GENERATION EXPANSION IN DEVELOPING COUNTRIES IN DEREGULATED MARKET

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CANDIDATE'S DECLARATION

I do hereby declare that the dissertation entitled, **"GENERATION EXPANSION IN DEVELOPING COUNTRIES IN DEREGULATED MARKET"** is being submitted by me for a partial fulfillment of Master's Degree in **Water Resources Development** is my own work carried out during the period from July 2005 to June 2006 under the guidance of Prof. **Devadutta Das**, Professor (Electrical), Department of Water Resource Development and Management, Indian Institute of Technology, Roorkee.

The works that are not my own, are quoted and acknowledged in the references. This work has not been submitted by me for the award of any degree at other institutes.

Dated: June, 2006

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(Raju Maharjan)

CERTIFICATE

This is to certify that above statement by the candidate is correct to best of our knowledge.

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Abstract

Generation system is one of the major components of the electric power industry. In deregulated power systems, generation system provides the required environment for competition among power market participants. The entry of Independent Power Producers (IPPs) in generation has become almost a necessity in deregulated market. The entry of IPPs paves the way for further reforms and contributes to increase the competitiveness of the electricity sector.

In this dissertation, the generation expansion scheme in deregulated market by considering the IPPs's participation has been studied. The IPPs are competed as the separate generation technologies to the similar type generators of Utility's and are used to replace them if their inclusion minimizes the cost of expansion. Mathematical models for the cost minimization of Utility's and the profit maximization of IPPs are separately formulated. The cost minimization problem of Utility includes the cost of investment, cost of introducing IPPs and cost of operation. A bidding strategy of IPPs and their energy limits are evaluated based on the scenario analysis. The problem is solved by using the deterministic method Dynamic Programming (DP) and the stochastic method Genetic Algorithm (GA) while maintaining the system reliability and the profits of IPPs.

Reliability indices, LOLP and EENS are estimated by using the probabilistic production simulation approach. An Equivalent Energy Function method is adopted for probability production simulation to calculate the reliability indices and feasibility of a particular generation mix.

The programs for Dynamic Programming, Genetic Algorithm and the probabilistic production simulation are written for the solution of the problem and tested with test system data. The two transaction prices for each type of IPP are selected based on the parameters of IPPs and scenario analysis and the total eight combinations are formed as the cases for finding the optimal generation mix of the expansion scheme. Each case is tested by both methods under two conditions (i) without reliability and (ii) with reliability. The results of the deterministic (Dynamic Programming) as well as stochastic methods (Genetic Algorithm) are compared and analysed for the optimal expansion cost. The reliability indices LOLP and EENS are also checked for each case of optimal generation mix.

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LIST OF ABBREVIATION

DP	Dynamic Programming
EPI	Electric Power Industry
EAP	East Asia and Pacific
EEF	Equivalent Energy Function
ELDC	Equivalent Load Duration Curve
EENS	Expected Energy Not Served
EGEAS	Electric Generation Expansion Analysis System
GA	Genetic Algorithm
GEP	Generation Expansion Planning
H	Hour
IGA	Improved Genetic Algorithm
ILDC	Inverted Load Duration Curve
IPP	Independent Power Producer
KW	Kilo-Watt
KWh	Kilo-Watt-hour
LDC	Load Duration Curve
LOLP	Loss of Load Probability
MW	Mega-Watt
MWh	Mega-Watt-hour
PGA	Parallel Genetic Algorithm
P_c	Crossover Probability
P_m	Mutation Probability
UG	Utility Generation
WASP	Wien Automatic System Planning Package

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CHAPTER ONE

INTRODUCTION

1.1 Overview of Deregulation

The Electricity Power Industries (EPI) got established and developed as a natural monopoly of the government. The three components of EPI (i.e. Generation; Transmission and Distribution) were traditionally owned by the government or state authority. Within a regulated environment it was made responsible for planning, building, operating and maintaining the integrated power systems. As such, all these components were traditionally found within franchise area (usually allocated through state regulation) providing electricity to everyone located within a pre-designated region. This is sometimes referred to a vertically integrated EPI with fixed franchise boundaries.

A vertically integrated electric utility owns and operates its generation plants, its electric transmission systems, and its distribution network that delivers electricity to customers Those with exclusive franchise areas were granted the right to provide service in a designated service territory. Within these service areas, public utilities were protected from competition from enterprises offering the same services. The utilities being vertically integrated, it was often difficult to segregate the costs incurred in generation, transmission or distribution. Therefore, the utilities often charged their customers an average tariff rate depending on their aggregated cost during a period. The price setting was done by an external regulatory agency and often involved considerations other than economics.

Apart from operational issues, such vertically integrated utilities also had a centralized system of planning for the long-term. All activities such as long-term generation and transmission expansion planning, medium term planning activities such as maintenance, production and fuel scheduling were coordinated centrally

In recent year, there have been widespread moves to deregulate, liberalize and privatize Electricity Power Industries (EPI) across the world. Under restructuring and deregulation, vertically integrated utilities, in which producers generate, transmit, and distribute electricity, have been legally or functionally unbundled. The EPI is moving from a monopoly structure to a more competitive one. Such structural reforms increase competition among electric utility companies. Competition has been introduced in the wholesale generation and retailing of electricity. Wholesale electricity markets are organized with several generation companies that compete to sell their electricity in a centralized pool and/or through bilateral contracts with buyers. Retail competition, in which customers can choose among different sellers or buy directly from the wholesale market, has also been implemented [8].

1.1.1 The World-Wide Deregulation Trend

The electricity market deregulation trend is in full swing or in revolution world-wide. This unprecedented restructuring of the industry started in South America and Europe, and is sweeping to the United States [22].

According to the World Bank's survey in 115 developing countries in 1998, seven of the nine countries surveyed in East Asia and Pacific (EAP) and all of the five countries surveyed in South Asia have allowed the entry of independent power producers (IPPs) for competition in electricity market. In 1996 and 1997, about half of the new IPP projects worldwide were in Asia and the Pacific. In 1997, Asia hosted 17% of the IPP projects worldwide. So, most of the Asian countries have introduced some degree of competition in generation by allowing IPPs to sell power to established government utilities, most of which have attained the status of state-owned corporations. Many are in transition to privatizing their electric utilities and introducing competition in wholesale and retail electricity supply [34].

1.1.2 The Goal of Deregulation

In all markets, deregulation is seen as the means to generally increase the efficiency of use of already installed generation assets.

In developed countries, Australia, New Zealand, Norway, Spain, the U.K., and the United States introducing competition would allow private sector decision making and investment in newer technologies, would reduce costs. In a competitive market, reduced costs would translate into reduced prices for end-users. It is seen as an immediate and timely solution that would end the infinite growth of public expenditure on the electricity sector and promise of freedom from rigidity, inefficiency of the state sector.

In developing countries, e.g. Argentina and Chile are motivated by their need to spur investment in generation infrastructures to meet their high growth rates of electricity demand. A "privatized" market would attract investment. Therefore, deregulation simply provides an opportunity for bringing in foreign investment and technologies, which could assist in lessening the nation's financial responsibility in the provision of electricity to the economy as a whole [8].

1.1.3 Potential Benefits of Deregulation

The primary promise of deregulation of electric power is that it will promote greater economic efficiency in electricity generation, transmission, distribution system than under a regulated environment. The main sources of economic efficiency gains commonly cited by proponents of deregulation include the potential deregulation offers to

- lower (total) generation costs by facilitating the interregional shipment of power (i.e., from low to high cost regions);
- stimulate investment in new low-cost generation and transmission resources through the removal of barriers to entry in generation and transmission; and
- promote improved use of electricity by allowing rates that more closely track the "true" cost of service and by the development of more product differentiation, for example, establishing markets for different levels of power reliability.

The potential benefits associated with deregulation are large because the system is large and the economic inefficiencies are, arguably, significant [22].

1.2 Generation Expansion in Deregulated Market

Generation system is one of the major components of the electric power industry. In deregulated power systems, generation system provides the required environment for competition among power market participants. Therefore as electric loads grow, generation expansion should be carried out in timely and proper way to facilitate and promote competition.

The main objective of generation expansion in regulated power system is to seek an optimal generation capacity scheme to meet the forecast demand of loads as economical as possible within a pre-specified reliability criterion over a planning horizon. In regulated environment, uncertainty is low. Generation expansion planning is centralized and coordinated with the transmission expansion planning. Planners have access to the required information for planning. Therefore, planners can design the least cost generation expansion plan based on the certain reliability criteria [19].

During the last two decades electric power generation industry in many countries and regions around the world has undergone a significant transformation from being a centrally coordinated monopoly to a deregulated liberalized market. In the majority of those countries, competition has been introduced through the adoption of a competitive wholesale electricity spot market [1]. It is a general trend in a number of developing countries as well. In most of developing countries, liberalisation means that the state-owned utilities are under privatization process. Many models of reforms are being experienced in these countries. In some of them, only the operation is privatized. The power plants remain the property of the state. In a few variants of these models, the new capacities are provided through a competitive bidding that allows the entry of independent power producers

(IPPs) in the system with various forms of organization: e.g., Built, Lease and Transfer (BLT), Built, Own, Operate, and Transfer (BOOT), or Built, Own and Operate (BOO) [5].

Deregulation is a new force in modern electric power systems where unbundled generation and transmission facilities can belong to different generation companies. Availability and unavailability of generation depends not only on variations in power demand but also on the competition between different generation companies. This new situation makes it difficult to assess the system reliability and for a particular company planner to determine what is the best offer and reliability that will satisfy different customers [17].

In deregulated power systems participants take their decisions independently. They change their strategies frequently to acquire more information from the market to maximize their benefits. Consumers adjust their loads according to the price signals. Availability of independent power producers is uncertain. Generation expansion planning is not coordinated with transmission expansion planning. Hence, there is not a specified pattern for load and dispatched power in deregulated power systems. Due to these uncertainties expansion of generation system have been faced with great risks in deregulated environments. Therefore, generation expansion planning is an important decision-making activity in a deregulated market. Accordingly, planning objectives need to redefine and new analytical tools need to be developed to support the market-based generation planning process and reduce the risks of competition [19].

CHAPTER TWO

REVIEW OF LITERATURES AND THEORETICAL APPROACHES

2.1 Introduction

This chapter presents a literature review of previous research efforts in the field of Generation Expansion planning. In the past decades, many approaches have been presented for Generation Expansion Planning in regulated market and a very few in deregulated market. A number of methodologies and models have been presented in the literature during the last two decades that deal with the GEP problem using several approaches of optimization techniques. However, the way that generation expansion planning has been approached and solved, has been totally redirected through the introduction of competition and deregulation of electricity markets. The problem of power GEP has been reformulated from being cost-minimisation to profit-maximisation. In the following, the applications of mathematical programming models, production costing simulation programs, and decision making techniques, in particular, as proposed and applied for the studies related to generation expansion planning (GEP) are discussed.

A good review of the earlier work could be found in [11], which presents a survey of models for determining least-cost investments in generation planning as the application of basic linear and mixed-integer programming. A survey of mathematical programming models from monopoly to competition in electric power generation planning could be found in [1], which focuses on the traditional modeling techniques developed for generation expansion planning under monopoly to recent new techniques for GEP under the new era of wholesale power competition, including nonlinear programming, stochastic programming and multi-objective programming, to address the issues of reliability of supply, uncertainty in demand and environmental consequences. Emerging optimization techniques in electric utility generation planning are discussed in [12], which involves several new techniques such as expert systems, simulated annealing (SA), fuzzy logic, artificial neural networks (ANN), genetic algorithm (GA), particle swarm optimization etc and their potential usage in solving the challenging GEP in future competitive environments in power industry.

Based on the Dynamic Programming (DP) approach, the optimal generation expansion planning considering IPP's participation and environmental impact (CO_2 emission) is presented in [24],[25],[26]. Genetic Algorithm (GA) based approaches for a least-cost GEP problem as well as GEP in a deregulated market are discussed in [6],[13]-[15],[35],[36],[29],[33]. Refined Immune Algorithm (RIA) for GEP in a deregulated market is presented in [30].

This section will discuss some fundamental problems and modeling techniques concerning optimal generation expansion of electric utilities.

2.1.1 Linear Programming

Linear programming (LP) models have been successfully applied to generation expansion planning for more than thirty years. LP popularity is due to its ability to model large and complex planning problems and the availability of effective algorithms. The LP approach is used to solve the problem of minimizing or maximizing a linear objective function with a set of linear equality and inequality constraints. The objective function is the sum of discounted investment and operational costs; the constraints represent the equilibrium between capacity and demand, capacity reserve requirement, environmental limitations, etc. LP models categorize the generation technologies by fuel type, hence, the total capacity of each generation technology, rather than the size or number of a project, are decision variables. However, the investment in a power plant is usually influenced by the location of the power plant even when the generating units are the same category. In addition to that, the generation technologies are commercially available only in certain sizes and the approximation of capacity requirement by a set of commercially available units may sacrifice the optimization benefits. Therefore, the LP formulation is not a very useful approach for the planning problems where actual project selection needs to be considered, although it is an appropriate model to determine the optimal generation mix.

2.1.2 Mixed-Integer, Stochastic, and Multi-Objective Programming

Alternative optimization models have been proposed in the literature and have been used in the power industry to cover aspects that cannot be solved by LP models. These models are mixed-integer programming to solve discrete decision variables problems, non-linear programming to solve non-linear objective functions problems, stochastic programming to solve random parameters problems, and multi-objective programming to solve multiple objectives problem [11]. Some of the models, i.e. linear multi-objective programming, still retain a linear programming framework, while others allow nonlinearity in dealing with capital costs and engineering constraints.

Mixed-integer programming models assign the project-specific capacities as investment variables with the remainders as continuous variables. A binary variable is assigned to each candidate project as a build/not-build indicator (one and zero, respectively), in a given time period, to simplify the optimization process.

2.1.3 Decomposition Methods

Decomposition refers to the breaking down of a large complicated problem into many smaller solvable ones, thereby reducing computer processing time. Generalized Bender's Decomposition (GBD) algorithm is used in [17] to sub-divide the master GEP problem into a set of sub-problems, which are solved in an iterative way until the optimum cost is found. The master problem is solved using linear programming, and the sub-problems are solved using probabilistic production cost simulation techniques. JASP Model for GEP is discussed using decomposition method in [37]. JASP decomposes the generation planning problem into a high-level power plant investment decision problem and a low-level operation planning problem and solves them by a decomposition-coordination method. Lagrangian Relaxation is used to solve the power plant investment decision problem and probabilistic production simulation is used to solve the operation planning problem.

2.1.4 Dynamic Programming

A dynamic programming (DP) based approach is one of the most widely used algorithms in GEP. Dynamic programming (DP) converts a multistage optimization problem into a series of simple problems and solves using the recursive application of the principle of optimality on the objective. The approach is flexible in using discrete variables, non-linear objective functions and constraints and is used in conjunction with probabilistic production costing simulation programs, i.e. Electric Generation Expansion Analysis System (EGEAS) and Wien Automatic System Planning Package (WASP) [10]. The approach searches all solutions to find the optimal sequence of decisions from the initial state to the least-cost final state, and this is the major drawback of the approach. Applying insight into the nature of the problem to reduce the state space can do some improvement. For instance, reserve margin can be used to eliminate system configurations that are either well below or well above a preferred level of system capacity; the number of units for each generation type selected each year is specified based on the resource availability and other limitations. Further enhancement can be achieved by introducing multiple objectives and random parameters into the models, as in multi-objective dynamic programming and stochastic dynamic programming models [3].

2.1.5 Evolutionary Computation Techniques

In solving the GEP problem, discrete variables and nonlinear constraints are not effectively handled using the above methods and may fail to give global optima. Nowadays Expert systems are introduced to overcome the disadvantages in existing DP method [2],[18],[31],[37]. Evolutionary Computation (EC) techniques are emerging as efficient approaches for various search, classification and optimization problems. The most popular EC techniques, such as Evolutionary Strategies (ES), Evolutionary Programming (EP) and Genetic Algorithm (GA) are based on the mechanics of natural selection, such as mutation, recombination, reproduction and selection. The main advantages of these techniques are their robustness, parallel searching, global convergence, etc. All these EC techniques are successfully applied to various areas of power system such as reactive power planning, unit commitment and economic dispatch [15]. Among these EC techniques, recently GA-based approaches have been successfully applied to for least- cost Generation Expansion Planning problem as well as GEP in a deregulated market [6],[13]-[15],[35],[36],[29],[30],[33].

Genetic Algorithm

GA is one of the stochastic search algorithms based on the mechanics of natural genetics. GA-based approaches for least-cost GEP have several advantages. Naturally, they can not only treat the discrete variables but also overcome the dimensionality problem. In addition, they have the capability to search for the global optimum or quasi-optimums within a reasonable computation time. However, there exist some structural problems in the conventional GA, such as premature convergence and duplications among strings [11].

An improved genetic algorithm (IGA) is developed to overcome the aforementioned problems of the conventional GA [11],[12]. The IGA incorporates the following two main features. First, an artificial creation scheme for an initial population is devised. Second, a stochastic crossover strategy is developed, where different crossover methods are randomly selected from a biased roulette wheel. An improved crossover and mutation mechanism is used with a competition and auto-adjust scheme to avoid prematurity in [35].

Since the efficiency of a GA-based solution algorithm depends greatly on the coding scheme and the selection method used, the Parallel Genetic Algorithm

(PGA) is discussed in [37]. PGA uses an effective coding scheme and selection method tailored to the problem. It can deal with discrete unit sizes of generation units and the execution time is almost proportional to the number of newly introduced generation units. Thus, the PGA is effective for high-dimension generation expansion problems.

2.1.6 Probabilistic Production Simulation Approach

In the past thirty years, the ELDC based simulation technology has dominated electric utility planning [34]. The ELDC is based on the inverted load duration curve (ILDC) and integrates the random outage of each generating unit with the probability density function of system load by a recursive procedure. Then the production costs and reliability indices are calculated using the resulting ELDC. The amount of computation is rather great in the original ELDC, since the function values at discrete points, which represent the equivalent load duration curve, must be recalculated with each convolution and de-convolution computation. Fourier Series method and cumulant method are the two major contributions from research efforts to improve the computation efficiency of ELDC based production simulation. In Fourier Series method, the original LDC is converted into ILDC by 50 to 100 Fourier series terms such that the convolution computation can be performed in the Fourier frequency domain [8]. However, this method does not show significant savings in the amount of computation, and poor curve fitting has been found when the actual ILDC has a flat tail. In the cumulant method, the system load duration curve and the random outage of generating units are described with random distribution numerical characteristic cumulants. This method has demonstrated substantial savings in computation because the convolution and de-convolution process are simplified to addition and subtraction of several cumulants. However, it may suffer from considerable errors when the system scale is relative small or the system load duration curve exhibits multi-mode distribution. An Equivalent Energy Function (EEF) approach for probabilistic production simulation is purposed in [7]. The EEF approach calculates electric energy consumed in different load level segments and modifies it directly when unit failure effects are taken into consideration

The time-dependent nature of system operation constraints is considered using a chronological simulation approach. The chronological simulation models explicitly trace the system states over time by using Monte Carlo techniques to capture the random variation of generation capacities and demand levels [21]. The results of Monte Carlo chronological simulation are more detailed than the results of ELDC-based analysis, with much higher computational requirements. A comparison of different probabilistic production costing simulation methods can be found in [20], where the test results of an investigation are reported in terms of the relative computational speed and solution quality. These include piece-wise linear approximation method, segmentation method, equivalent energy function method, cumulant method, mixture of normal approximation method and fast Fourier transform method. The equivalent energy function method was shown to be preferred, considering both computational efficiency and accuracy. A more recent multi-parameter Beta distribution function method has been introduced, which was more accurate than the cumulant method with little addition of computation time.

2.2 Problem Definition

The entry of Independent Power Producers (IPPs) in generation has become almost a necessity in the transition of electricity sectors from being dominated by vertically-integrated government monopolies to one characterized by competition. The entry of IPPs paves the way for further reforms and contributes to increasing the competitiveness of the electricity sector. In the past years, only a few approaches have been presented for GEP considering IPP's participation in a deregulated market. No one of them has presented the suitable approach for GEP in developing countries. The approaches developed so far may not fully meet the objectives of some of the socially and economically less developed countries. The role of IPPs is also changing with the introduction of competition at the wholesale and retail levels. This trend will see a decrease in the traditional IPP contracts and the rise of merchant power plants. The setbacks of the Asian power sector due to the regional financial crisis in 1997-1998 exposed flaws in the IPP model and have stressed the need for more competitive arrangement than the single buyer model [32].

Restructuring and deregulation have increased the desires of IPPs. IPPs have different desires and expectations from the performance and expansion of the system. The objective function of each IPP for investment decision-making is to maximize its profit, while the objective of profit maximization of each IPP is linked to others. Therefore, it requires developing new generation expansion methodologies facilitating competition, minimizing the risk of investments, increasing the reliability of the system, increasing the flexibility of operation and minimizing the environmental impacts.

2.3 The Objective of Work

The main goal of this dissertation is to present a static approach for Generation Expansion in deregulated power systems from the viewpoint of utility. Restructuring and deregulation of power industry have changed the objectives of generation expansion from the cost minimization to profit maximization. The optimal generation mix problem including IPP's needs to be considered so that the utility will have choice to replace the generating units with the similar type from IPPs.

