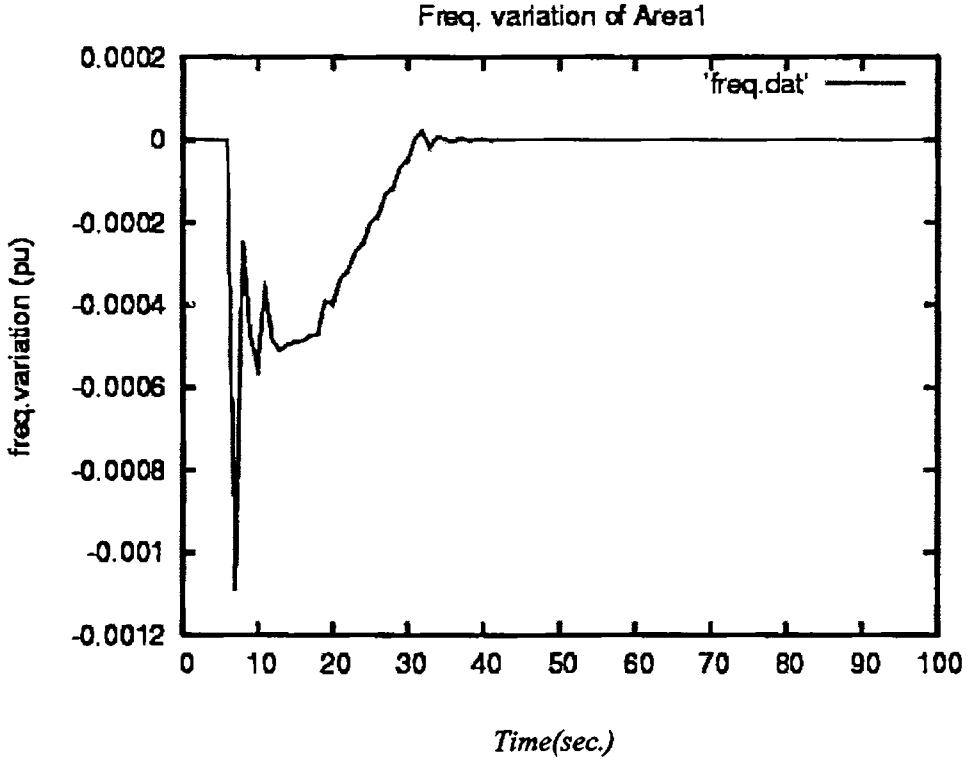


Fig 6.9 Variation of system frequency

In order to compare the performance of RL controller, an integral controller is used for the same system and performance is evaluated for the same load disturbance. Variation of frequency with the integral controller is given in Fig 6.10.