CHAPTER THREE

MATHEMATICAL FORMULATION OF GENERATION EXPANSION PROBLEM CONSIDERING IPPS

3.1 Load Duration Curve and merit order

The demand for power is traditionally described by a *load duration curve* (LDC), i.e. by a graphical summary of demand levels with corresponding (non-chronological) time durations. In regulated markets, the LDC is typically used together with *screening curves* (in which, for comparing the generation costs of different technologies, annual revenue requirements are plotted as a function of capacity factors, *CF*) to determine the optimal mix of generation technologies [29]. This procedure, also referred to as the *merit order approach*, is no longer applicable in a competitive market environment because of uncertainty (e.g. regarding cost and demand). Still, the LDC provides a useful summary of a year's worth of hourly fluctuations in electricity demand.

Various generation technologies can be used to fill the load duration curve so as to decrease the cost of the overall supply. The optimal method is to have the generation technology with the lowest variable cost occupy the lowest horizontal slice of the load duration curve and so on, in rising variable cost order. According to this, the merit order for generation technologies from bottom to top under the load curve is shown in Fig. 1.

The Annual Load Duration Curve (LDC) can be estimated for known peak demand and annual load growth rate using the following analytical function (23).

$$L(t)=0.01p^*r+((p-0.01p^*r)/\tan(-0.5^*s))^*\tan(s^*t-0.5s)$$

where

s is the parameter for change the LDC's sharp and $1.0<s<3.14$
t is the annual duration time (H)
p is the max load(MW)
and r is the annual load rate (%)

The parameters s, p and r can be changed to estimate the LDC more exactly.

3.2 IPPs in the generation mix

The IPPs are to be dealt as the separate generation technologies when they are introduced by the utility. IPPs can be divided into three types by power generation characteristic as shown in Table 1: base type, middle type and peak type.

Table-3.1: Characteristics of IPPs

IPP Type	Operation time (One day)	Duration time (One year)
Base_type	24h	8760h
Middle_type	18h	6520h
Peak_type	6h	2190h

The difference in duration of generation determines the difference in their location under the load curve. When IPPs are introduced by the utility, they replace generating plants that are with similar characteristics. Therefore IPPs are regarded as individual generation technologies and their locations under the load curve can be treated the same as other generation that belongs to the utility. Based on questionnaires on potential capacity of IPP's in the electric power wholesale market, IPPs of three fuel types are considered as follows:

Base-type: coal

Middle-type: Oil

Peak-type: LP gas

Considering that variable costs for IPPs are lower than for those of comparable utility generation, the merit order for generating plants, as shown in Figure-3.1, is Nuclear (N), base-type IPP, Coal, middle-type IPP, LNG (L), Oil (O), Hydro(H), peak-type IPP, Gas turbine (G). In addition, the peak-type IPP is positioned below gas turbine to secure the reliable supply of peak load. The gas turbine fills the peak load of the load duration curve.

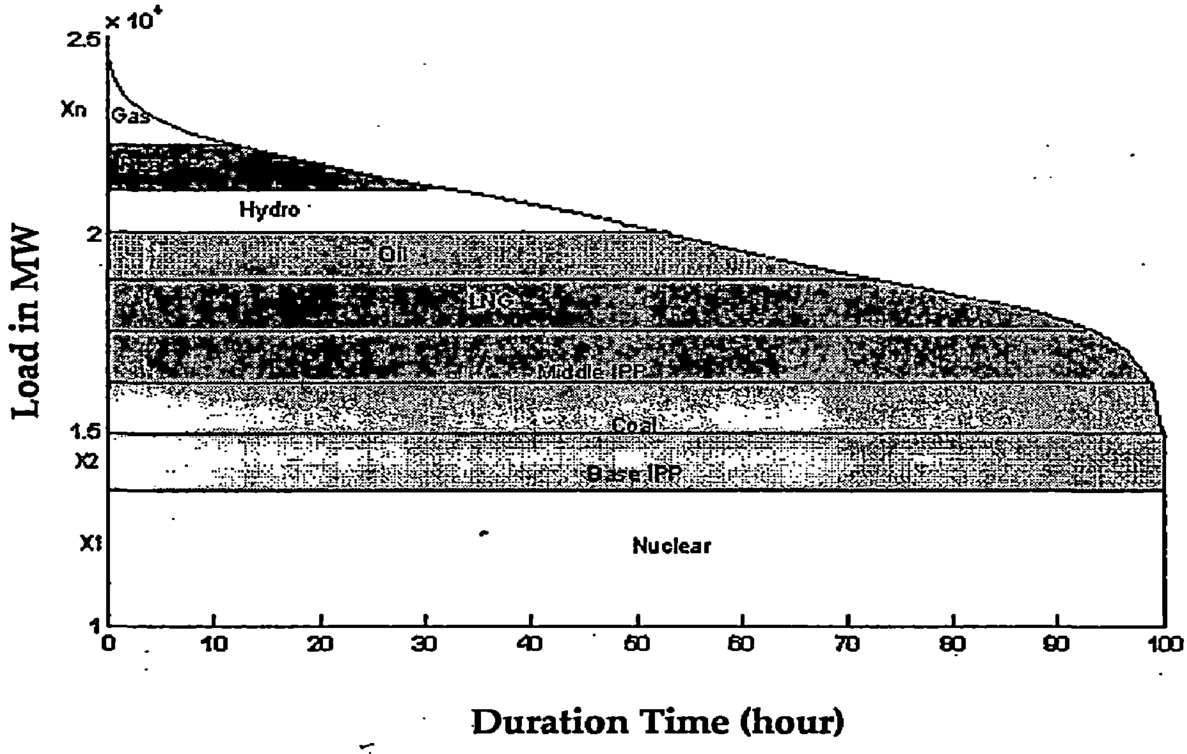

Figure-3.1: Optimal Loading order of Utility and IPPs Units

3.3 Formulation:

To formulate the problem of optimal generation mix including IPPs, the following hypotheses are set up.

1) Annual load demand, load factor, and peak load at the target year are known;
2) The utility has Nuclear, Coal, Oil and Gas generation;
3) IPPs are classified into three types: Base, middle and peak type;
4) These three types of IPPs bid against each other on generation expansion of utility.
5) The variable costs of IPPs are lower than for those of comparable utility generation.
6) To secure the reliable supply of peak load, Peak_type IPP is below gas turbines.
7) The merit order for generation technologies from bottom to top under the load curve are Nuclear, Base_type IPP, Coal, Middle_type IPP, Oil, Peak_type IPP and Gas.

The optimization model of the utility and IPPs can be formulated by the following equations, taking into consideration the interaction of the utility and the IPPs.

3.3.1 For the utility

Objective function:

Total cost of Utility can be minimized by the following equation

$$\text{Min } f(x) = \sum_{i=1}^{M}(a_i x_i + b_i Q_i) + \sum_{j=1}^{3}\lambda_j Q_j \qquad (3.1)$$

3.3.2 For IPP

Objective Function:

Maximum profit for the IPP can be expressed by

$$Max\, \lambda_{Rj} x_{Rj} + \lambda_j Q_j - C_j \qquad (j = 1, 2, 3) \tag{3.2}$$

The constraints considered in above objective functions are as follows.

1. Power balance constraint

   The sum of power generating from all the Utility generators and IPPs must be equal to or greater than the peak load and reserve power.

   i,e $$\sum_{i=1}^{M} x_i + \sum_{j=1}^{3} x_j \geq P_D + P_R \tag{3.3}$$

2. Capacity limit constraint

   The capacity of new plants of Utility and IPPs are restrained by their upper and lower limits.

   i,e $$x_{i,j\min} \leq x_{i,j} \leq x_{i,j\max} \tag{3.4}$$

3. Total capacity constraint

   If k is used to index the technologies including IPPs in merit order and x_k to represent the capacity of technology k, the total capacity X_t should be the cumulative introduced capacity of 1 to k^{th} generating technologies.

   i,e $$X_0 = 0, \quad X_t = \sum_{k=1}^{t} x_k \tag{3.5}$$

4. Energy Production constraint

   Letting $L_T(u)$ represent the fraction of time that demand equals or exceeds level u, each technology's energy production is

$$Q_i = \int_{X_{i-1}}^{X_{i-1}+x_i} L_T(u)du \tag{3.6}$$

5. Energy limit constraint

   The energy generation of each technology should be within the upper and lower limits

   i,e $Q_{i\min} \le Q_i \le Q_{i\max}$ $\quad (j = 1, 2, 3)$ (3.7)

6. Reliability constraints

   The reliability indices LOLP and EENS should be within the specified limits.

   i,e $LOLP \le LOLP_T$ (3.8)

   $EENS \le EENS_T$ (3.9)

$\lambda_{Rj}x_{Rj}$ is the reserve capacity purchased by the utility. As for securing the reliable supply of power, the peak load of the utility is filled by gas turbines belonging to the utility, it is considered to be zero.

In case that the reservation capacities are provided by IPPs in the electric market, not only the gas turbines of utilities, but also the supply of reservation from IPPs should be considered in the formulation.

Where,

a_i : Fixed cost of i^{th} generating plant (Rs./MW)

b_i : Variable cost of i^{th} generating plant (Rs./MWh)

x_i : Introduced capacity of i^{th} Utility generation (MW)

Q_i : Annual generated power energy of i^{th} Uility generation at target year (MWh)

x_j : Installed Capacity of j^{th} IPP (MW)

Q_j : Introduced Energy of IPP by Utility (MWh)

λ_j : Purchase price of power energy of j^{th} IPP (Rs./MWh)

M : Total number of generating plants of Utility

N : Total number of generating plants and IPPs (N=M+3)

P_D : Peak load at target year (MW)

P_R : Supply reservation at target year (MW)

X_i : Cumulative introduced capacity from 1^{st} to i^{th} generating plant (MW)

$L_T(u)$: Inverse function of load duration curve supplied by utility in target year

λ_{Rj} : Purchase price of capacity as reversed (Rs./MW)

x_{Rj} : Reserved capacity (MW)

C_j : Cost of j^{th} IPP (Rs.)

$LOLP_T$: Level of loss of load probability

$EENS_T$: Level of expected energy not supplied

CHAPTER FOUR

OPTIMIZATION MODEL OF IPPS BASED ON SCENARIO ANALYSIS

In a competitive generation market, IPPs want to sell electricity to the utility with some prices as high as possible; on the other hand the utility wants to purchase electricity from IPPs with some prices as low as possible for maximizing their own profits. Therefore, it is important to make sure the transaction price at the time when IPPs are introduced by utility. The followings give a standard to determine the compromising price based on the analysis of scenarios of IPPs, and obtain the limitation conditions of electric energy of IPPs at same time.

4.1 Case of one IPP:

The IPP's cost can be formulated by a linear relation as follows:

Total cost = Fixed cost + Variable cost coefficient X *Power generated by IPP* (4.1)

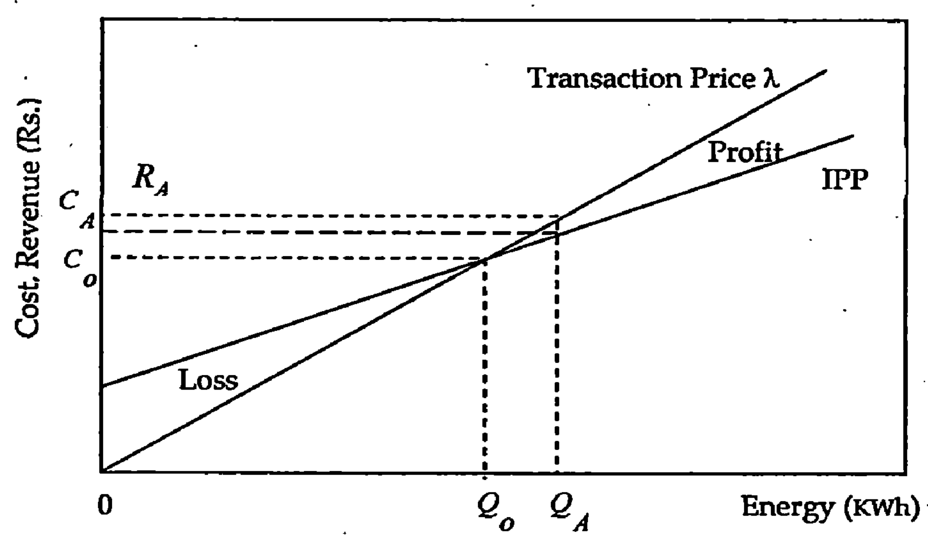

Figure-4.1: Scenario of One IPP

In Figure-4.1, suppose that λ is the utility's purchase price from an IPP. If IPP sells power Q_o to the utility, IPP makes no profit as cost equals revenue. But if IPP sells power Q_A ($Q_A > Q_o$) to the utility, then revenue is over cost, the IPP will make profit and the profit is R_A - C_A.

4.2 Case of Two IPPs

In Figure-4.2, IPP1 and IPP2 represent different types of IPPs, whose fixed costs and variable costs satisfy the following conditions:

Fixed cost of IPP1< Fixed cost of IPP2

Variable cost of IPPI >Variable cost of IPP2

When IPPs sell power over Q_o (such as Q_A) to the utility with some prices, it can make profit for IPP1 only if the transaction price is over λ_1. Similarly, it can make a profit for IPP2 if the transaction price is greater than λ_2. As price $\lambda_2 < \lambda_1$, the utility will choose IPP2 for purchasing power above Q_o rather than IPP1.

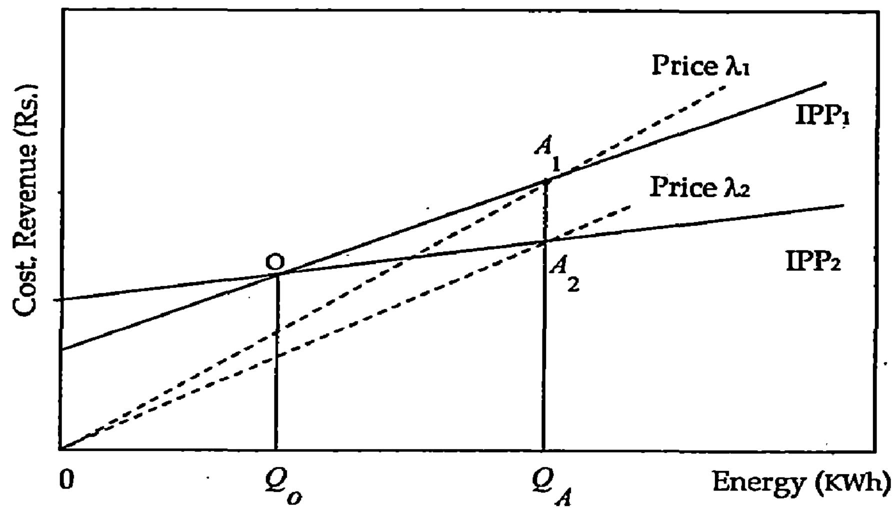

Figure-4.2: Scenarios with two types of IPPs

If the utility wants to purchase power less than Q_o, it will choose IPP1 rather than IPP2. The energy Q_o can be regarded as an energy limit for the two types of IPP's at the time they bid together.

4.3 Case of Three IPPs

In Figure-4.3, there are three types of IPP: peak-type IPP, middle-type IPP and base-type IPP. Suppose Q_0 is the amount of energy that the utility wants to purchase from IPPs. Based on the above analyses, the following conclusions can be drawn:

1) If $Q_O < Q_A$ the utility will select the peak-type IPP, and λ_A will be the minimum purchase price for the peak-type IPP.

2) If $Q_O > Q_A$ and $Q_O < Q_B$, the utility will select the middle-type IPP. λ_A will be the maximum purchase price and λ_B will be the minimum purchase price for the middle-type IPP.

3) If $Q_O > Q_B$, the utility will select the base-type IPP and λ_B will be the maximum purchase price for the base-type IPP.

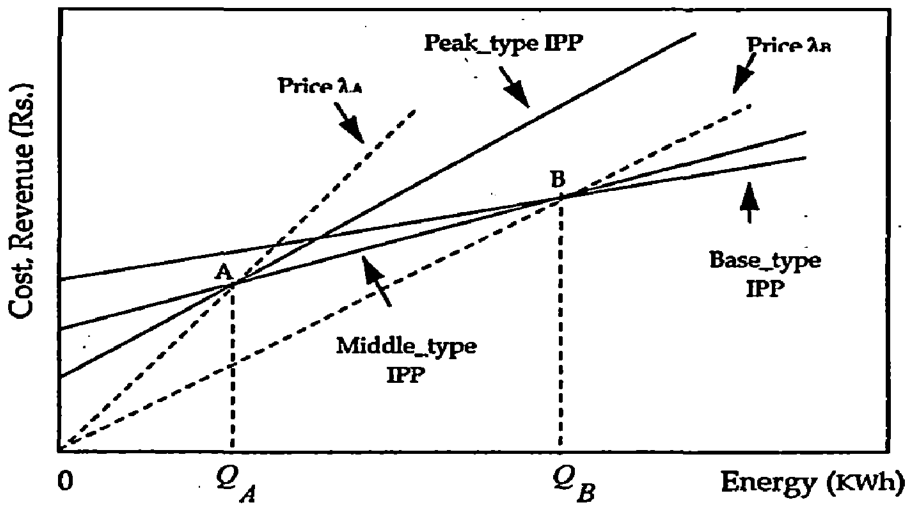

Figure-4.3: Scenario with three types of IPPs

The above conclusions can be generalized to the general case of optimization of the IPPs, in which the IPPs all try to maximize their own profits and balance is reached in the end. The two transaction prices for each type of IPP with different energy limits can be assumed to take changes in price into account. The maximum price or minimum price for each IPP is one case. The values in the range between the maximum and minimum prices are the other cases.

CHAPTER FIVE

SOLUTION OF GENERATION EXPANSION PROBLEM

5.1 Dynamic Programming (DP) approach

Dynamic programming is a computational method which uses a recursive relation to solve the optimisation in stages. A complex problem is decomposed into a sequence of nested sub-problems, and the solution of one sub-problem is derived from the solution of the preceding sub-problem. A stage in DP is defined as the portion of the problem that possesses a set of mutually exclusive alternatives from which the best alternative is to be selected. A state is normally defined to reflect the status of the constraints that bind all the stages together.

The Dynamic Programming (DP) algorithm is generally used in the generation expansion problem to find the best expansion policy with minimum cost satisfying the reliability of power system.

For using the DP algorithm, each generation technology is taken as one stage in a cost accumulation process, while the total capacity of various generation technologies is expressed by the state of the process. The problem is characterized as a dynamic program, whose stages are generation technologies and whose states are cumulative capacities. The states are modified as the integer multiple of single generation technology by using maximum common divisor of all the generating units as state unit. Therefore, the number of state at every stage is fixed which equals the multiple of maximum common divisor by which total introduced capacity divided.

The principle of DP is as follows:

Objective function:

$$\text{Min} \quad Z = \sum_{i=1}^{n} g_i(x_i) \tag{5.1}$$

Subject to

$$\sum_{i=1}^{n} a_i x_i \le b \qquad (i = 1 \sim n) \tag{5.2}$$

Suppose $k = 1 \sim n$, $y = 0 \sim n$, then base on the DP approach, the following equation can be obtained

$$f_k(y) = f_{k-1}(y - a_k x_k) + g_k(x_k) \tag{5.3}$$

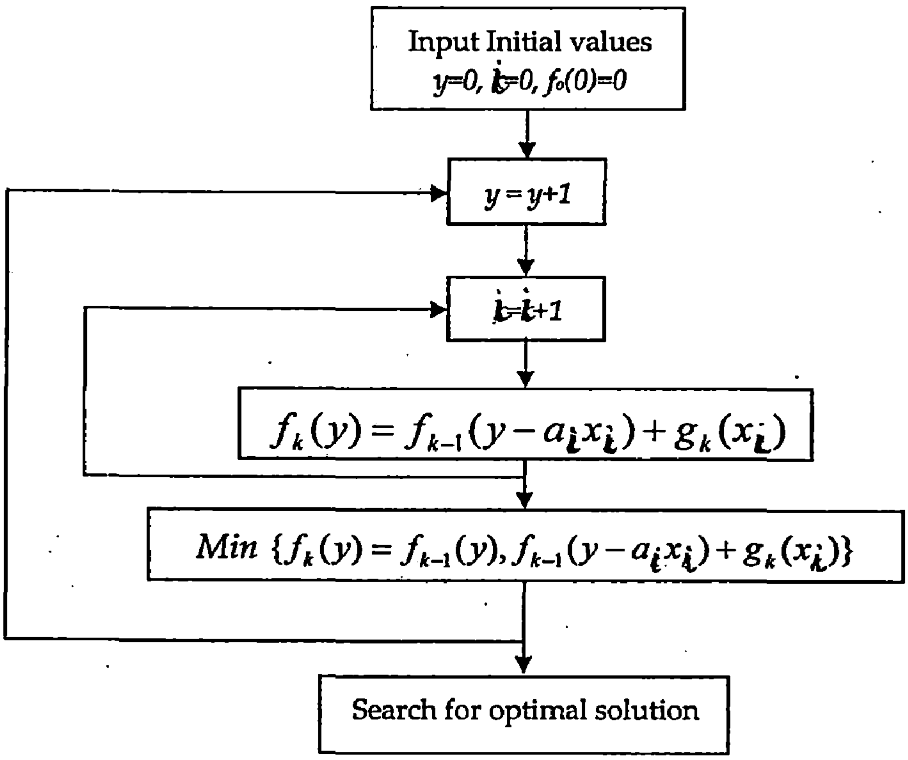

Figure-5.1: The Principle of DP

5.2 Genetic Algorithm (GA) Approach

5.2.1 Introduction

The Genetic Algorithm (GA) is a randomized search and optimization technique guided by the principle of natural genetic systems [27]. Genetic Algorithms are very different from most of the traditional optimization methods. Genetic Algorithms need design space to be converted into genetic space. So, genetic algorithms work with a coding of variables. The advantage of working with a coding of variables space is that coding discretizes the search space even though the function may be continuous. A more striking difference between genetic algorithms and most of the traditional optimization methods is that GA uses a population of points at one time in contrast to the single point approach by traditional optimization methods [33]. They work not with the parameters themselves but with strings of numbers representing the parameter set, and they use probabilistic rules to guide their search. By considering many points in the search space simultaneously, they reduce the chances of converging to local minima [27].