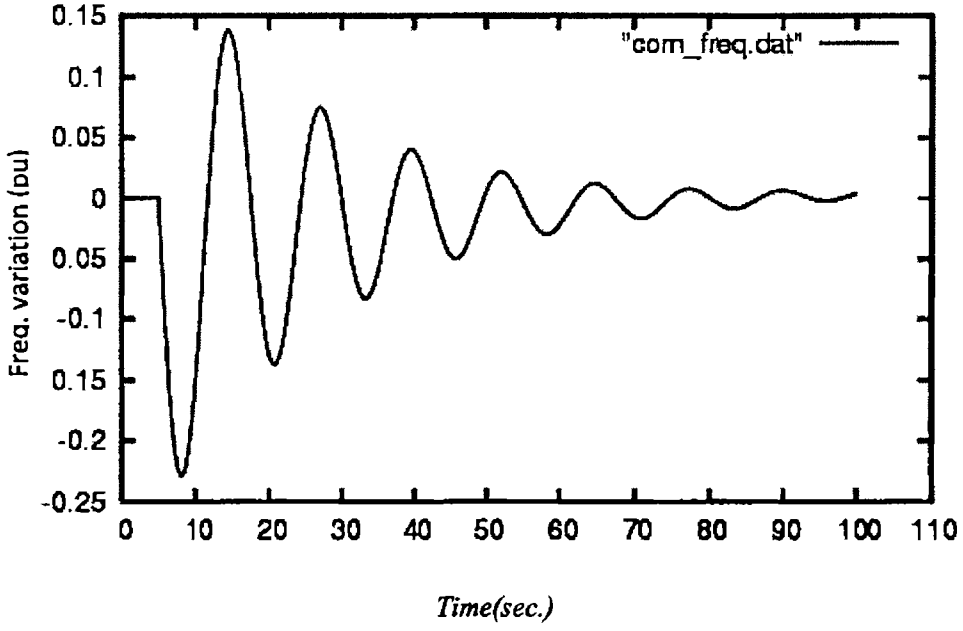


Fig 6.10 Variation of system frequency with Integral controller

Comparing the frequency variations in Fig 6.9 and 6.10, it is clear that the RL controller makes the frequency settled exactly to zero in 30 sec., while with integral controller the frequency does not settle even in 100sec. Variation of frequency with much lesser oscillations ensure good performance for frequency sensitive loads.

6.8 Conclusion

Choosing the power system as a common frequency operated one gives more chance of implementation at practical level. Since AGC is a supervisory control action to handle stochastic load, apart from all modern control methods, RL is the best choice due to the separate time scales considered for the system. Also the flexibility it offers is more so as to include the AGC objectives.

CHAPTER 7

UNIT COMMITMENT AND ECONOMIC DISPATCH OF NEYVELI THERMAL POWER STATION

7.1 Introduction

Reinforcement solutions to the economic scheduling problems: Unit Commitment and Economic Dispatch, applied for several standard test cases were discussed in the previous chapters. Performance of the algorithms has found to be satisfactory. Since there is only one learning procedure, schedule for any load demand can be obtained instantaneously. So it is assumed to be suitable for practical systems.

One of the practical systems is now taken to study the suitability and evaluate the performance of the developed algorithms. Due to the lack of availability of data to compute the cost details, case study is confined to only one of the thermal stations in the Southern grid.

Neyveli Thermal Power Stations are South Asia's first and only lignite fired Thermal Power Stations and also the first pit-head power stations in India. Today Neyveli Lignite Corporation Power Stations are generating about 2490 MW of Power. NLC's Power Stations are maintaining very high level Plant Load Factor (PLF) when compared to the National average. There are two Power stations NTPS I and NTPS II.

7.2 Neyveli Thermal Power Station I

NTPS I station is having a total of 10 generating units with different capacities giving a total of 600MW power. The Power station was first started in 1962 by Indo-Soviet collaboration. The plant was commissioned with one unit of 50 MW in May 1962. Presently this power station consists of six units of 50 MW each and three units of 100 MW each. The last unit of this power station was synchronized in Feburary1970. This Thermal Power Station-I continuously achieved over 70% load

factor from 1982-83 to 1991-92 against the National Average of around 50%. It is the first large thermal power station in South India and is a lignite based station. The power generated from the Thermal Power Station is fed to the grid of Tamil Nadu Electricity Board in order to meet the base load in the country.

7.3 Neyveli Thermal Power Station II

Thermal power station - II has been a major source of power to all southern states of India. The 1470MW capacity power station consists of 7 units of 210MW each. The power station was constructed in two stages of 630MW and 840MW.The first 210MW unit was synchronized in March 1986 and the last unit in June 1993. It is the largest lignite fired thermal power station in Asia. It is having software based burner management system and is equipped with distributed digital control system (DDC) and data acquisition system (DAS) for control and instrumentation. The power generated from Second Thermal Power Station is shared by the Southern States viz., Tamil Nadu, Kerala, Karnataka, Andhra Pradesh and Union Territory of Pondicherry.