A simple genetic algorithm that yields good results in many practical problems is composed of three operators.

1. Reproduction
2. Crossover
3. Mutation

Reproduction is usually the first operator applied on population. Chromosomes are selected from the population of parents to crossover and produce offspring. According to Darwin's evolution principle of "Survival of the Fittest", the best one should survive and create new offspring.

Reproduction operator is also known as the Selection operator. Normally, the roulette-wheel selection operator is used for selecting chromosomes for parents to crossover. In roulette-wheel selection, a string is selected from the mating pool with a probability proportional to the fitness. There also exist other selection operators such as Rank Selection, Tournament Selection, Boltzmann Selection etc.

Crossover is a recombination operator. The fittest string is preferentially chosen for recombination, which involves the selection of two strings and the switching of the segments to the right of the meeting point of the two strings [27]. The probability of crossover rate varies from 0 to 1. This is calculated in GA by finding out the ratio of the number of pairs to be crossed to some fixed population. Typically for a population size of 30 to 200, crossover rates, usually denoted by P_C, are ranged from 0.5 to 1 [33].

After crossover, the strings are subjected to mutation. Mutation is used to maintain genetic diversity within a small population of strings. There is a small probability P_m that any bit in a string will be flipped from its present value to its opposite (e.g. 0 to 1) [27]. Mutation rate is the probability of mutation which is used to calculate number of bits to be muted. Mutation probabilities are smaller in natural populations leading us to conclude that is appropriately considered a secondary mechanism of genetic algorithm adoption. Typically, the simple genetic algorithm uses the population size of 30 to 200 with the mutation rates varying from 0.001 to 0.5.

The GA maintains a set of possible solutions (population) represented as string of, typically, binary numbers (0, 1). New strings are produced in each and every generation by the repetition of a two-step cycle. This involves first decoding each individual string and assessing its ability to solve the problem. Each string is assigned fitness values, depending on how well it has performed in an environment. In the second stage, the fittest string is preferentially chosen and new chromosomes are formed by either (a) merging two chromosomes from the current generation using a crossover operator or (b) modifying a chromosome using a mutation operator. A new generation is formed by selecting, according to the fitness value, some of the parents and offspring, and rejecting others in order to keep the population size constant. After several generations, the algorithm converges to the best chromosome, which hopefully represents the optimal or near optimal solution to the problem. GAs have been quite successfully been applied to optimization problems like wire routing, optimal control problems, power system optimization problems etc.

5.2.2 Procedures of Genetic Algorithms

5.2.2.1 Genetic Representation or Encoding :

The coding scheme can be illustrated as shown in Figure-5.2, where each gene indicates a combination of generation power output. The gene is encoded as a chromosome string which produced by equation (5.4). If the GA search is terminated, the chromosome will then be decoded.

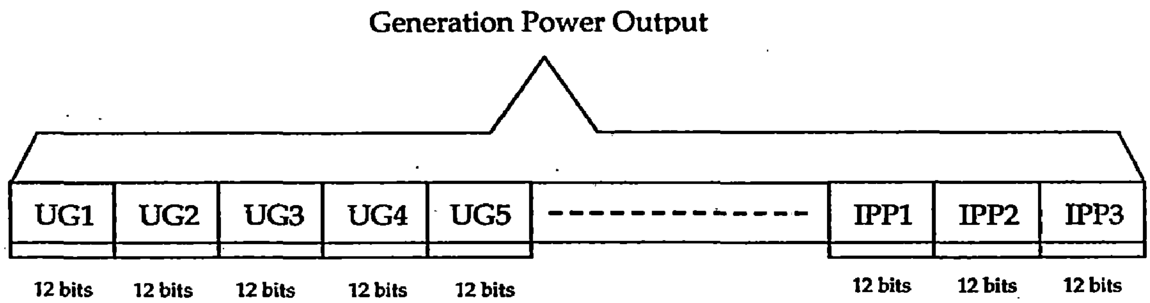

Figure-5.2: Chromosome String of the Gene

The following formula encodes the genes.

$$D2B\left\{ \left[\left(PG_i - PG_i^{\min}\right)/\,resol_i\right] \right\} \tag{5.4}$$

where

$resol_i = \left(PG_i^{\max} - PG_i^{\min}\right)/\left(2^{bit} - 1\right)$

$D2B$: Convert decimal to binary

PG_i : the i^{th} generation power output

$PG^{\max}$: the upper limit of i^{th} generation power output

$PG^{\min}$: the lower limit of i^{th} generation power output

bit : the number of bit for a gene

5.2.2.2 Initialization :

The initial populations of decision variables satisfying the upper and lower limits (and constraints) are selected randomly from the set of uniformly distributed population. The distribution of initial population should be uniform. Totally N_P populations are generated where N_P is the total number of parents selected.

5.2.2.3 Fitness Function Evaluation :

The fitness score of each gene is obtained by calculating the objective function of the optimization problem (taking constraints into account for constraint problem). The maximum (f_{max}), minimum (f_{min}), sum (f_{sum}) and average of fitness (f_{avg}) are also calculated.

5.2.2.4 Selection :

The selection of individuals in GA is done by various methods such as Roulette wheel selection, ranking method and tournament selection method.

In roulette wheel selection method, the roulette wheel is biased with the fitness function value of each of the solution candidates. This operation yields a new population of strings that reflect the fitness of the previous generation's fit candidates.

5.2.2.5 Crossover :

Each individual of the population are assumed to be a chromosome. Crossover or recombination means exchanging some portions of the chromosomes of two individuals to yield offspring. Crossover can occur at single point, two points or at multiple points. The various crossover techniques used are tail to tail crossover, head to tail crossover and binary window crossover.

5.2.2.6 Mutation :

In GA, the mutation involves selecting a string as well as a bit position at random and altering its value. The number of bits and the number of populations to be mutated depends upon the mutation probability. After mutation, the next generation starts with the fitness function calculation for these individuals and the steps are repeated.

5.2.2.7 Improved crossover and mutation scheme (ICM) :

Crossover generally executes before mutation throughout the SGA searching process. In SGA, a higher crossover rate allows the exploration of solution space around the parent solution. The mutation rate controls the rate new genes are introduced, and explores new solution territory. If it is too low, the solution might settle at a local optimum. On the contrary, a high rate could generate too many possibilities. The offspring lose their resemblance to the parents; the algorithm won't learn from the past and could become unstable. It is a dilemma to choose suitable crossover and mutation rate for

SGA. An improved crossover and mutation scheme (ICM) is thus proposed below to avoid such a difficulty.

(i) Randomly select two parents, and generate offsprings by introducing C(g) with

   (a) If rand < C (g) : use mutation;

   (b) If rand > C (g) : use crossover.

where

rand : the uniform random number in (0,1),

C : the control parameter with initial value set to 0.5,

$0.1 \leq C \leq 0.95$

g : the current generation number.

The offsprings will be generated until all parents are processed. Figure-5.3 shows the initial relationship of crossover and mutation in ICM. Mutation operation will play a more important role than that in SGA, since mutation is more capable of exploring new regions. If the search is very close to the local or global optimum, mutation may need to become dominant, especially in the absence of the critical good genes in a generation. Since crossover and mutation are both random operators, there is no telling which one is better of the two. A competition mechanism is thus implemented in the searching process according to the fitness score. If the best current solution comes from crossover, there is a more likelihood for crossover to generate better offsprings for the next population. On the contrary, there is a more likelihood for mutation to generate better offsprings. If the best solution remains the same, the operation of crossover or mutation needs to hold back. The sum of probability of crossover and mutation is equal to one.

(ii) If $F_{min}(g) < F_{min}(g-1)$ comes from crossover, the control parameter C(g+1) will decrease. Then

$$C(g+1) = C(g) - \frac{K_1}{g_{max}} \quad (5.5)$$

where K_1 is the regulating factor, and g_{max} is the maximum generation number. Figure-5.4 shows the variation of probability of crossover.

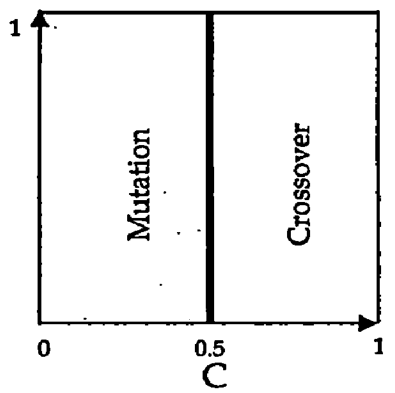

Figure-5.3:. Probability map of crossover and mutation in ICM for C = 0.5

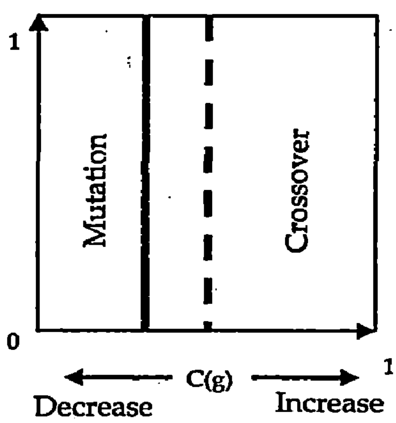

Figure-5.4: Variation of probability of Crossover

(iii) If $F_{min}(g-1) > F_{min}(g)$ comes form mutation, the control parameter C(g+1) will increase. Then

$$C(g+1) = C(g) + \frac{K_1}{g_{max}} \tag{5.6}$$

The variation of probability of mutation is illustrated in Figure-5.5.

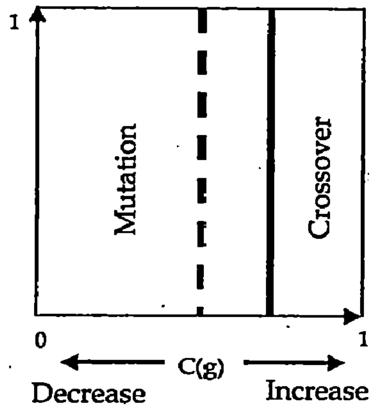

Figure-5.5: Variation of probability of Mutation

(iv) If $F_{min}(g-1) \leq F_{min}(g)$, the control parameter needs to hold back.

If C(g) > C(g-1)

$$C(g+1) = C(g) - \frac{K_2}{g_{max}} \tag{5.7}$$

elseif C(g) ≤ C(g-1)

$$C(g+1) = C(g) + \frac{K_2}{g_{max}} \tag{5.8}$$

in general, $K_1 < K_2$

5.2.2.8 Elitism selection :

An additional common feature of the GA is the automatic inclusion of the best performing string of the parent generation in the new offspring generation. This is Elitism selection and this procedure prevents a good string from being lost by the probabilistic nature of reproduction and speeds the convergence to a good solution.

The 2p chromosomes (p parents and p offsprings) are ranked in ascending order according to their fitness values. "b" individuals with the best fitness are kept as the parents for the next generation. Other individuals in the combined population of size (2p-b) have to compete by adopting the roulette wheel approach to get selected in the next generation.

5.2.2.9 Stopping rule :

The process of generating new trials with the best fitness will be continued until the fitness values are optimized or the maximum generation number is reached.

5.2.3 Genetic Algorithm Application to Constrained Optimization Problem:

GAs are ideally suited to unconstrained optimization problems. Many practical problems contain one or more constraints that must also be satisfied. Constraints are usually classified as equality or inequality relations. It is necessary to transform a constrained optimization problem to an unconstrained optimization problem to solve it using GA. In traditional transformation methods (such as penalty method), a constrained problem is transformed to unconstrained problem either by using exterior or interior penalty functions with all constraint violations. Such transformations are ideally suited for sequential searches. GA performs the search in parallel using populations of points in search space. Hence, traditional transformations using penalty or barrier functions are not appropriate for genetic algorithm. A formulation based on the violation of normalized constraints is generally adopted.

Consider, for example, the original constrained problem in minimization form:

Minimize $f(x)$ (5.9)

Subjected $g_j(x) \le b_j$; j = 1, 2, ..., m (5.10)

Where

x and b are m vectors

m is the number of constraints

The constraint in normalized form is given by

$$\frac{g_j(x)}{b_j} - 1 \le 0 \tag{5.11}$$

A violation coefficient C is computed in the following manner

$$C_j = g_j(x), \quad \text{if } g_j(x) > 0$$

$$C_j = 0, \quad \text{if } g_j(x) \le 0$$

then

$$C = \sum_{j=1}^{m} C_j \tag{5.12}$$

where m is the number of constraints

Now the modified objective function $\phi(x)$ is written as

$$\phi(x) = f(x)\{1 + KC\} \tag{5.13}$$

where parameter K has to be judiciously selected depending on the required influence of a violation individual in the next generation. A value of 10 was found to be suitable for most of the problems. Now the genetic algorithm is used to carry out unconstrained optimization of $\phi(x)$.

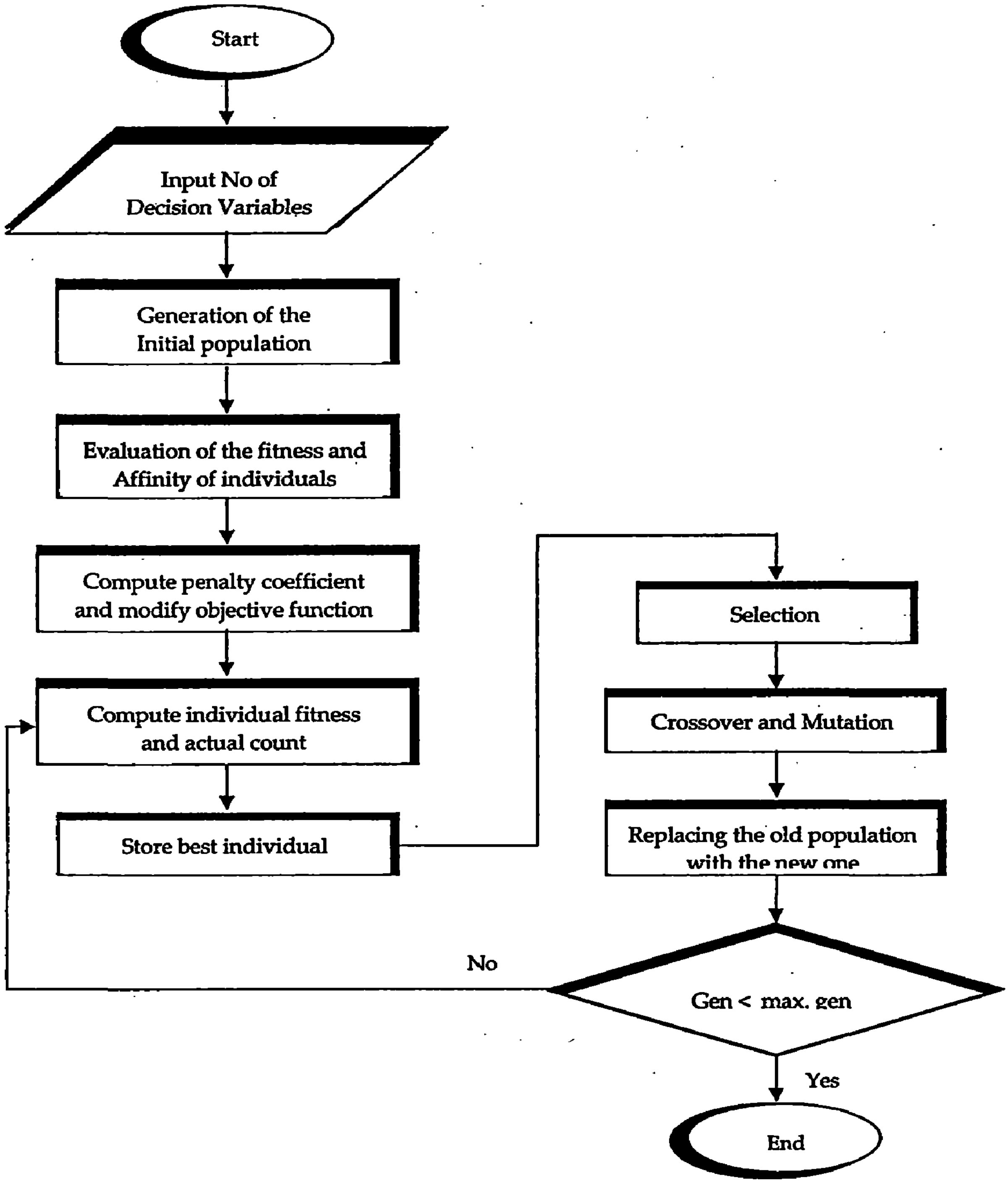

Figure-5.6: Flowchart of GA for Constraint Optimization

The solution procedure of generation expansion planning is shown in figure-5.7 and the procedure consists of the following steps cited below:

1) The annual demand at the target year is assumed and the annual load duration curve $L(t)$ at the target year are determined.

2) Input of data necessary for the generation expansion, i,e the fixed cost, the variable cost, unit capacity, outage rate and the generation capacity of the existing and the new candidate plants including IPP type classified by the type of energy generated, that are needed for make out generation plans.

3) Cases for the purchasing price for three types of IPPs competitively bidding against one another is set up.

4) The corresponding bidding conditions (energy limits) of the IPPs based on the optimization model for competing IPPs is determined.

5) The optimal generation plan of utility while considering IPPs is determined by applying the solution techniques discussed above.

6) LOLP and EENS are calculated. If it is not possible to satisfy LOLP one gas turbine is added.

7) Step 6 is repeated until the conditions are satisfied.

8) The minimum cost is calculated and the optimal combination of plants is recorded. Then the conditions of IPP are changed in step – 4 and the whole calculation is repeated again.

9) The results are compared and the lowest cost is selected.

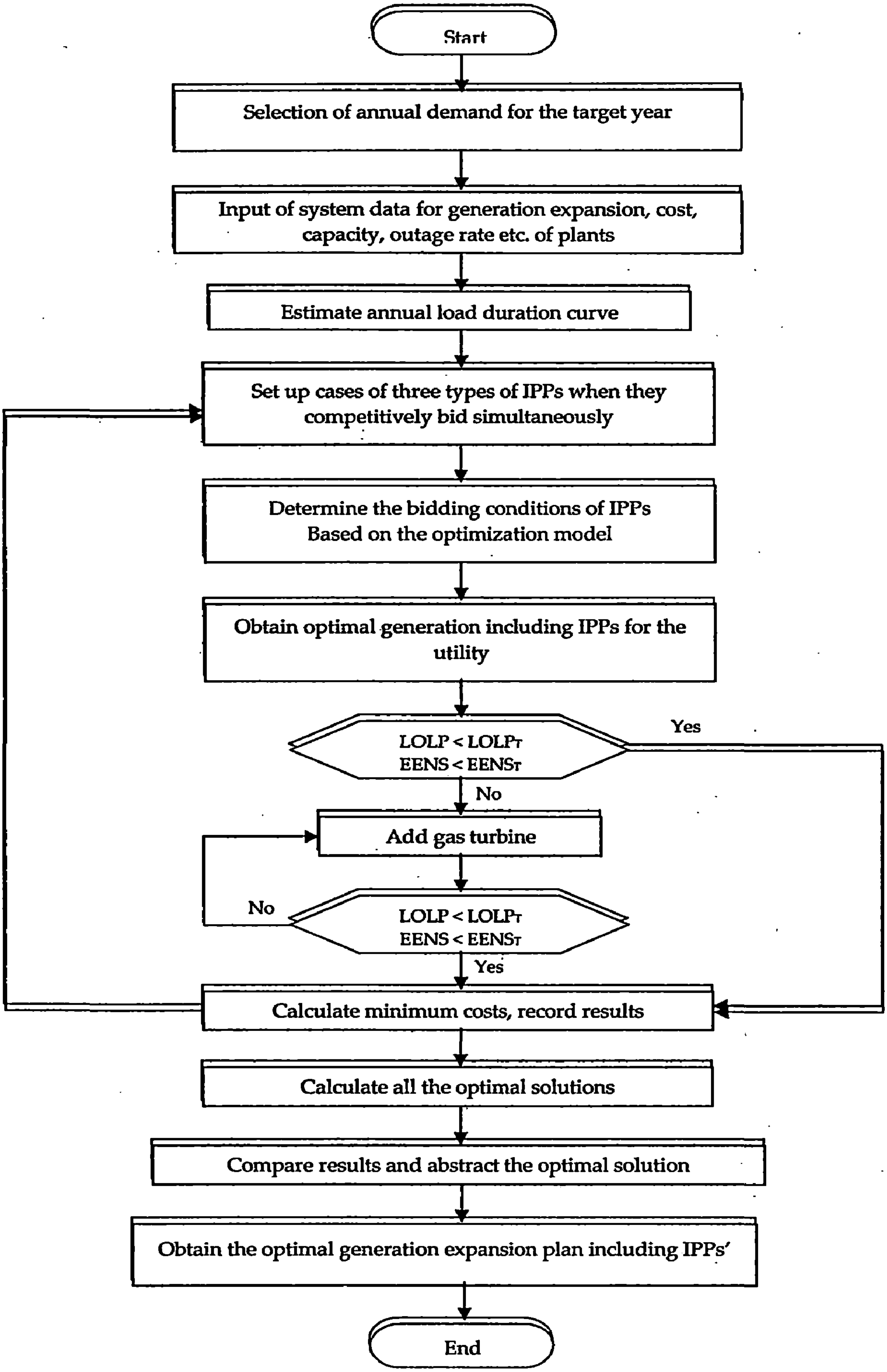

Figure- 5.7: Solution Flow chart of Generation Expansion Problem

CHAPTER SIX

PROBABILISTIC PRODUCTION SIMULATION

6.1 Introduction

The probabilistic production simulation is used to analyse the feasibility of generation expansion scheme and to evaluate the technique and economic indices to provide the basis for the final policy. The results of probabilistic production simulation often play a crucial role in the energy source extension schemes since the cost of the primary generation is more and predominant in the total cost of power systems [36].