7.4 Scheduling of Generating units at NTPS II

Due to the variation in the efficiency of boiler attached to the different units, all the units having even the same capacity are not capable of generating up to its maximum limit. The range of available power generation is different for the different units. Since the NTPS II is generating power for export purpose, economic scheduling of these units is important. As the plant works in a more sophisticated environment, computational scheduling methods are easy to be incorporated. Economic scheduling of the units at the two stations has been done by various methods like Neural networks, Fuzzy Dynamic Programming (Senthilkumar *et al.* [2008]), Evolutionary Programming based Tabu search (Rajan and Mohan [2004]) *etc.*

The Reinforcement Learning based algorithms are used for solving the two parts of scheduling problem in NTPS II (7 unit system)

The cost characteristics of the generating units are expressed in quadratic cost coefficient form, $a_i(P_i^2) + b_i(P_i) + c_i$. The startup costs of the units are calculated based

on the number of hours the unit has been down and the start up cost coefficients. The start up cost of i^{th} unit during time period t is calculated using the equation:

$S_{i,t} = Sc_i [\ 1 - d_i e^{(-t\ off\ (i)\ /\ D)_i}] + e_i$, where

S_{ci} - cold start up cost

d_i, e_i - start up cost co efficient for unit i.

$t_{off(i)}$ - Number of hours i^{th} unit has been shut down

D_i - Minimum Shut down time of i^{th} unit

The unit characteristics of the seven generating units of NTPS II are given in Table 7.1

Table 7.1 – Generating Unit Characteristics of NTPS II

Unit	P_{min} (MW)	P_{max} (MW)	c_i	b_i	a_i	Sc_i	d_i	e_i	Min. Up time(Hr.)	Min.Down time(Hr.)
1	15	60	750	70	0.255	4250	29.5	10	3	3
2	20	80	1250	75	0.198	5050	29.5	10	3	3
3	30	100	2000	70	0.198	5700	28.5	10	3	3
4	25	120	1600	70	0.191	4700	32.5	9.0	3	3
5	50	150	1450	75	0.106	5650	32	9.0	5	5
6	50	150	4950	65	0.0675	14100	3705	405	5	5
7	75	200	4100	60	0.074	11350	32	5.5	6	6

A load profile or 24 hr. duration is considered and the schedule is obtained through Reinforcement Learning algorithms. Load profile is given in Table 7.2

Table 7.2 - Load Profile

Hour	1	2	3	4	5	6	7	8	9	10	11	12
Load	840	757	775	773	770	778	757	778	770	764	598	595
Hour	13	14	15	16	17	18	19	20	21	22	23	24
Load	545	538	535	466	449	439	466	463	460	434	530	840

For practical implementation both Unit Commitment and Economic Dispatch are to be carried out. In the literature there are solutions which consider the problems separately and also as together. Fuzzy Dynamic Programming (FDP) solution (Senthilkumar *et al.* [2008]) and Evolutionary Programming based Tabu search method (Rajan and Mohan. [2004]) give the Unit Commitment and Economic schedule of the generating units. For comparing the performance of the proposed methods the two problems are solved. The proposed RL approach find an optimum Unit Commitment schedule and then economic generation levels are obtained.

Reinforcement Learning based algorithm RL_UCP4 is used to obtain the commitment schedule. Optimum schedule is obtained in 11.67 sec with 80000 iterations. The commitment schedule obtained is given in Table 7.3.

Table 7.3 – Commitment Schedule of NTPS II

Hour	Unit I	Unit II	Unit III	Unit IV	Unit V	Unit VI	Unit VII
1	1	1	1	1	1	1	1
2	1	1	1	1	1	1	1
3	1	1	1	1	1	1	1
4	1	0	1	1	1	1	1
5	1	0	1	1	1	1	1
6	1	0	1	1	1	1	1
7	1	0	1	1	1	1	1
8	1	0	1	1	1	1	1
9	1	0	1	1	1	1	1
10	1	0	1	1	1	1	1
11	1	0	1	1	1	0	1
12	1	0	1	1	1	0	1
13	0	0	1	1	1	0	1
14	0	0	1	1	1	0	1
15	0	0	1	1	1	0	1
16	0	0	0	1	1	0	1
17	0	0	0	1	1	0	1
18	0	0	0	1	1	0	1
19	0	0	0	1	1	0	1
20	0	0	0	1	1	0	1
21	0	0	0	1	1	0	1
22	0	0	0	1	1	0	1
23	1	0	0	1	1	0	1
24	1	1	1	1	1	1	1

After obtaining a commitment schedule, The Economic Dispatch algorithm (RL_ED2) was run to obtain the economic allocation among the generating units. The obtained allocation is given in Table 7.4. The allocation algorithm took only 36.87sec.

for finding the schedule for the entire period of time. Thus, the entire time taken by the Reinforcement Learning based algorithms is only 48.34 sec.

Table 7.4 – Economic Schedule

Hr.	Load (MW)	P_1 (MW)	P_2 (MW)	P_3 (MW)	P_4 (MW)	P_5 (MW)	P_6 (MW)	P_7 (MW)
1	840	60	80	100	101	149	150	200
2	757	60	60	100	81	106	150	200
3	775	60	60	100	85	120	150	200
4	773	60	0	100	113	150	150	200
5	770	60	0	100	110	150	150	200
6	778	60	0	100	118	150	150	200
7	757	60	0	100	100	147	150	200
8	778	60	0	100	118	150	150	200
9	770	60	0	100	110	150	150	200
10	764	60	0	100	104	150	150	200
11	598	60	0	99	97	142	0	200
12	595	60	0	100	96	139	0	200
13	545	0	0	100	99	146	0	200
14	538	0	0	99	97	142	0	200
15	535	0	0	100	96	139	0	200
16	466	0	0	0	116	150	0	200
17	449	0	0	0	101	148	0	200
18	439	0	0	0	97	142	0	200
19	466	0	0	0	116	150	0	200
20	463	0	0	0	116	150	0	200
21	460	0	0	0	110	150	0	200
22	434	0	0	0	95	139	0	200
23	530	60	0	0	120	150	0	200
24	840	60	80	100	101	149	150	200

The algorithms are implemented in C language and the CPU times are taken for a Pentium IV 2.4GHZ, 512 MB RAM personal computer. The time for getting the schedule for 24 hours load pattern is compared with other methods in Table 7.5

Table 7.5 Comparison of Execution time for NTPS II

Method	Cost	Execution Time (sec)
EP_TS	80818	65
FDP	85050	158
RL	81049	48.34

The graphical layout of the comparison is given in Fig 7.1

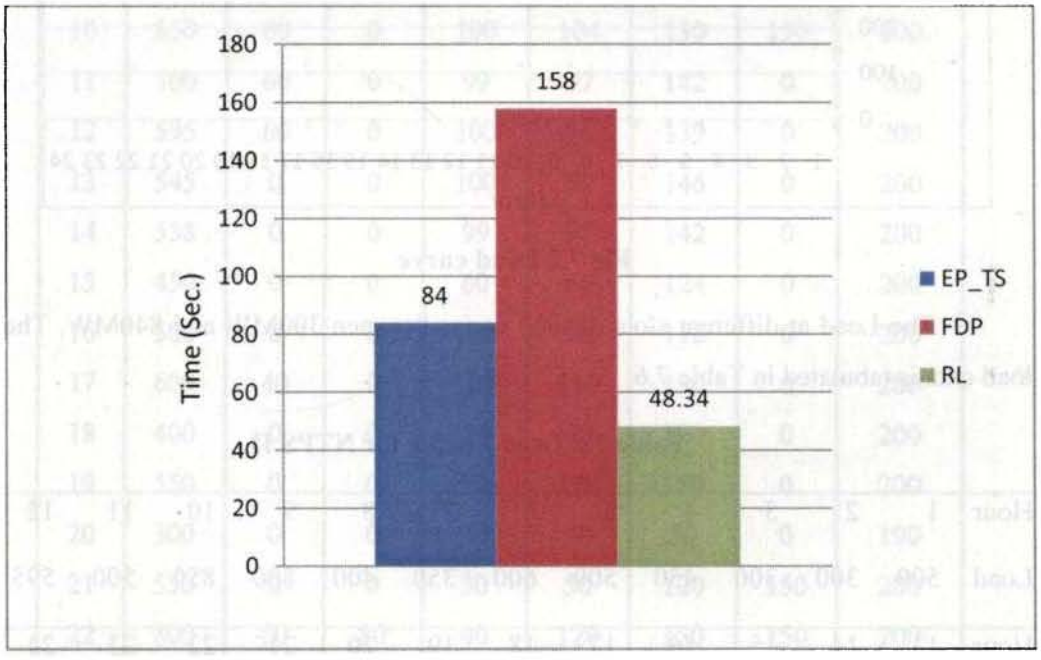


Fig 7.1 Comparison of execution time (sec) for NTPS II

Comparisons with the recent methodologies reveal that Reinforcement Learning based methods provide appropriate results with lesser computation time. This makes it a suitable methodology for power scheduling problems.