In laying down the operational plans for existing power system, the probabilistic production simulation not only determines the output of the generating unit and carries out cost analysis from the point of optimization but also provides important data for dealing with many problems arising during operation [36].

The main purpose of probabilistic production simulation is to simulate the dispatch of generating units, and to estimate the production cost [7]. The probabilistic production simulation considers the relevant uncertain factors like the future power load fluctuation, the random outage of generating units in operation, etc [36]. By taking the effect of unit forced outage and maintenance, the more reasonable and accurate production cost estimation and the system reliability indices such as Expected Energy Not Served (EENS) and Loss of Load Probability (LOLP) can be determined [7].

In power system operation and planning, EENS is more meaningful than LOLP, and that means electric energy is the key variable. An Equivalent Energy Function (EEF) approach is adopted for probabilistic production simulation. The EEF approach calculates electric energy consumed in different load level segments and modifies it directly when unit failure effects are taken into consideration [7].

6.2 Equivalent Energy Function Method

A Load Duration Curve is shown in figure-6.1. The horizontal axis expresses the system load and the vertical axis the duration time. T is the investigated period, which could be a year, a month, a week, a day, etc.

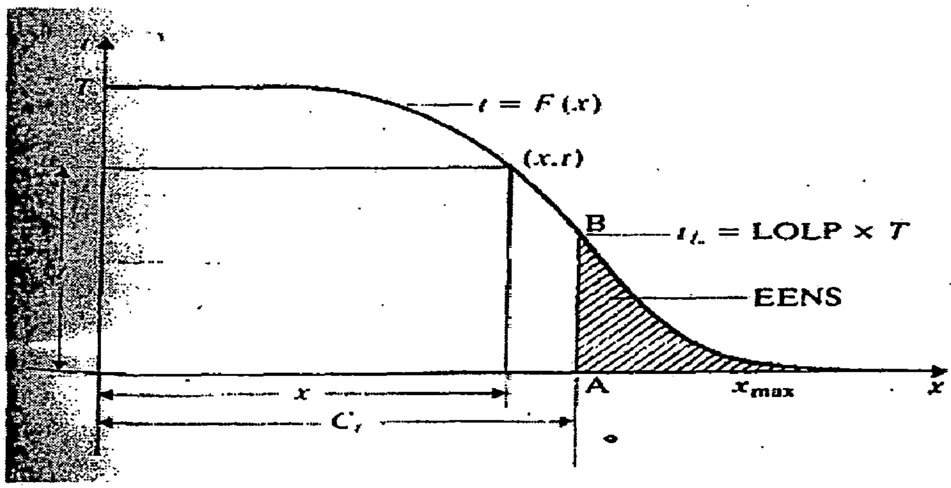

Figure-6.1: Load Duration Curve

A load duration curve can be described by

$$t = F(x) \tag{6.1}$$

where x is the load level, and t is the time interval during which the load is larger than or equal to x.

Dividing both sides with the period T and we can get

$$P = F(x)/T = f(x) \tag{6.2}$$

where p is considered as the probability at which the load is larger than or equal to x.

Divide the x axis into sections Δx lengths. A discrete energy function can be defined as follows

$$E(J) = \int_{x}^{x+\Delta x} F(x)dx = T\int_{x}^{x+\Delta x} f(x)dx \tag{6.3}$$

where

$$J = \langle x/\Delta x \rangle + 1$$

Here the bracket ⟨ ⟩ means the biggest integer not greater than x/Δx. $E(J)$ corresponds to the area under a section of the load curve from x to Δx, or the energy that corresponds to this section of the load. If the system maximum load is X_{max}, the corresponding discrete variable value is

$$N_E = \langle X_{max}/\Delta x \rangle + 1$$

The power system's total energy is

$$E_D = \int_0^{X_{max}} F(x)dx = \sum_{j=1}^{N_E} E(J) \tag{6.4}$$

The equivalent energy function is an energy function that takes into account the influence of the generating unit random outage. In the conventional recursive algorithm, the generating unit outage is considered by revising the equivalent load duration curve (ELDC). In the equivalent energy function method, the energy function is revised with respect to the generating unit outage.

Suppose $f^{(0)}(x)$ is the original load duration curve and $E^{(0)}(J)$ is the corresponding energy function. The first generating unit first takes the load, which has a capacity C1 and a forced outage rate of q_1. When generating unit 1 in operation, it shares load $f^{(o)}(x)$ together with other generating units. When it has a fault, the load expressed by f (x) should be taken by other generating units. Equivalently, generating unit 1 and other units share a load represented by a curve shifted C1 to the right (illustrated by $f(x-c_1)$ in the figure-6.2).

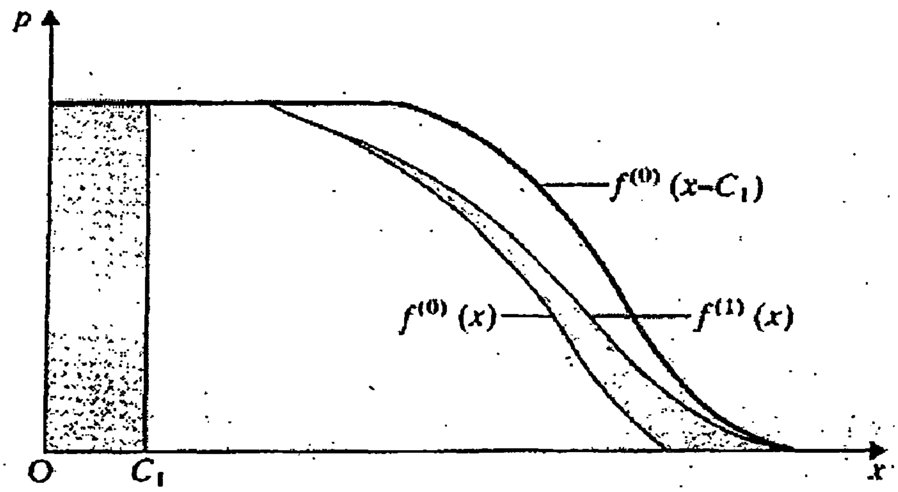

Figure-6.2: The formation of the Equivalent Load Duration Curve

Since the forced outage rate of generating unit 1 is q_1, the probability of normal operation is $p_1 = 1 - q_1$, and the system's load duration curve should be expressed as follows when consideration is given to the influence of random outages of generating unit 1 :

$$f^{(1)}(x) = p_1 f^{(o)}(x) + q_1 f^{(o)}(x - c) \tag{6.5}$$

The equivalent load duration curve $f^{(1)}(x)$ is higher than the maximum load of $f^{(o)}(x)$ by C_1, and the total load energy has increased by ΔE, as shown by the shaded portion. It can be proved that ΔE equals the reduction of the supplied energy as a result of faults in generating unit 1.

Similarly, the equivalent load duration curve when generating unit i-1 has been committed is $f^{(i-1)}(x)$ and the corresponding energy function is $E^{(i-1)}(J)$. If the generating unit i has a capacity of C_i and a forced outage rate of q_i, then the convolution for generating unit i is

$$f^{(i)}(x) = p_i \; f^{(i-1)}(x) + q_i \; f^{(i-1)}(x - C_i) \tag{6.6}$$

in which $p_i = 1 - q_i$.

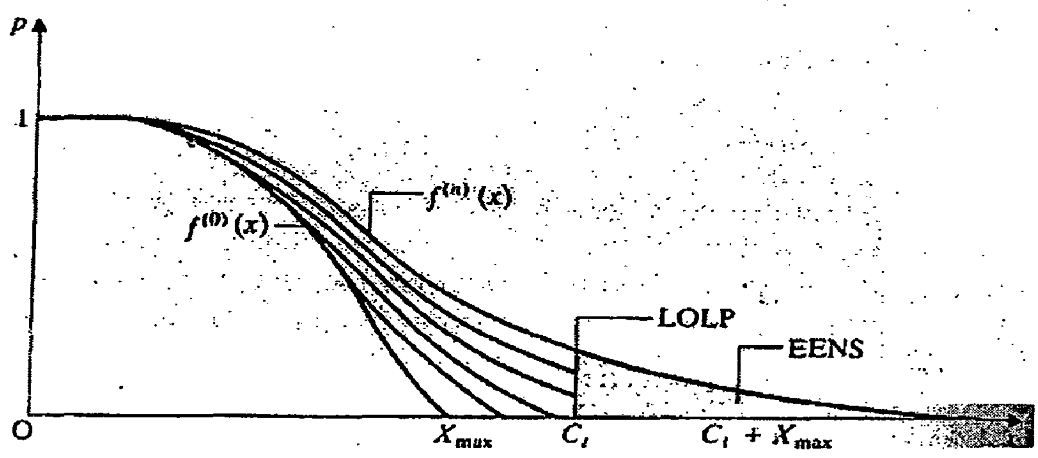

Figure-6.3: Equivalent Load Duration Curve and Reliability Indices

As each generating unit goes through the convolutions process, the equivalent load duration curve also constantly changes and the maximum equivalent load increases.

The above can be transformed into the corresponding equivalent energy function according to eq.(3)

$$E^{(i)}(J) = T\int^{x+\Delta x} f^{(i)}(x)dx$$

Substituting eq.(5),

$$E^{(i)}(J) = T\int^{x+\Delta x} [p_i f^{(i-1)}(x) + q_i f^{(i-1)}(x-C_i)]\, dx$$

$$= p_i T\int^{x+\Delta x} f^{(i-1)}(x)\, dx + q_i T\int_{x-ci}^{x+\Delta x-ci} f^{(i-1)}(x)\, dx$$

$$E^{(i)}(J) = p_i\ E^{(i-1)}(J) + q_i\ E^{(i-1)}\left(J-k_i\right) \quad (6.7)$$

where

$$k_i = \frac{C_i}{\Delta x} \quad (6.8)$$

k_i is an integer because Δx is chosen to be the greatest common factor of all the generating unit capacities.

Equation (6.6) is similar to Eq.(6.5). It is the convolution formula in the equivalent energy function method.

Generating unit i's energy output E_{gi} is calculated as below

$$E_{gi} = p_i T\int_{x_{i-1}}^{x_{i-1}+C_i} f^{(i-1)}\left(x\right) dx$$

Divide the integration interval (x_{i-1},$x_{i-1}+C_i$) into k_i sections of Δx and calculate the integral on each section separately.

$$E_{gi} = p_i \sum_{k=1}^{K_i} [T \int_{x_{i-1}+(k-1)\Delta x}^{x_{i-1}+C_i} f^{(i-1)}(x)dx]$$

$$= p_i \sum_{J=J_{i-1}+1}^{J_i} E^{i-1}(J) \tag{6.9}$$

in which

$$J_{i-1} = \frac{x_{i-1}}{\Delta x} \tag{6.10}$$

$$J_i = \frac{x_{i-1}+C_i}{\Delta x} = J_{i-1} + k_i$$

From Eq.(6.8) the sum of the equivalent energy function between the discrete points J_{i-1} and J_i is needed to multiply by p_i in order to calculate generating unit i's energy output. The load in the interval $(1, J_i)$ has been shared by the preceding i generating units when generating unit has been committed. The load energy not served by the system is

$$E_{Di} = \sum_{J>J_i} E^{(i)}(J) \tag{6.11}$$

in which E_{Di} is the energy that the system is still short of when the preceding i generating units have shared the load. Substituting Eq.(6.6) into the above equation.

$$E_{Di} = \sum_{J>J_i} p_i [E^{(i-1)}(j) + q_i E^{(i-1)}(J - K_i)]$$

$$= p_i \sum_{J>J_i} E^{(i-1)}(J) + q_i \sum_{J>J_i} E^{(i-1)}(J - K_i)$$

$$= p_i \sum_{J>J_{i-1}} E^{(i-1)}(J) - p_i \sum_{J=J_{i-1}+1} E^{(i-1)}(J)$$

$$= \sum_{J>j_{i-1}} E^{(i-1)}(J) + p_i \sum_{J=J_{i-1}+1} E^{(i-1)}(J) \qquad (6.12)$$

From Eq.(6.10), We know that

$$E_{D,i-1} = \sum_{J>J_{i-1}} E^{i-1}(J) \qquad (6.13)$$

is the energy that system still has not supplied when the preceding i-1 generating units have been committed. The last term in Eq.(6.11) is identical to Eq.(6.8) and this is the generating unit i's energy output. Therefore, Eq.(6.11) can be changed to

$$E_{Di} = E_{D,i-1} - E_{gi} \qquad (6.14)$$

Assuming that there are n generating units in the power system, E_{Dn} is then the expected energy not served:

$$\text{EENS} = E_{Dn} = \sum_{J>J_n} E^{(n)}(J) \qquad (6.15)$$

The equivalent load duration curve $f^{(0)}(x)$ is needed to show the way that the system's loss of load probability (LOLP) is computed. Figure-6.4 shows the right tail of $f^{(0)}(x)$. Suppose that the total operation capacity of the system's generating units is C_t; then the value of LOLP should be higher than the function value of any point in the right contiguous region of Δx and therefore higher than the average function value of $f^{(n)}(x)$ in this region because $f^{(n)}(x)$ is a monotonically decreasing continuous curve:

$$p_1 = \frac{1}{\Delta x}\int_{C_t}^{C_t+\Delta x} f^{(n)}(x)dx \qquad (6.16)$$

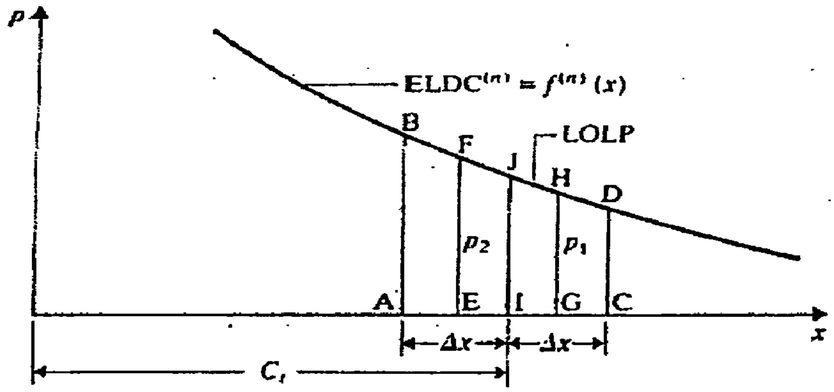

Figure-6.4: The Right Tail of $f^{(n)}(x)$ and the method to calculate LOLP

The above can be rewritten as the following according to the definition of the equivalent energy function:

$$\bar{p}_1 = \frac{E^{(n)}(J_n+1)}{T\Delta x} \qquad (6.17)$$

Likewise, LOLP should be lower than the function value of any point in the left contiguous region of Δx and therefore lower than the average value of the function $f(x)$ in this region.

$$\bar{p}_2 = \frac{E^{(n)}(J_n)}{T\Delta x} \qquad (6.18)$$

Hence Eqs(6.17) and (6.18) provide the upper and lower limits of LOLP.

$$\bar{p}_1 = \frac{E^{(n)}(J_n+1)}{T\Delta x} < LOLP > \bar{p}_2 = \frac{E^{(n)}(J_n)}{T\Delta x} \qquad (6.19)$$

Equations (6.17) and (6.18) indicate that the equivalent energy function contains information about the cumulative probability of $f^{(n)}(x)$ in each section. The required LOLP is given by the average of the upper and lower limits.

$$LOLP \cong \frac{E^{(n)}(j_n) + E^{(n)}(j_n+1)}{2T\Delta x} \qquad (6.20)$$

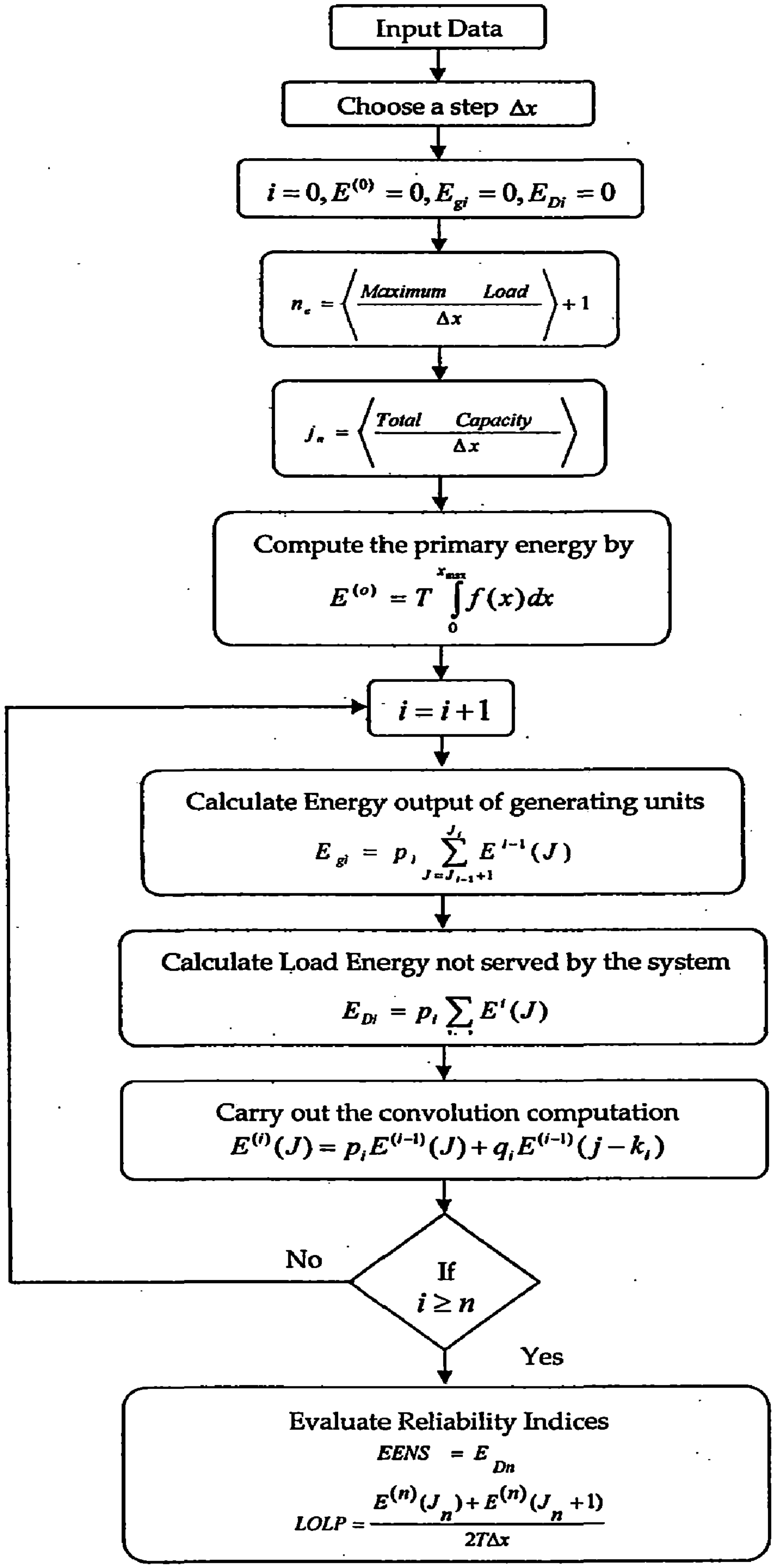

Figure-6.5: Flowchart of EEF Method

CHAPTER SEVEN

TESTING OF MODEL ON A TEST POWER SYSTEM

7.1 Test Data

For the testing of the model, a peak load of 4100 MW is assumed and the hypothetical test data given in table-7.1 & table-7.2 are taken for Utility and IPPs respectively.