In order to prove the efficiency of the proposed algorithms, we also consider one more load profile obtained from a load curve. The load curve of 24 hour duration is shown in Fig 7.2.

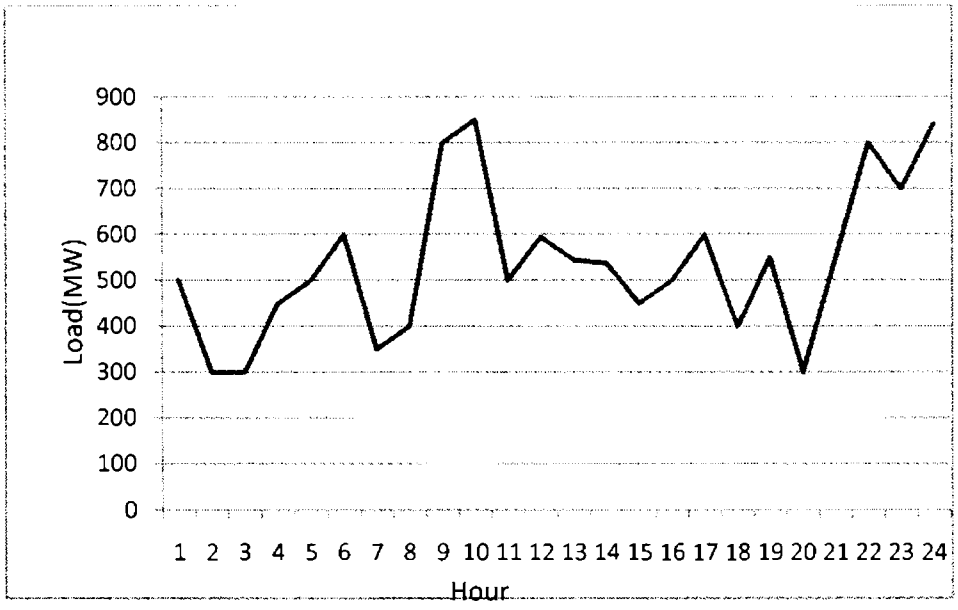


Fig 7.2 Load curve

The Load at different slots of time varies between 300MW and 840MW. The load data is tabulated in Table 7.6

Table 7.6 Load Profile for NTPS II

Hour	1	2	3	4	5	6	7	8	9	10	11	12
Load	500	300	300	450	500	600	350	400	800	850	500	595
Hour	13	14	15	16	17	18	19	20	21	22	23	24
Load	545	538	450	500	600	400	550	300	550	800	700	840

As the load demand varies across each time interval, the generation schedule to be changed accordingly. The Reinforcement Learning algorithms are executed to get

the optimum schedule for each slot of time. The obtained schedule gives a total cost of Rs. 48764/- for 24 hour. Economic schedule obtained is given in Table 7.7

Table 7.7 Economic Schedule for NTPS II

Hour	Load (MW)	P_1 (MW)	P_2 (MW)	P_3 (MW)	P_4 (MW)	P_5 (MW)	P_6 (MW)	P_7 (MW)
1	500	0	0	100	90	110	0	200
2	300	0	0	0	30	70	0	200
3	300	0	0	0	30	70	0	200
4	450	0	0	50	100	100	0	200
5	500	0	0	100	90	110	0	200
6	600	60	0	100	96	144	0	200
7	350	30	0	40	30	50	0	200
8	400	30	0	40	80	50	0	200
9	800	60	0	100	110	150	150	200
10	850	60	0	100	104	150	150	200
11	500	60	0	99	97	142	0	200
12	595	60	0	100	96	139	0	200
13	545	0	0	100	99	146	0	200
14	538	0	0	99	97	142	0	200
15	450	0	0	60	66	124	0	200
16	500	0	0	100	90	110	0	200
17	600	40	0	100	110	150	0	200
18	400	0	0	40	40	120	0	200
19	550	0	0	80	120	150	0	200
20	300	0	0	30	30	50	0	190
21	550	0	0	30	50	120	150	200
22	800	60	80	40	120	150	150	200
23	700	60	40	40	120	110	150	200
24	840	60	80	100	101	149	150	200