Table: 7.1 Parameters for various Utility Generation technologies

Unit type	Unit Capacity (MW)	Fixed Cost ($/MW)	Variable cost ($/MWh)	Outage rate (%)	Existing Number	Expanding Number
Nuclear	750	257320	6.6	4.0	2	1
Coal	400	159600	15	3.5	1	2
Oil	250	216570	27.5	2.5	2	2
Gas	200	76820	39.1	2.0	0	4

Table: 7.2 Parameters of IPPs

Unit type	Unit Capacity (MW)	Fixed Cost $	Variable cost ($/MWh)	Outage rate (%)
Base	800	$12.82 * 10^7$	9.375	4.0
Middle	550	$9.09 * 10^7$	18.75	3.5
Peak	400	$5.94 * 10^7$	36.25	3.0

The load duration curve for a peak demand of 4100 MW load is estimated by using the analytical equation given in section 3.1. For estimating the load duration curve, the annual load growth rate of 5% is assumed for the target year. The load duration curve sharpness factor (s) is varied between 1 and 3.14 depending upon the previous load data to get the required LDC. The estimated LDC is shown in figure-7.1 and its resulting load data is given in table-7.3 and table-7.4. The generator technologies of Utility and three IPPs are loaded in merit order in LDC. The three types of IPPs are introduced as Base_type IPP, Middle_type IPP and Peak_type IPP as given in table-3.1.

The maximum and minimum range of purchasing price for each type of IPP is determined from the parameters of IPPs based on scenario analysis. In scenario analysis, the three types of IPPs are competed for expansion capacity (peak load – existing capacity) i,e 1700MW at target year. Taking the load factor 60%, the annual energy that has to be generated in yearly hours by each IPP is calculated. The total cost of each IPP is then calculated from the parameters given in table-7.2. The graph is plotted for these calculated results. The y-axis is the total cost/revenue of IPPs and the x-axis is the energy to be generated. The graph is shown in figure-7.2. The maximum and minimum purchasing prices and the energy limits for each IPP are determined from the graph. Accordingly, the two transaction prices for each type of IPPs are selected, one is the minimum purchasing price and other is within the maximum and minimum range. The total eight cases are formed for three types of IPPs. The energy limit for each case is determined from the scenario analysis graph. The purchasing prices and the energy limits are given in table-7.6. Each case is finally tested for the optimal generation mix for the generation expansion at the target year.

Table:7.3 Estimation of Annual Load Duration Curve

Peak Demand in MW (p)	Load Growth Rate (%) r	LDC Sharpness Factor (s)	Annual Hours (t)	0.01*p*r	p-0.01*p*r	s*t	0.5*s	tan(-0.5*s)	tan(s*t-0.5*s)	L(t) = 0.01p*r + ((p-0.01p*r)/tan(-0.5*s))*tan(s*t-0.5*s)
4100	5	1.00000	0	205	3895	0	0.5000	-0.546	-0.546	4100
4100	5	1.04822	9	205	3895	9	0.5241	-0.578	-0.566	4018
4100	5	1.19600	39	205	3895	47	0.5980	-0.681	-0.649	3915
4100	5	1.19940	131	205	3895	157	0.5997	-0.684	-0.624	3760
4100	5	1.22843	350	205	3895	430	0.6142	-0.705	-0.642	3749
4100	5	1.00980	722	205	3895	729	0.5049	-0.553	-0.491	3666
4100	5	1.16000	1327	205	3895	1539	0.5800	-0.655	-0.572	3606
4100	5	1.10000	2094	205	3895	2303	0.5500	-0.613	-0.523	3526
4100	5	1.00000	3047	205	3895	3047	0.5000	-0.546	-0.454	3444
4100	5	1.00000	3896	205	3895	3896	0.5000	-0.546	-0.443	3362
4100	5	1.01000	4644	205	3895	4690	0.5050	-0.553	-0.436	3279
4100	5	1.00000	5309	205	3895	5309	0.5000	-0.546	-0.420	3198
4100	5	1.30000	6061	205	3895	7879	0.6500	-0.760	-0.568	3116
4100	5	1.00000	6902	205	3895	6902	0.5000	-0.546	-0.397	3034
4100	5	1.50000	7699	205	3895	11549	0.7500	-0.932	-0.657	2952
4100	5	1.12000	8188	205	3895	9170	0.5600	-0.627	-0.429	2870
4100	5	1.00000	8454	205	3895	8454	0.5000	-0.546	-0.362	2788
4100	5	1.00000	8589	205	3895	8589	0.5000	-0.546	-0.351	2706
4100	5	1.00000	8674	205	3895	8674	0.5000	-0.546	-0.339	2624
4100	5	1.20000	8710	205	3895	10452	0.6000	-0.684	-0.411	2542
4100	5	1.40000	8729	205	3895	12221	0.7000	-0.842	-0.488	2460
4100	5	1.80000	8737	205	3895	15727	0.9000	-1.260	-0.703	2378
4100	5	1.35000	8741	205	3895	11800	0.6750	-0.800	-0.430	2296
4100	5	1.20000	8744	205	3895	10493	0.6000	-0.684	-0.353	2214
4100	5	1.24000	8749	205	3895	10848	0.6200	-0.714	-0.353	2132
4100	5	1.00000	8753	205	3895	8753	0.5000	-0.546	-0.259	2050
4100	5	1.05000	8755	205	3895	9193	0.5250	-0.579	-0.262	1968
4100	5	2.48964	8760	205	3895	21809	1.2448	-2.958	-1.270	1878

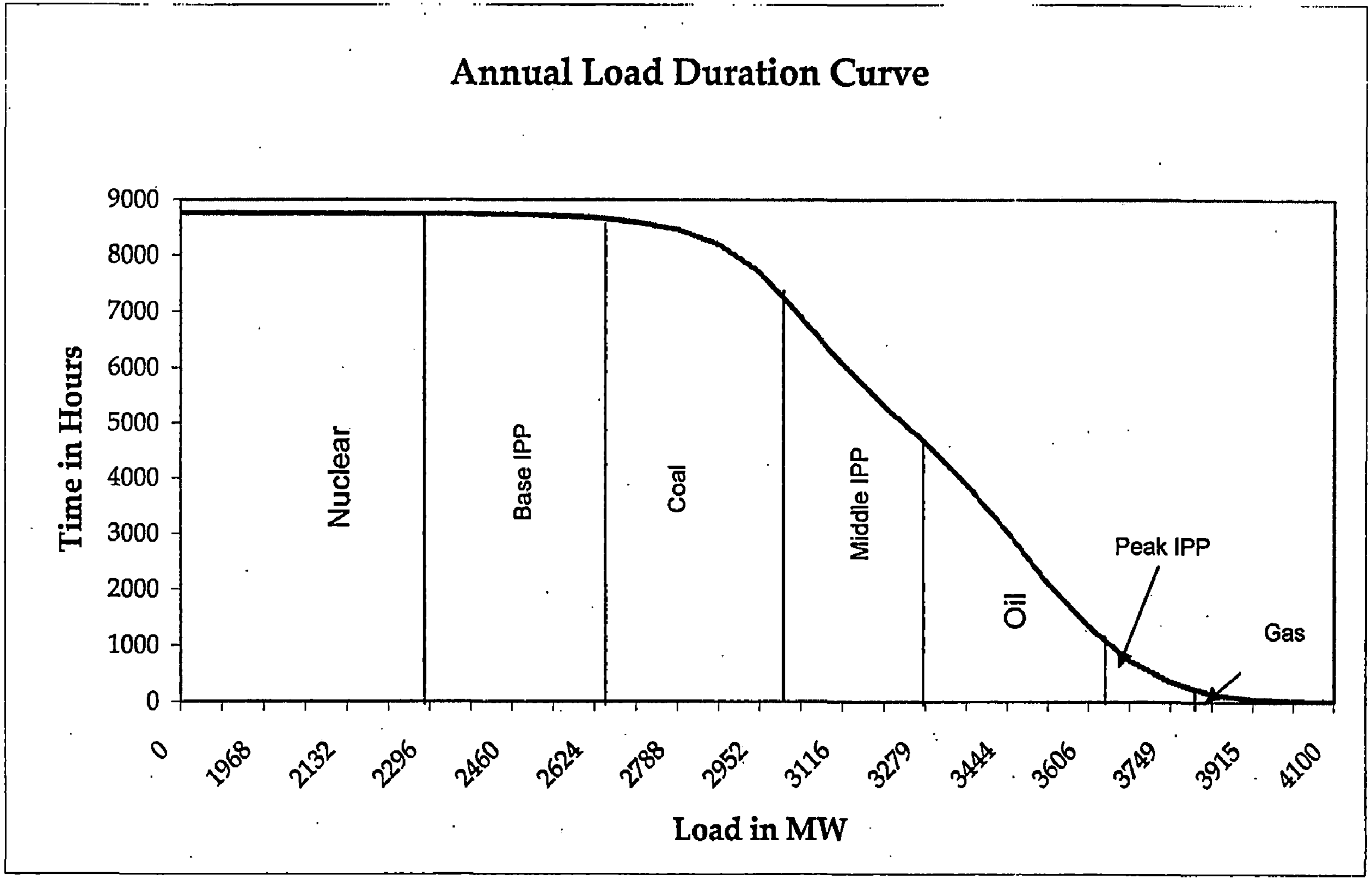

Figure-7.1: Estimation of Load Duration Curve

Table:7.4 Load Data

Load in MW	Time in Hours
0	8760
1878	8760
1968	8755
2050	8753
2132	8749
2214	8744
2296	8741
2378	8737
2460	8729
2542	8710
2624	8674
2706	8589
2788	8454
2870	8188
2952	7699
3034	6902
3116	6061
3198	5309
3279	4644
3362	3896
3444	3047
3526	2094
3606	1327
3666	722
3749	350
3760	131
3915	39
4018	9
4100	0

Table: 7.5 Determination of Transaction Prices for IPPs

Peak Demand = 4100 MW
Existing Capacity = 2400 MW
Load Factor = 0.6

Power Demand in MW	Load Factor	Hours in Year	Energy per year in GWh	Fixed Cost of IPP in Million $			Variable Cost of IPP in $/MWH			Total Cost of IPP in Million $			Transaction Price of IPP in $/MWH			Total Cost of Selling in Million $		
				Base	Middle	Peak	Base	Middle	Peak	Base	Middle	Peak	Base	Middle	Peak	Base	Middle	Peak
1700	0.6	0	0	128.20	90.90	59.40	9.375	18.75	36.25	128.20	90.90	59.40	27.74	40.94	68.14	0.00	0.00	0.00
1700	0.6	365	372	128.20	90.90	59.40	9.375	18.75	36.25	131.69	97.88	72.90	27.74	40.94	68.14	10.33	15.24	25.37
1700	0.6	730	745	128.20	90.90	59.40	9.375	18.75	36.25	135.18	104.86	86.39	27.74	40.94	68.14	20.66	30.48	50.74
1700	0.6	1095	1117	128.20	90.90	59.40	9.375	18.75	36.25	138.67	111.84	99.89	27.74	40.94	68.14	30.98	45.73	76.11
1700	0.6	1460	1489	128.20	90.90	59.40	9.375	18.75	36.25	142.16	118.82	113.38	27.74	40.94	68.14	41.31	60.97	101.47
1700	0.6	1825	1862	128.20	90.90	59.40	9.375	18.75	36.25	145.65	125.80	126.88	27.74	40.94	68.14	51.64	76.21	126.84
1700	0.6	2190	2234	128.20	90.90	59.40	9.375	18.75	36.25	149.14	132.78	140.38	27.74	40.94	68.14	61.97	91.45	152.21
1700	0.6	2555	2606	128.20	90.90	59.40	9.375	18.75	36.25	152.63	139.76	153.87	27.74	40.94	68.14	72.29	106.69	177.58
1700	0.6	2920	2978	128.20	90.90	59.40	9.375	18.75	36.25	156.12	146.75	167.37	27.74	40.94	68.14	82.62	121.94	202.95
1700	0.6	3285	3351	128.20	90.90	59.40	9.375	18.75	36.25	159.61	153.73	180.86	27.74	40.94	68.14	92.95	137.18	228.32
1700	0.6	3650	3723	128.20	90.90	59.40	9.375	18.75	36.25	163.10	160.71	194.36	27.74	40.94	68.14	103.28	152.42	253.69
1700	0.6	4015	4095	128.20	90.90	59.40	9.375	18.75	36.25	166.59	167.69	207.85	27.74	40.94	68.14	113.60	167.66	279.05
1700	0.6	4380	4468	128.20	90.90	59.40	9.375	18.75	36.25	170.08	174.67	221.35	27.74	40.94	68.14	123.93	182.90	304.42
1700	0.6	4745	4840	128.20	90.90	59.40	9.375	18.75	36.25	173.57	181.65	234.85	27.74	40.94	68.14	134.26	198.15	329.79
1700	0.6	5110	5212	128.20	90.90	59.40	9.375	18.75	36.25	177.06	188.63	248.34	27.74	40.94	68.14	144.59	213.39	355.16
1700	0.6	5475	5585	128.20	90.90	59.40	9.375	18.75	36.25	180.55	195.61	261.84	27.74	40.94	68.14	154.91	228.63	380.53
1700	0.6	5840	5957	128.20	90.90	59.40	9.375	18.75	36.25	184.05	202.59	275.33	27.74	40.94	68.14	165.24	243.87	405.90
1700	0.6	6205	6329	128.20	90.90	59.40	9.375	18.75	36.25	187.54	209.57	288.83	27.74	40.94	68.14	175.57	259.11	431.26
1700	0.6	6570	6701	128.20	90.90	59.40	9.375	18.75	36.25	191.03	216.55	302.33	27.74	40.94	68.14	185.90	274.36	456.63
1700	0.6	6935	7074	128.20	90.90	59.40	9.375	18.75	36.25	194.52	223.53	315.82	27.74	40.94	68.14	196.22	289.60	482.00
1700	0.6	7300	7446	128.20	90.90	59.40	9.375	18.75	36.25	198.01	230.51	329.32	27.74	40.94	68.14	206.55	304.84	507.37
1700	0.6	7665	7818	128.20	90.90	59.40	9.375	18.75	36.25	201.50	237.49	342.81	27.74	40.94	68.14	216.88	320.08	532.74
1700	0.6	8030	8191	128.20	90.90	59.40	9.375	18.75	36.25	204.99	244.47	356.31	27.74	40.94	68.14	227.21	335.32	558.11
1700	0.6	8395	8563	128.20	90.90	59.40	9.375	18.75	36.25	208.48	251.45	369.81	27.74	40.94	68.14	237.53	350.57	583.48
1700	0.6	8760	8935	128.20	90.90	59.40	9.375	18.75	36.25	211.97	258.44	383.30	27.74	40.94	68.14	247.86	365.81	608.84

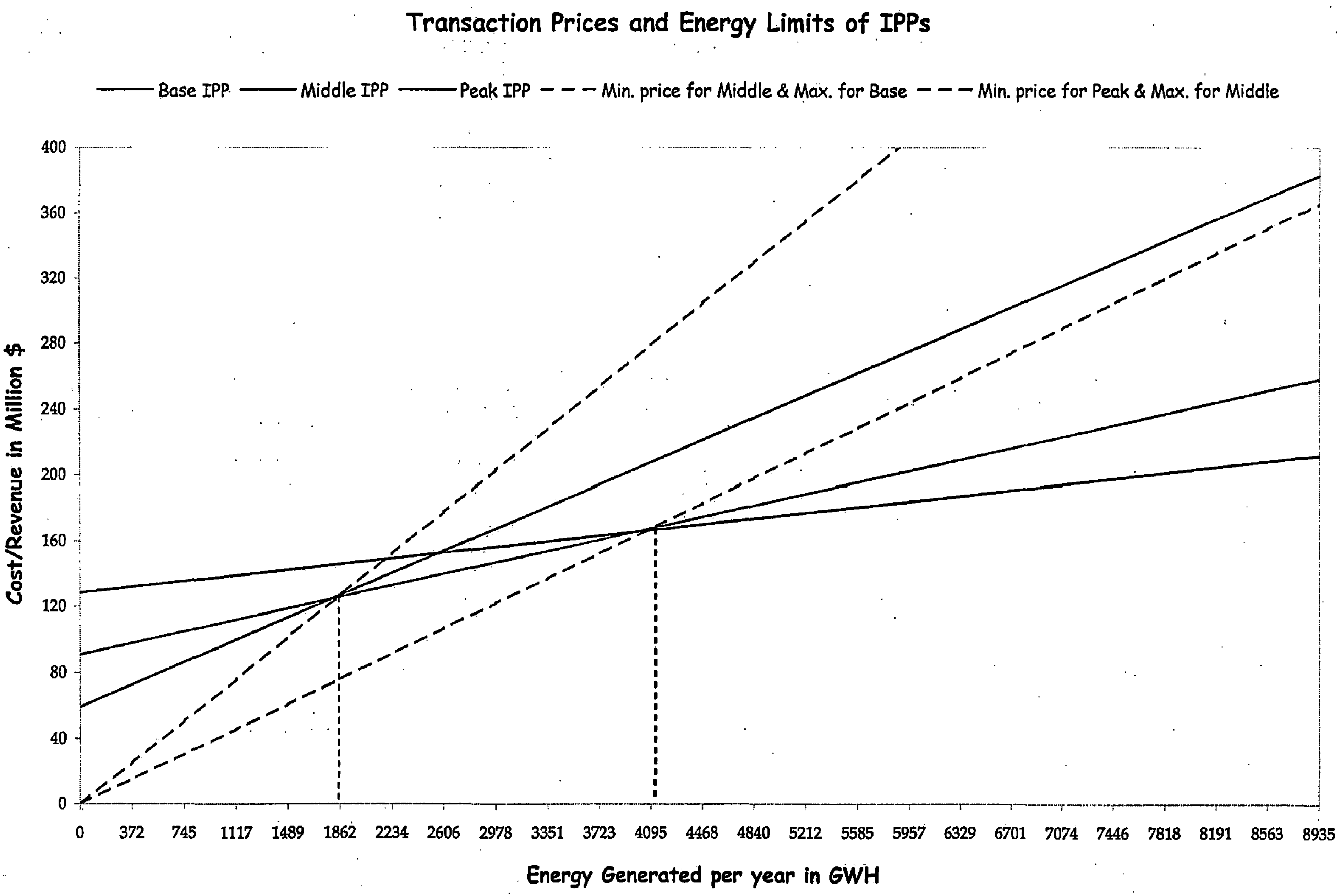

Figure-7.2: Purchasing Price and Energy Limits of IPPs

Table: 7.6 IPPs transaction prices and Energy Limits

Case	Base_type		Middle_type		Peak_type	
	λ_j	Q_j (GWh)	λ_j	Q_j (GWh)	λ_j	Q_j (GWh)
Case 1	27.74	Above 4095	40.94	1862-4095	68.14	Upto 1862
Case 2	27.74	Above 4095	40.94	1303-4095	81.69	Upto 1303
Case 3	27.74	Above 2680	53.22	1862-2680	68.14	Upto 1862
Case 4	27.74	Above 2680	53.22	1303-2680	81.69	Upto 1303
Case 5	36.00	Above 4095	40.94	1862-4095	68.14	Upto 1862
Case 6	36.00	Above 4095	40.94	1303-4095	81.69	Upto 1303
Case 7	36.00	Above 2680	53.22	1862-2680	68.14	Upto 1862
Case 8	36.00	Above 2680	53.22	1303-2680	81.69	Upto 1303

The model is tested for the two conditions. (1) without reliability (2) with reliability. The two methods are used for the testing.

(i) Deterministic Method (Dynamic Programming)

(ii) Stochastic Method (Genetic Algorithm)

The programs are written for these methods and run with the test data. The programs are given in appendix. The results of each method are further tested with the probabilistic production simulation program for the calculation of reliability indices LOLP and EENS. If the reliability indices are not satisfied, the gas unit is added to meet the required LOLP and EENS and the total cost of generation is recalculated.

7.2 Results and Discussion

The results coming from Dynamic Programming and Genetic Algorithm are given in tables 7.7 & 7.8 and tables 7.9 & 7.10 respectively. The optimal generation mix including IPPs is shown in figure-7.3 to figure-7.6. The result curves of genetic algorithm are shown in figure-7.7 to figure-7.22 for both ccondition-1 and condition-2. The results are compared and analysed. The comparison results are shown in figure-7.23 and figure-7.24.

(i) Without Reliablity

In tables 7.7-7.10, the case-1 is the generation mix at minimum purchasing price for each type of IPP. In all cases, IPPs are introduced and the total cost calculated is the optimal one. It means that IPPs are cheaper and they are used to replace the similar type of Utility's plants. In case-5 to case-8, the purchasing price of Base_type IPP is increased from its minimum value and the optimal generation mix and the total cost for these cases are calculated. The contribution of Base_type IPP in generation mix becomes zero in cases 5 & 6 and the capacity of Base-type is reduced in cases 7 & 8. The Utility's new coal units are added to accomplish the demand of power in these cases. In adding the new coal units, the total generation costs have increased to higher value than that in case-1 to case-4. This shows that when the Base_type IPP bids at lower rates in a competing environment, it is cheaper to introduce Base_type IPP than constructing new plants for Utility. Hence the Utility can reduce its (investment) generation cost in new technologies by introducing the Base_type IPP at lower price.