7.5 Conclusion

In this chapter the previously developed scheduling algorithms based on Reinforcement Learning strategy were applied to a practical power system. NTPS II seven unit system is scheduled using the Unit commitment and Economic Dispatch algorithms. When compared with some of the recent strategies, the newly proposed methodologies seem to be very much promising on comparing the computational speed. The method proved to be a suitable and efficient one for actual power system scheduling task. It also proves the ability of Reinforcement Learning techniques to handle practical problems of power stations.

CHAPTER 8

CONCLUSION AND SCOPE FOR FURTHER WORK

8.1 Introduction

One of the main objectives when controlling power generation systems, to make the best use of available resources of generation to satisfy the instantaneous variations in the load demand without violating any of the constraints existing in the system. The various constraints arise in a power system from the operational limitations of the generating units and their accessories. Active power generated in a power system is controlled in three time based loops: Unit Commitment, Economic Dispatch and Automatic Generation Control. Unit Commitment and Economic Dispatch loops schedule the generating resources to meet the forecasted load demand. Automatic Generation Control provides the on line control by continuously monitoring the load variations and adjusting the generation accordingly. This also ensures efficient constant frequency operation.

Review of various existing methods for the scheduling problems in power system is carried out. All these methods are proved to be efficient only for deterministic data. The promising features of Reinforcement Learning in the solution of general multi stage decision making problems are investigated. The main objective of the work is to solve the scheduling problems in the power generation using Reinforcement Learning strategy.

8.2 Summary and Major Findings

The review on the existing solution strategies led to the scope of developing efficient scheduling methods in the field of power generation. Reinforcement Learning is a good solution strategy and has been used for solution in many optimization tasks. Number of application of Reinforcement Learning in the field of power system has

been a few even now. In this thesis, efficient Reinforcement Learning solutions are proposed for solution of the three scheduling problems in the power generation sector.

8.2.1 Unit Commitment Problem

In order to develop a Reinforcement Learning based solution strategy, UCP is formulated as a Multistage Decision Problem (MDP). The number of stages in the problem corresponds to the number of hours to be scheduled. Q learning strategy is employed to achieve the optimum scheduling of the units at each time slot.

For introducing the new approach of solution minimum up time and down time constraints are neglected in the initial stages. Then the state of the system at any time slot is represented by a binary string indicating the ON/OFF status of the different generating units. Action set in this Reinforcement Learning task consists of actions of making the units ON /OFF. Q- learning is employed to get the optimum scheduling at the different time slots. e greedy strategy of exploration is used in the first solution, termed as RL_UCP1. Pursuit strategy of exploration is then tried in the second solution, termed as Rl_UCP2. Comparison of these two solution approaches indicate that pursuit algorithm is faster compared to e – greedy.

In the next step of solution, minimum up time and down time constraints are incorporated. Then the problem becomes more complex and the state information includes the number of hours the units have been ON /OFF. To handle the large state space a straight forward strategy is suggested in RL_UCP3. In this case an indexing method is used to manage the large number of states. This method also finds difficulty in handling problems with units having large number of hours as minimum up /down times. An improved method of solution is suggested through state aggregation (RL_UCP4). In this case the number of Q values to be handled is enormously reduced and hence the time of execution is decreased. Also the method proved to be efficient for systems with large number of units having different values of minimum up time and down time.

The developed algorithms are validated with different test cases. Also comparison is made with hybrid methods: Lagrange Relaxation with Genetic algorithm and Simulated Annealing with Local search. The time of execution of Reinforcement Learning algorithm is found to be lesser and the schedule and costs are comparable.