In cases-3 to 4, the bidding price of Middle_type IPP is increased when the Base_type IPP is bidding at lower price. In these cases, the capacity of Middle_type IPP is reduced in generation mix and it is accomplished by the Utility's coal unit. The generation cost in these cases has also increased to higher value than that in identical cases (cases 1 & 2). Similarly, in cases-7 to 8, the price of Middle_type is increased when Base type is at higher price. The contribution of Middle_type reduces to zero and it is accomplished by the Utility's coal unit increasing the total cost of generation than that in identical cases (case 5 & 6). This also indicates that the profit of Utility can be raised by introducing the Middle_type IPP at lower rate.

But the similar prediction is not applicable for Peak_type IPP. In alternate cases 2,4,6 and 8, the purchasing price of Peak_type IPP is increased from its initial value but there is no change in its contribution to generation mix. The generation costs in cases 2,4,6 and 8 are higher than that in the identical cases 1,3,5 and 7 respectively. This shows that the Utility can get benefit (lower its generation cost) eventhough, the Peak_type bids at higher price. This depends upon the parameters of Utility's and IPPs generation technologies and LDC. For the given particular data and LDC, the peak_type IPP is cheaper than the similar type of Utility's plants eventhough the peak_type bids at higher rates (about 80% more). Therefore, the Utility can reduce its generation cost by introducing Base_type IPP and Middle_type IPP at lower sales price and Peak_type IPP at both high and low price. When the Peak_type IPP bids at lower price, the Utility can prefer to introduce a large amount of Peak_type IPP.

(ii) With Reliability

For electric Utilities, the LOLP index is typically on the order of 0.1-1.0 days/per year depending upon the required reliability of service, which is generally equivalent to 15-20% capacity reserve. Since there are approximately 100 peak-load days per year, the daily probability is approximately 0.001-0.01days/day [9]. So the reliability criteria LOLP is set as 0.01 days per day and the optimal costs of generation satisfying the reliability for all 8 cases are calculated. To meet the required reliability, the three gas units are added in cases 1-4,7,8 and two gas units are added in cases 5-6. In adding different number of gas units as per the requirement of conditions or reliability criteria, the overall generation cost of Utility will further raise. The results of production simulation program for reliability indices and the energy generation for condition-1 and condition-2 are given in table-7.11 and table-7.12 respectively.

Table- 7.7: Optimal Generation Mix in condition-1 (DP)

Cases	Nuclear MW	base IPP MW	Coal MW	Middle IPP MW	Oil MW	Peak IPP MW	Gas MW	Total power MW	Cost in Million $
1	1440	768	386	483	488	388	0	3953	535.333
2	1440	768	386	483	488	388	0	3953	540.454
3	1440	768	772	97	488	388	0	3953	537.585
4	1440	768	772	97	488	388	0	3953	542.422
5	1440	0	1158	483	488	388	0	3956	577.141
6	1440	0	1158	483	488	388	0	3956	582.262
7	1440	480	1158	0	488	388	0	3954	587.241
8	1440	480	1158	0	488	388	0	3954	592.362

Table: 7.8 Optimal Generation Mix in condition-2 (DP)

Cases	Nuclear	base IPP	Coal	Middle IPP	Oil	Peak IPP	Gas	power in MW	Cost in Million $
1	1440	768	386	483	488	388	588	4540	587.104
2	1440	768	386	483	488	388	588	4540	592.224
3	1440	768	772	97	488	388	588	4541	590.120
4	1440	768	772	97	488	388	588	4541	594.193
5	1440	0	1158	483	488	388	392	4348	613.601
6	1440	0	1158	483	488	388	392	4348	618.359
7	1440	480	1158	0	488	388	588	4542	636.389
8	1440	480	1158	0	488	388	588	4542	641.226

Table- 7.9: Optimal Generation Mix in condition-1 by GA

Cases	Nuclear	base IPP	Coal	Middle IPP	Oil	Peak IPP	Gas	power in MW	Cost in Million $
1	1438	762	386	491	487	387	0	3951	535.652
2	1439	765	385	489	486	388	0	3952	540.774
3	1440	767	772	98	488	386	0	3951	538.412
4	1440	766	772	99	488	387	0	3952	542.777
5	1440	0	1157	486	487	380	0	3950	579.504
6	1440	0	1158	480	488	384	0	3950	582.781
7	1440	485	1158	3	488	384	0	3958	588.460
8	1440	491	1158	0	486	378	0	3953	593.546

Table-7.10: Optimal Generation Mix in condition-2 by GA

Cases	Nuclear	base IPP	Coal	Middle IPP	Oil	Peak IPP	Gas	power in MW	Cost in Million $
1	1440	765	386	489	488	385	588	4541	587.500
2	1440	760	386	493	488	385	588	4540	592.610
3	1440	767	772	103	486	386	588	4542	590.774
4	1440	766	772	101	488	385	587	4539	594.981
5	1439	0	1158	484	487	386	392	4346	613.935
6	1440	0	1157	488	486	387	390	4348	619.732
7	1440	477	1156	5	486	388	588	4540	637.191
8	1440	482	1158	3	486	385	588	4542	642.749

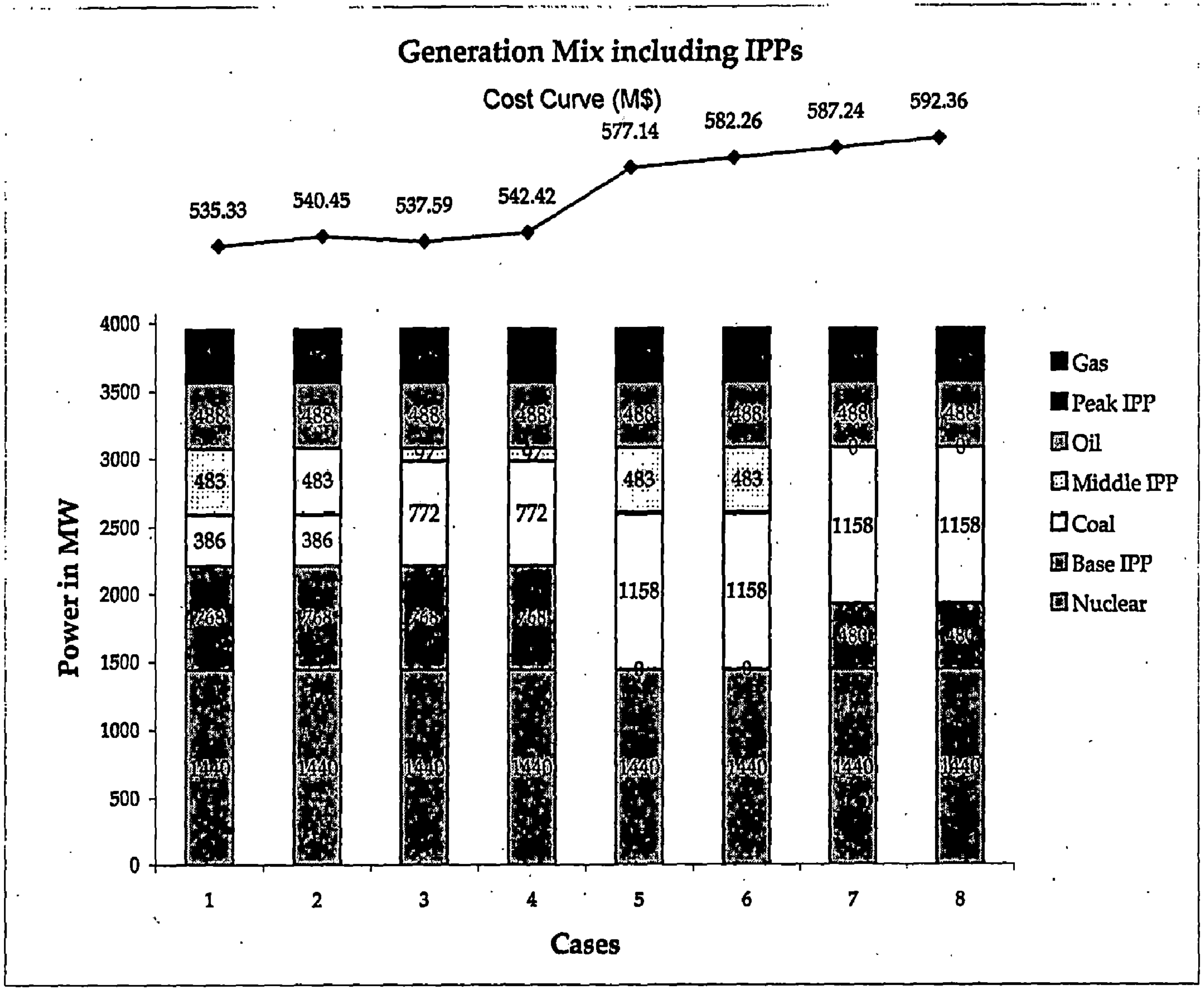

Figure-7.3: Optimal Generation Mix in condition-1

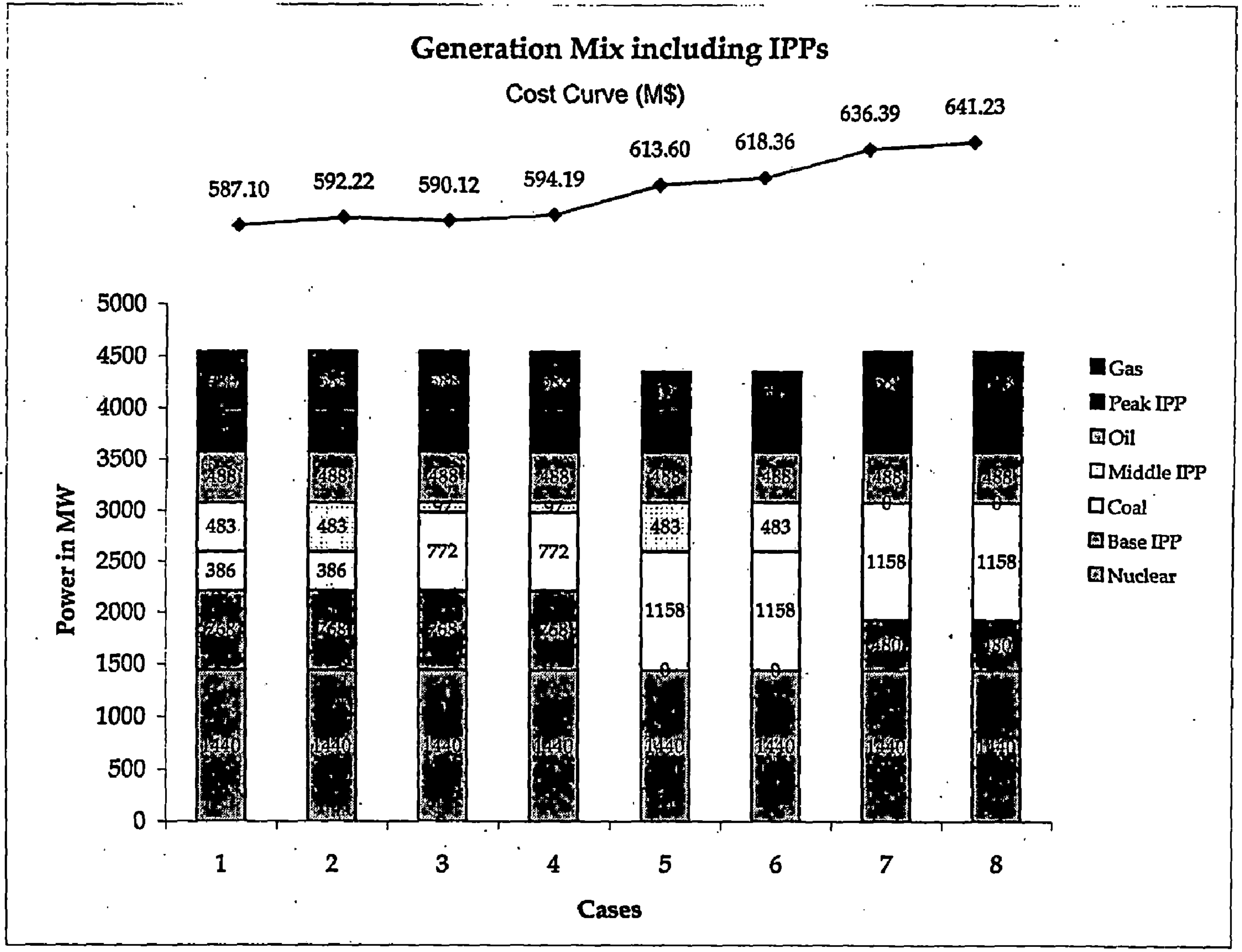

Figure-7.4: Optimal Generation Mix in condition-2

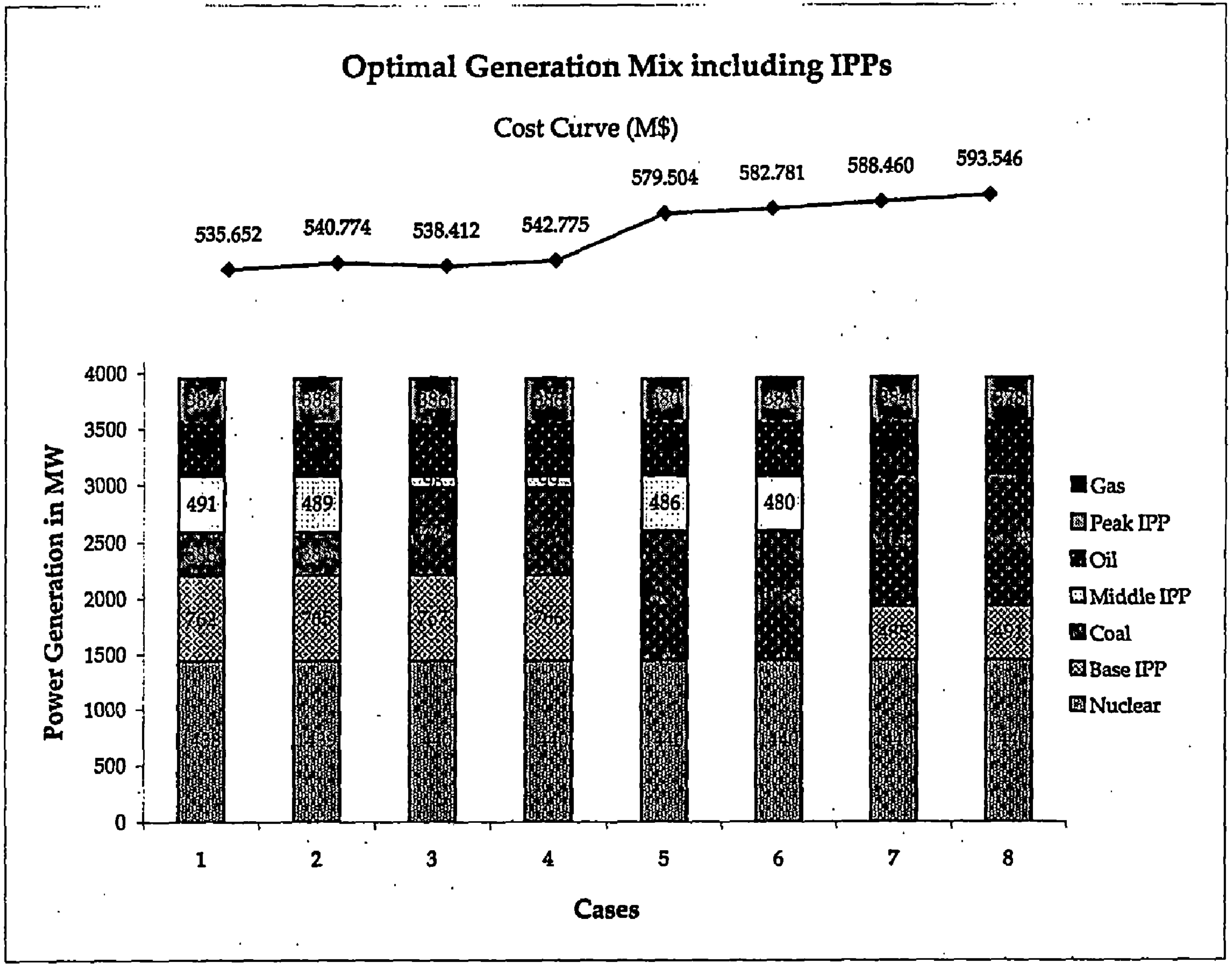

Figure-7.5: Optimal Generation Mix by GA for condition-1

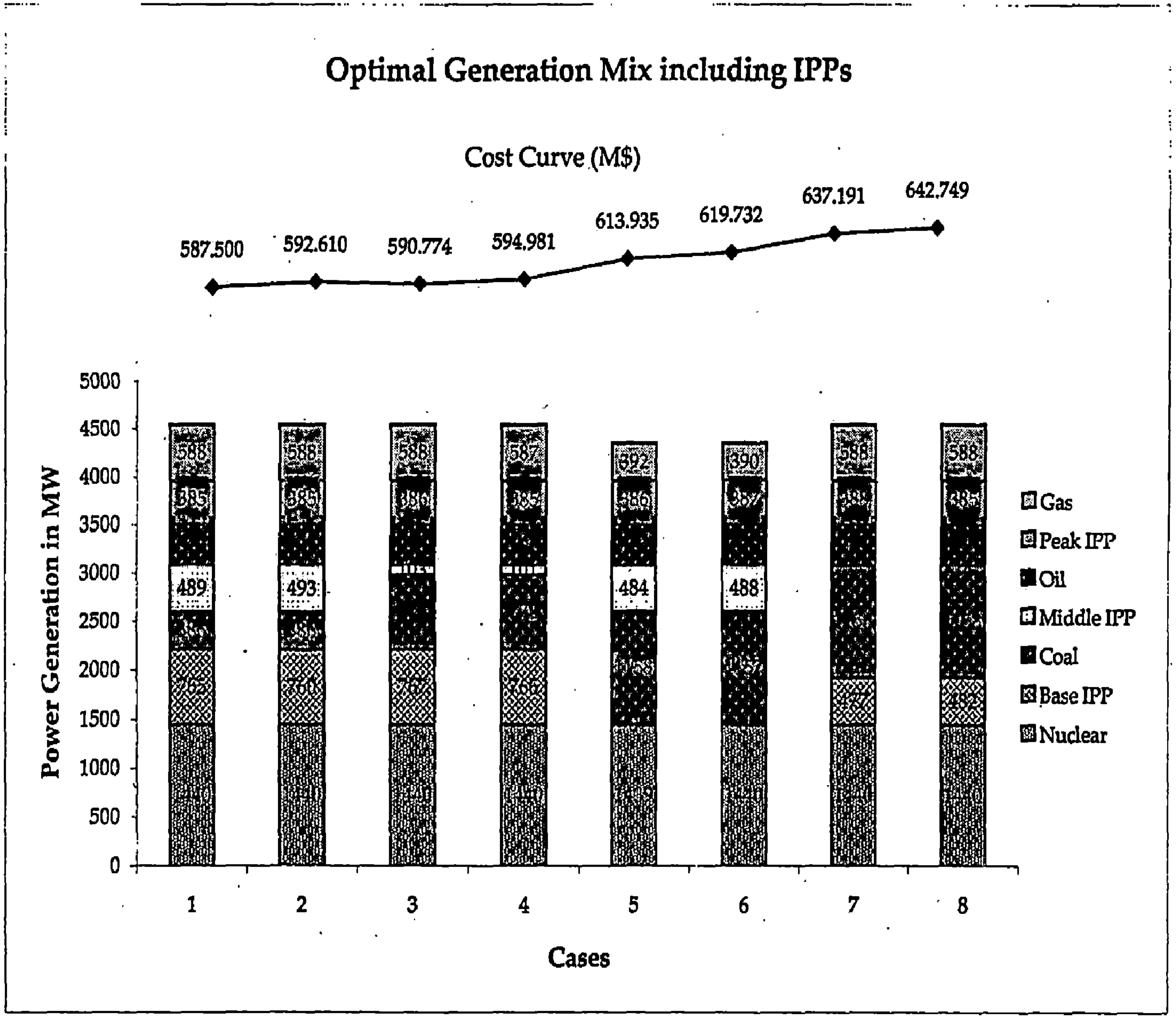

Figure-7.6: Optimal Generation Mix by GA for condition-2

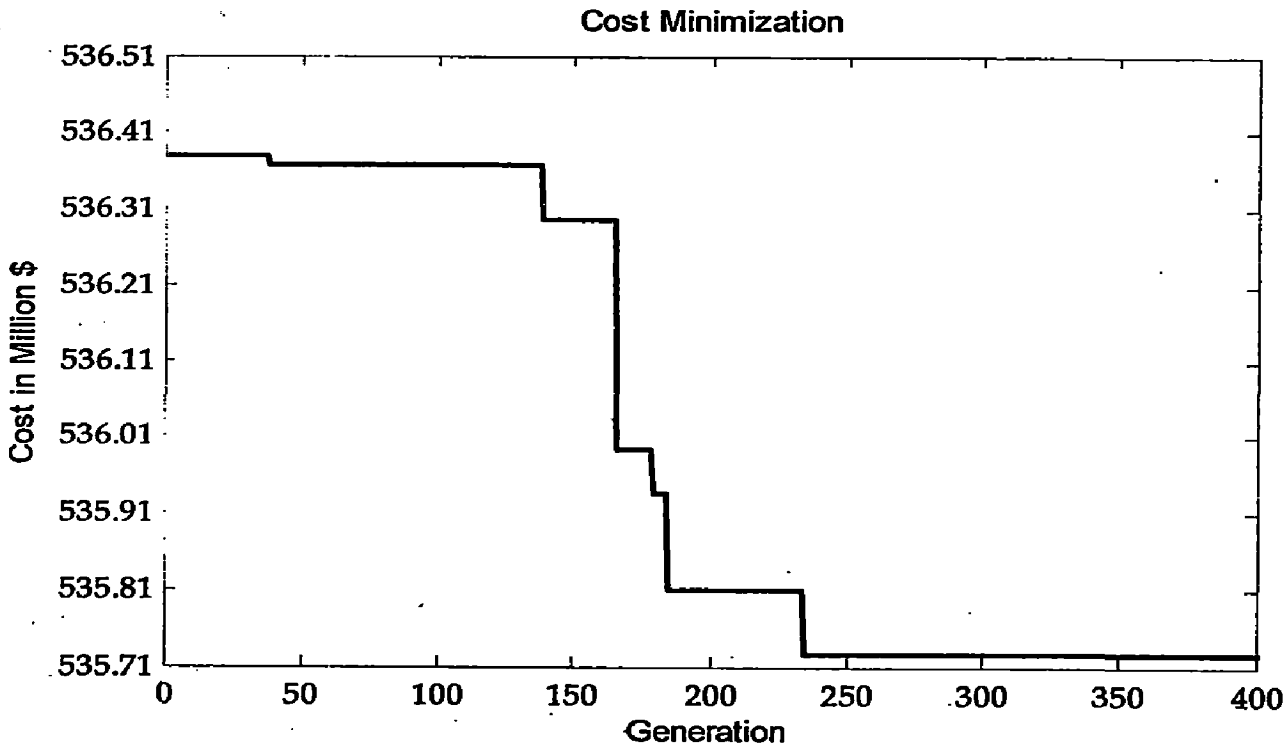

Figure-7.7: Convergence Curve of GA (case1, condition1)

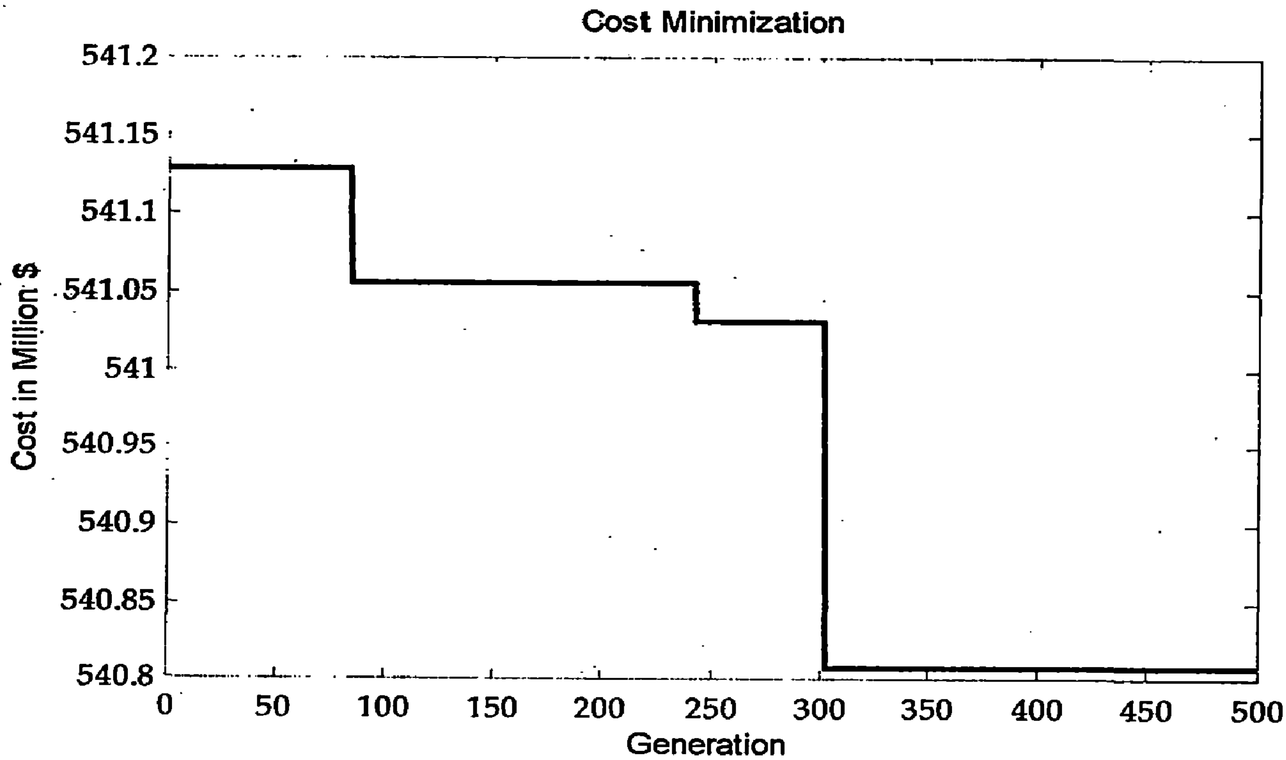

Figure-7.8: Convergence Curve of GA (case2, condition1)

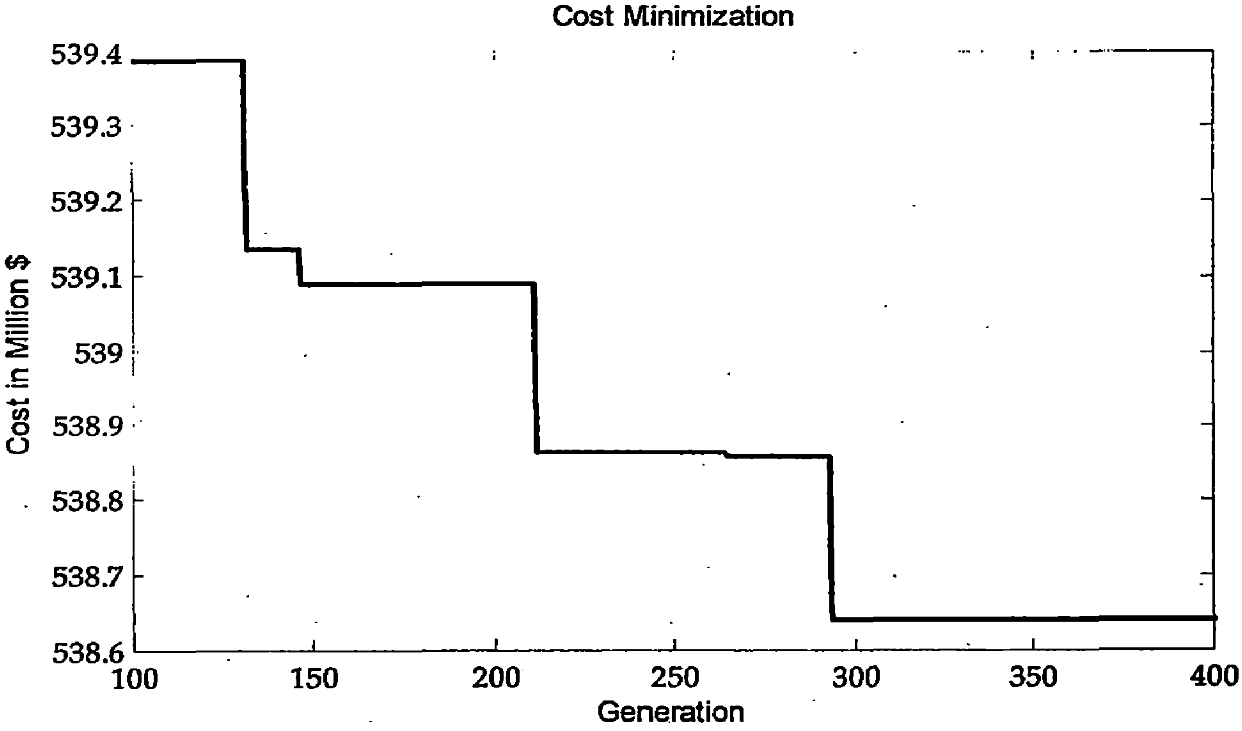

Figure-7.9: Convergence Curve of GA (case3, condition1)

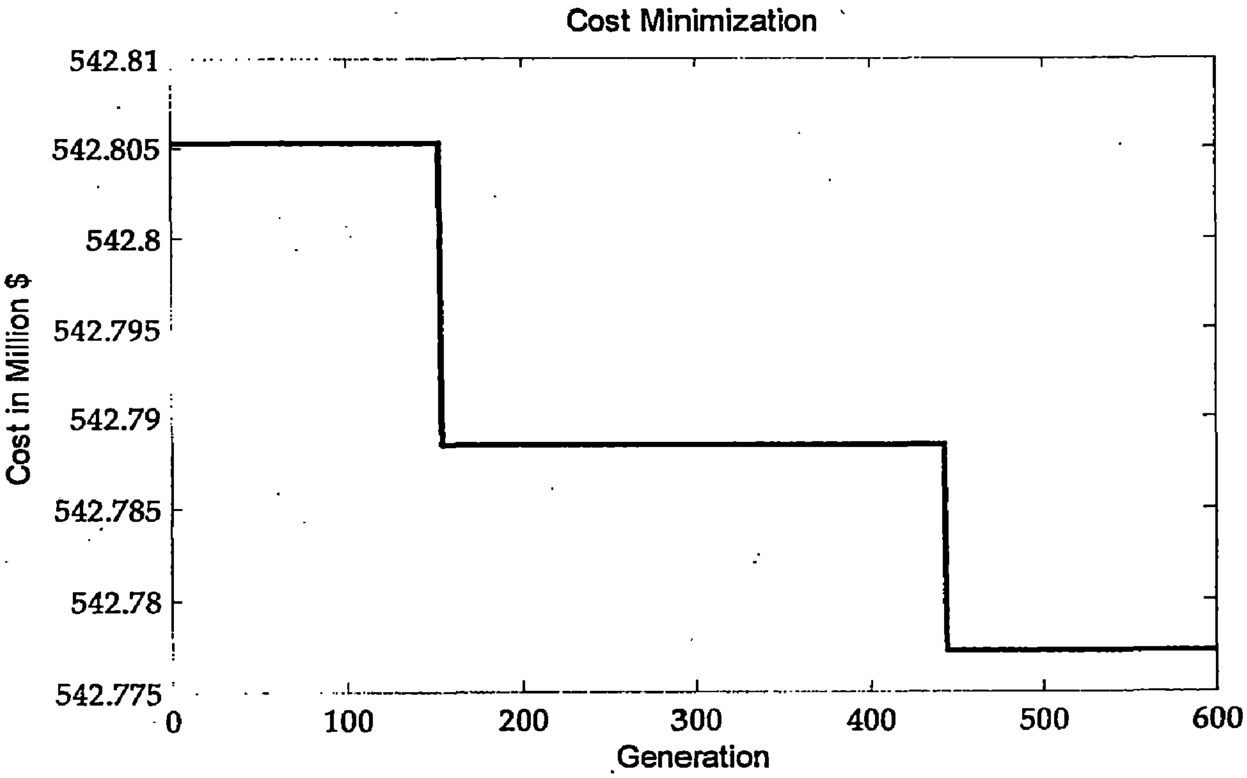

Figure-7.10: Convergence Curve of GA (case4, condition1)

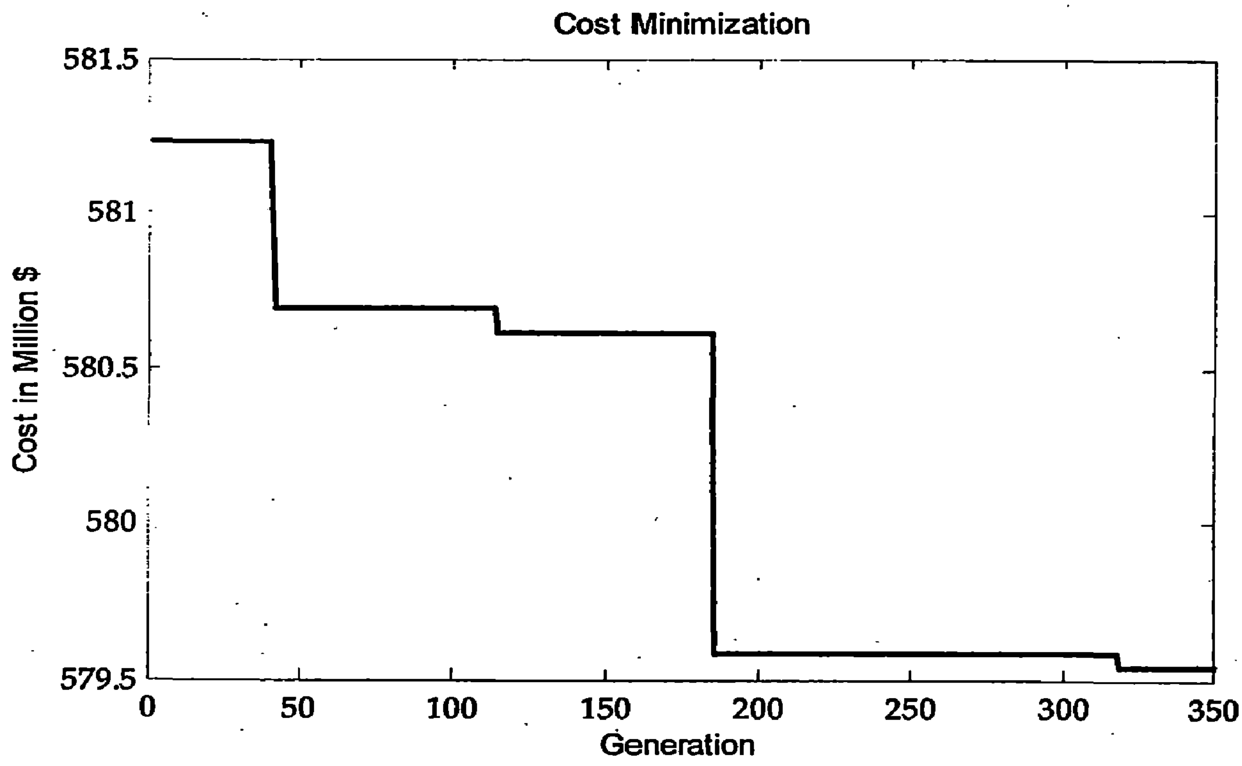

Figure-7.11: Convergence Curve of GA (case5, condition1)

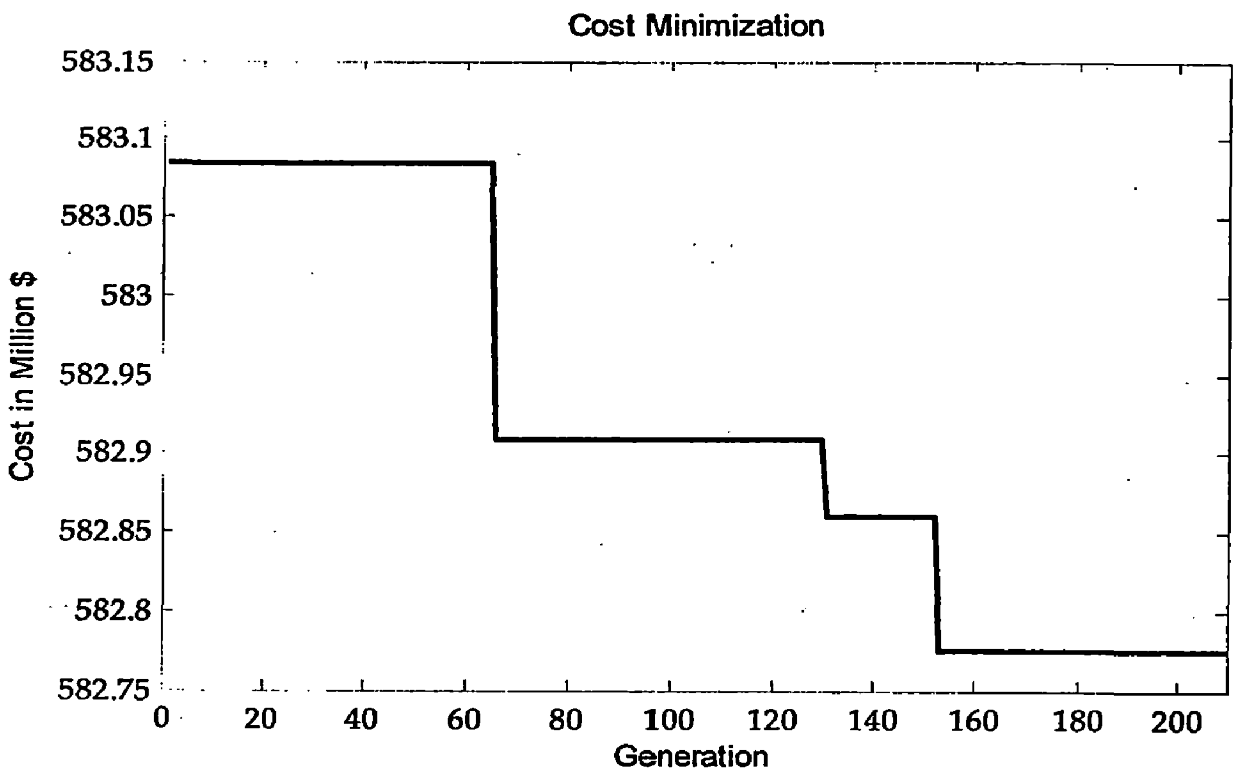

Figure-7.12: Convergence Curve of GA (case6, condition1)

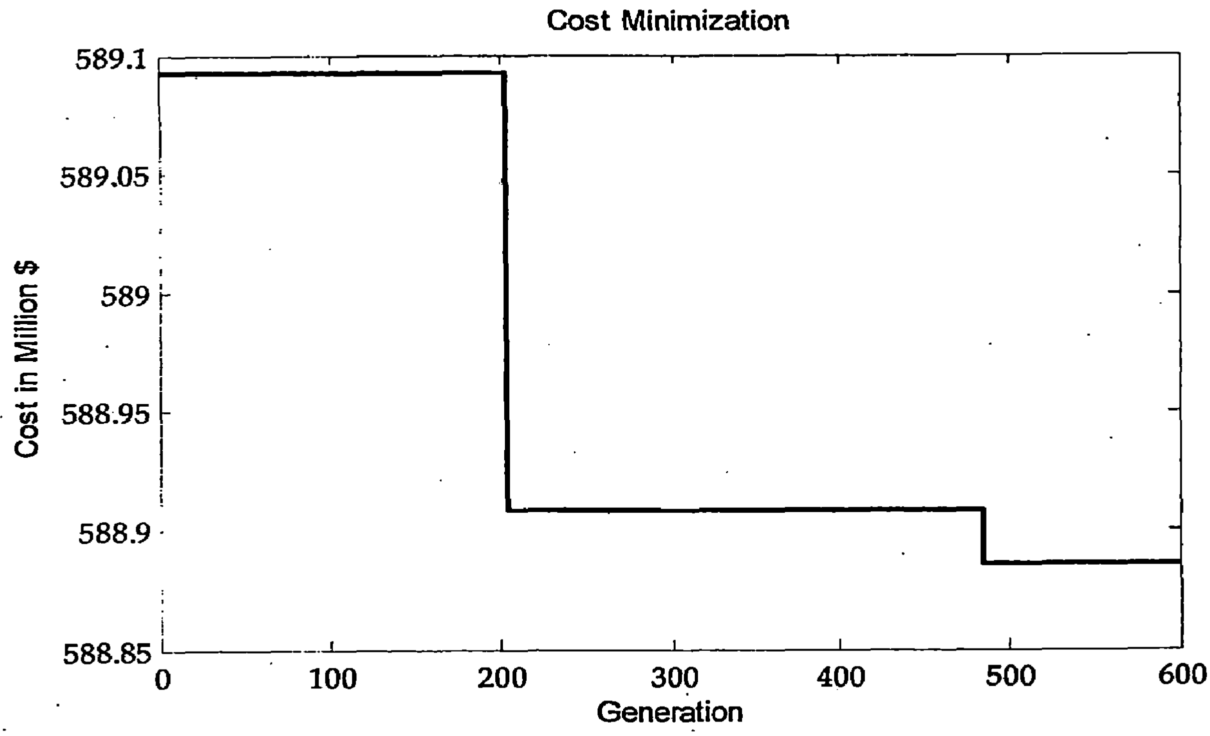

Figure-7.13: Convergence Curve of GA (case7, condition1)