8.2.2. Economic Dispatch Problem

As the second stage of the work, Economic Dispatch problem is solved using Reinforcement Learning approach. Initially the transmission losses are neglected to get the optimum schedule of generation. First a Learning automata algorithm is suggested as RL_ED1. In this case the different possible power combinations are tried through a scientific approach. The goodness of the different actions are stored using performance indices and based on the same an action is selected. This novel strategy is found to be simple and fast but is found to be insufficient to handle large number or generating units.

In order to develop a solution strategy to handle larger problems, Economic Dispatch is formulated as a multi stage decision making process and Reinforcement Learning solutions are proposed. Here at each stage, allocation is made to one of the generating units. Then the action set at each stage comprises the different power allocations possible to the particular unit concerned.

Using Q learning strategy, the system learns for the best action at each state at the different stages. For selecting an action from the action space, taking into account the learnt Q values, ε - greedy and pursuit methods are employed and the corresponding algorithms are RL_ED2 and RL_ED3.

The transmission loss in the system is also considered while finding the economic allocation schedule and the algorithm for the same is developed as RL_ED4. In order to make the solution more efficient by handling continuous state space at each stage, a function approximation approach is proposed as RL_ED5. The Radial Basis Function networks employed in the solution learns the weights of the network through Reinforcement Learning scheme.

The different RL algorithms are tested with IEEE standard systems and systems having non convex and stochastic cost functions. On evaluating the performance of the algorithms, one main attraction is that with a single learning sequence, policy or allocation for any load value can be easily obtained. Reinforcement Learning algorithms can efficiently handle stochastic cost functions also. Also Reinforcement Learning algorithms are found to take lesser computation time compared to other stochastic solution methods like Simulated Annealing, partition Approach Algorithm.

8.2.3 Automatic Generation Control

The third problem in the active power scheduling is the on line dispatch or meeting the instantaneous variation in the load through AGC. Extending Reinforcement Learning solution to AGC is the next step solved. An interconnected system with two control areas is taken for developing RL controller schemes. The frequency of the two areas is taken as the same. Learning of the RL controller in both areas is done by random perturbations. After learning, the policy is available in the form of look up tables. Using the learnt policy, the performance of the system for a given load disturbance is evaluated. The performance of system with RL controller is compared to that of integral controller.

In order to ascertain the suitability and efficiency of the Reinforcement Learning algorithms for practical systems, the NTPS II system is taken for case study. The performance of the algorithm is compared with that of two recent methods: Fuzzy Dynamic Programming and Evolutionary Programming with Tabu search. Results proved that RL based algorithm took lesser computing time compared to other methods.

8.3 Major Research Contributions

Reinforcement Learning solutions are developed for the scheduling problems in the power generation sector. The performance of the algorithms is found to be good compared to other recent methods. In summary, main contributions of this thesis are,

- Reinforcement Learning approach to Unit commitment problem has been proposed.
- Economic Dispatch problem is solved through Reinforcement Learning technique.
- Reinforcement Learning solution to AGC has been extended with a common frequency model for interconnected systems
- The suitability of Reinforcement solution to schedule the thermal generation in NTPS II system is investigated

Proposed solution provides a scope for getting more profit as the economic schedule is obtained instantaneously. Since Reinforcement Learning method can take the stochastic cost data obtained time to time from a plant, it gives an implementable method. This work can be taken as s step towards applying Reinforcement Learning towards the scheduling problems in the power industry.

8.4 Limitations and Scope for further work

In this work, only thermal stations are considered for the scheduling problems. It does not consider the hydro and nuclear sources. Along with the short term scheduling task, long term scheduling is also to be solved efficiently for any practical power system. A large number of social and economical factors impose restrictions on this scheduling process. This scheduling process is also to be solved through such efficient and fast optimization methods.

In this thesis simulation model is employed to learn the system. The learning system is capable to take time to time data from an actual system.

As a further step, all the generating sources in the power system can be incorporated in the solution task, which will give efficient and fast scheduling mechanism which in turn will increase the economic profit in the power generation sector. Also actual data from a power industry can be incorporated by making use of online learning of the system.

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