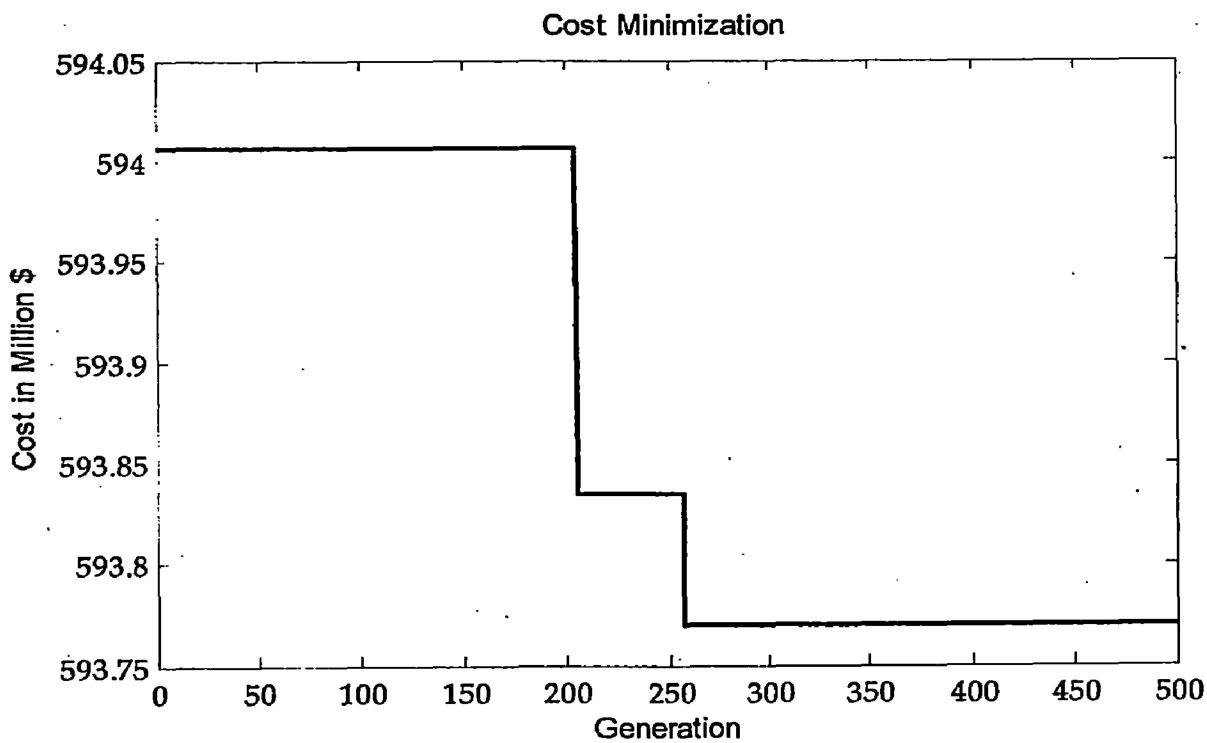

Figure-7.14: Convergence Curve of GA (case8, condition1)

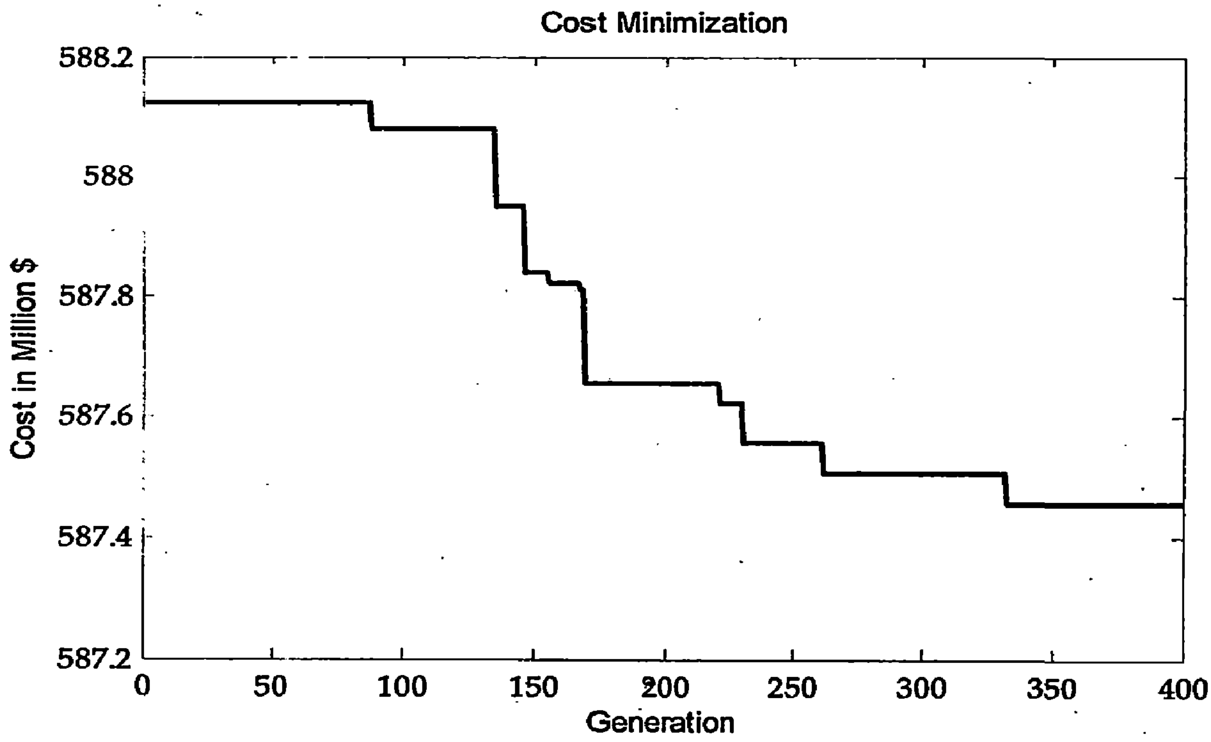

Figure-7.15: Convergence Curve of GA (case1, condition2)

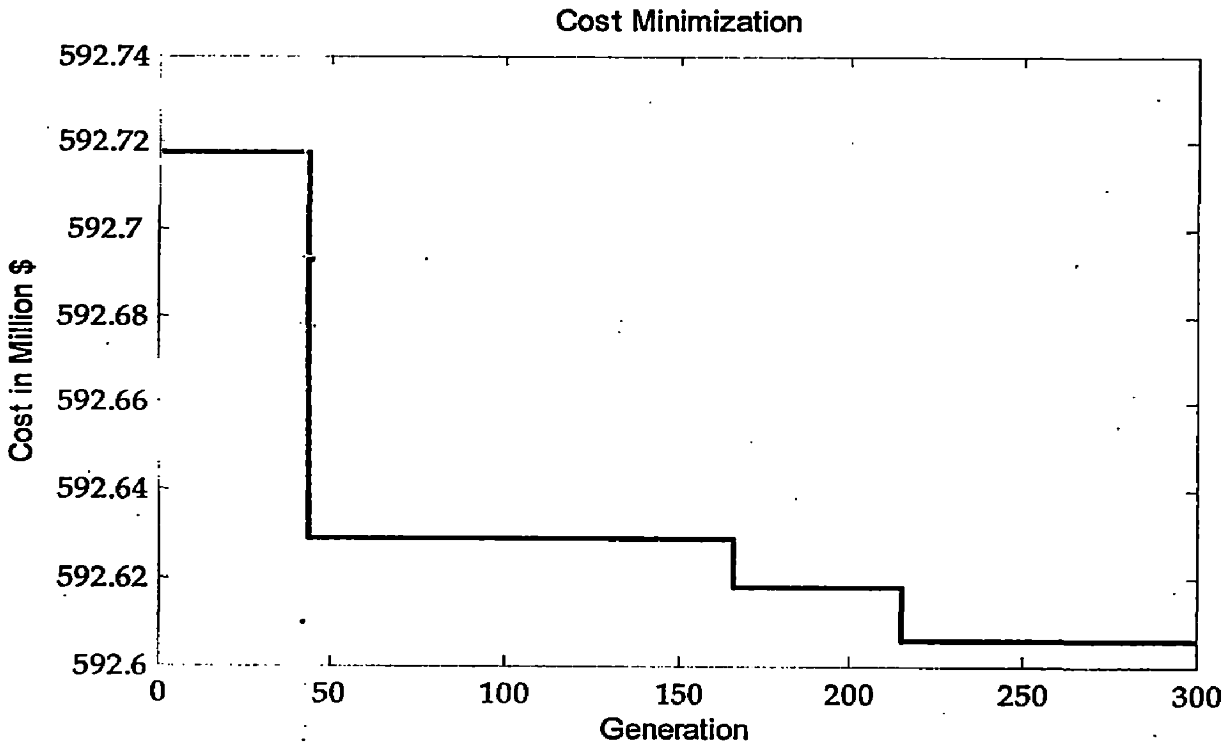

Figure-7.16: Convergence Curve of GA (case2, condition2)

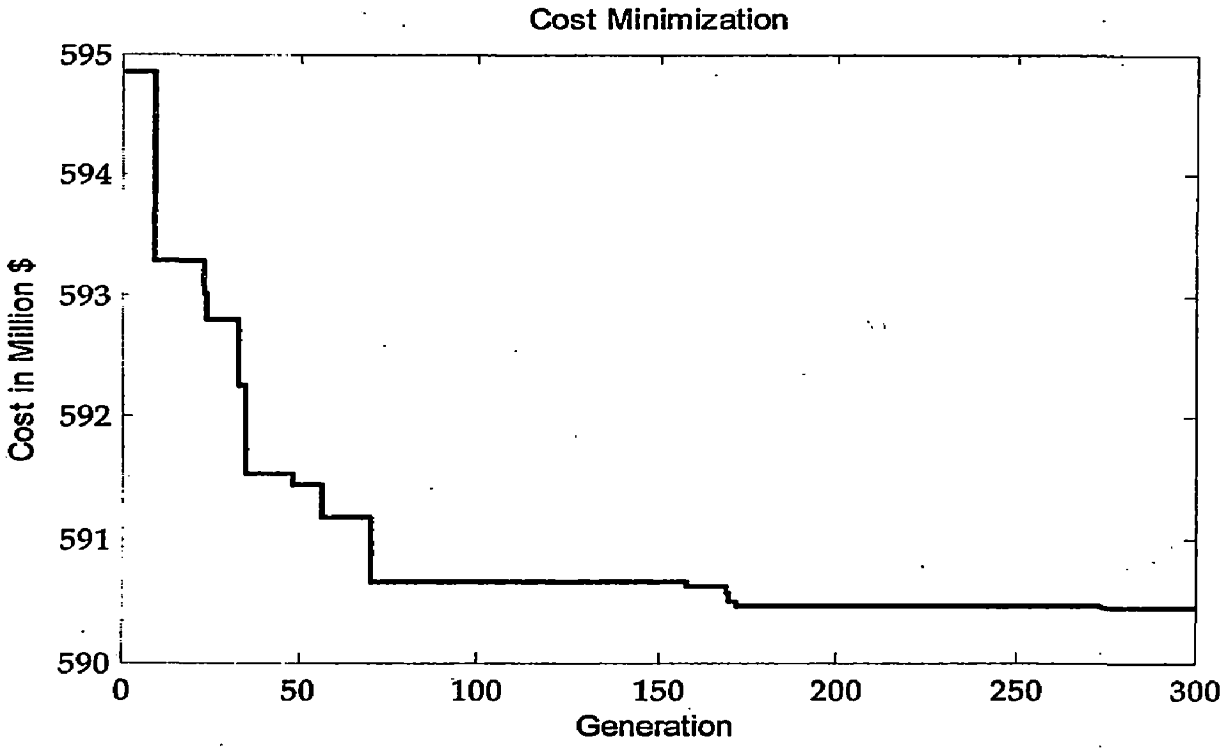

Figure-7.17: Convergence Curve of GA (case3, condition2)

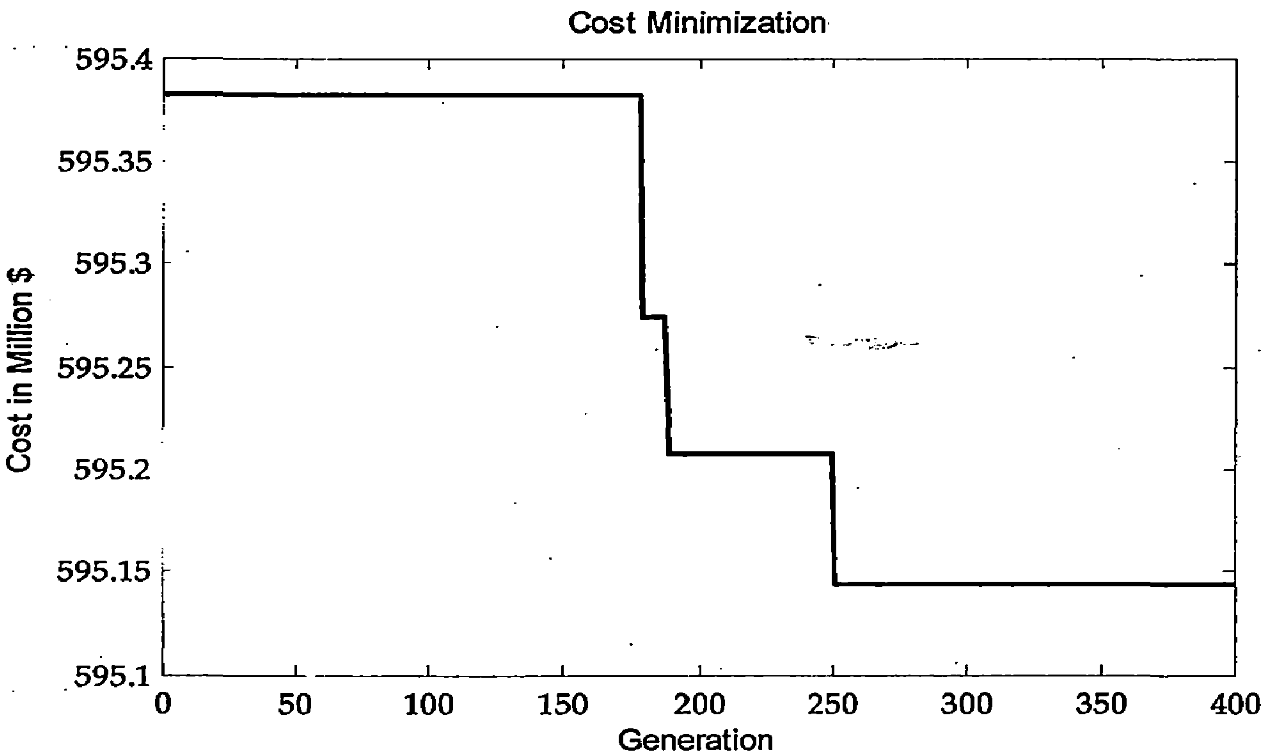

Figure-7.18: Convergence Curve of GA (case4, condition2)

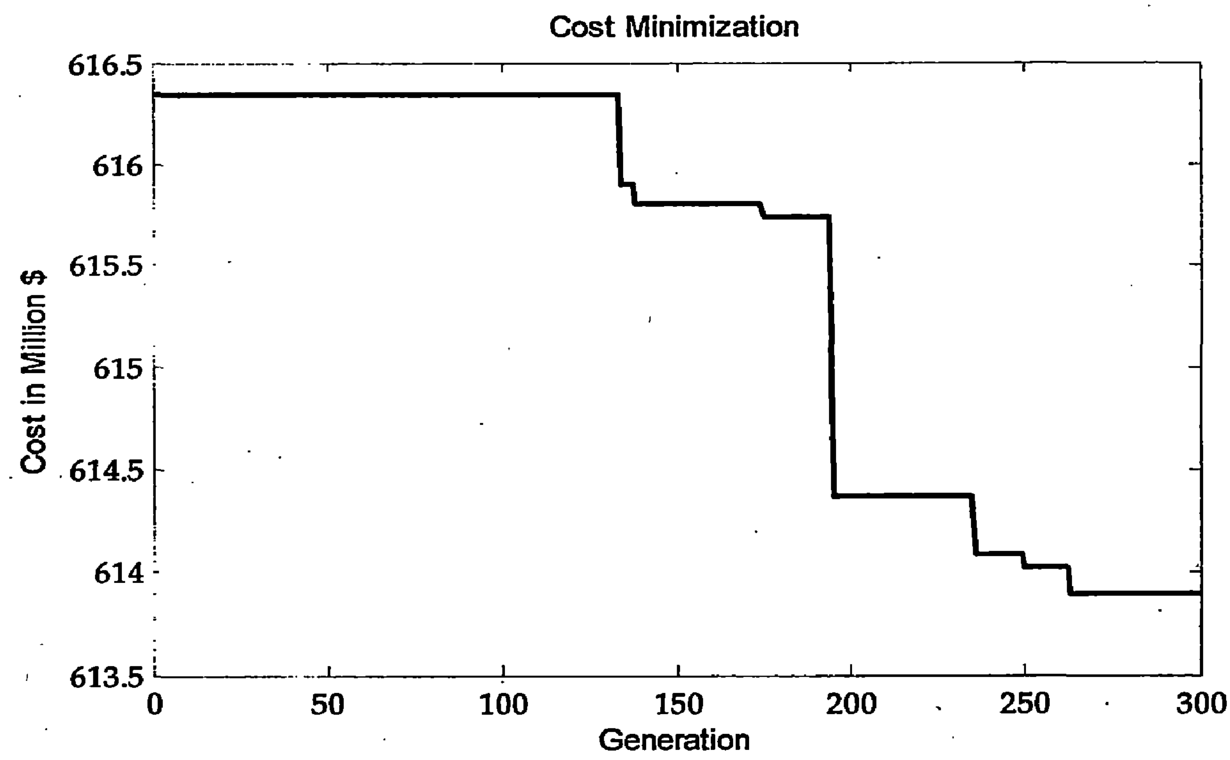

Figure-7.19: Convergence Curve of GA (case5, condition2)

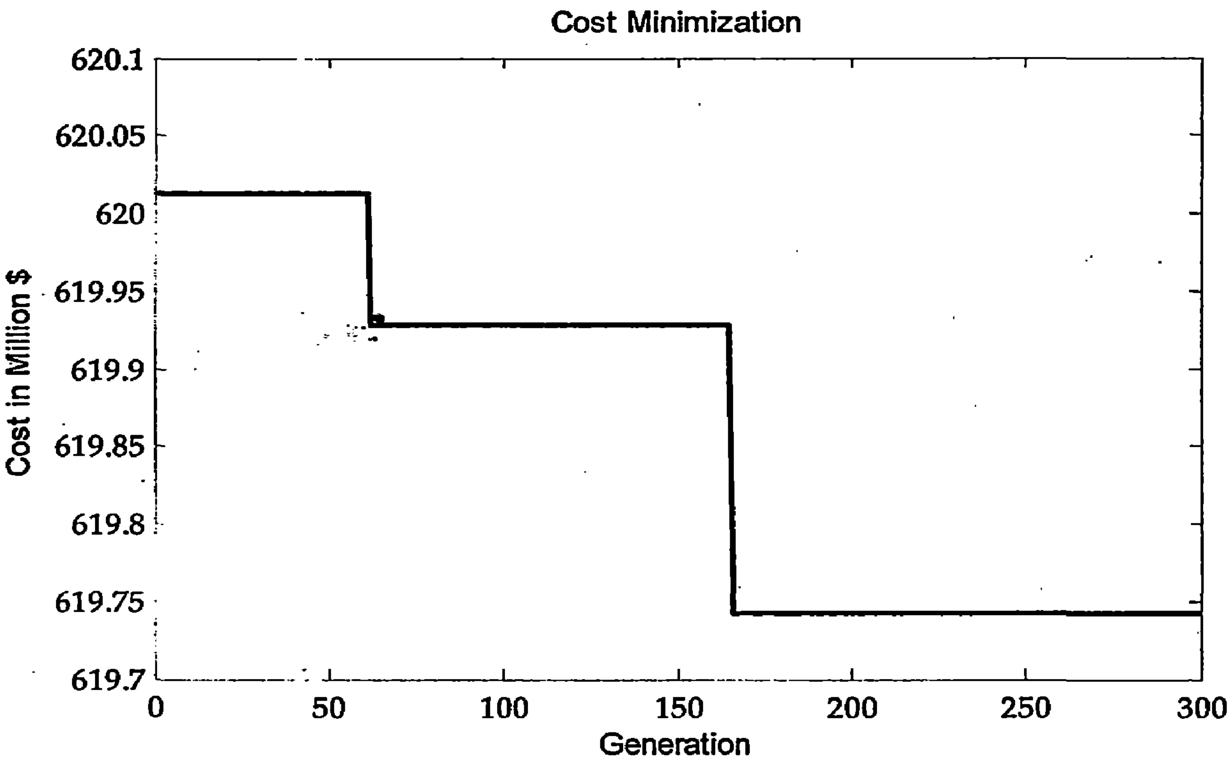

Figure-7.20: Convergence Curve of GA (case6, condition2)

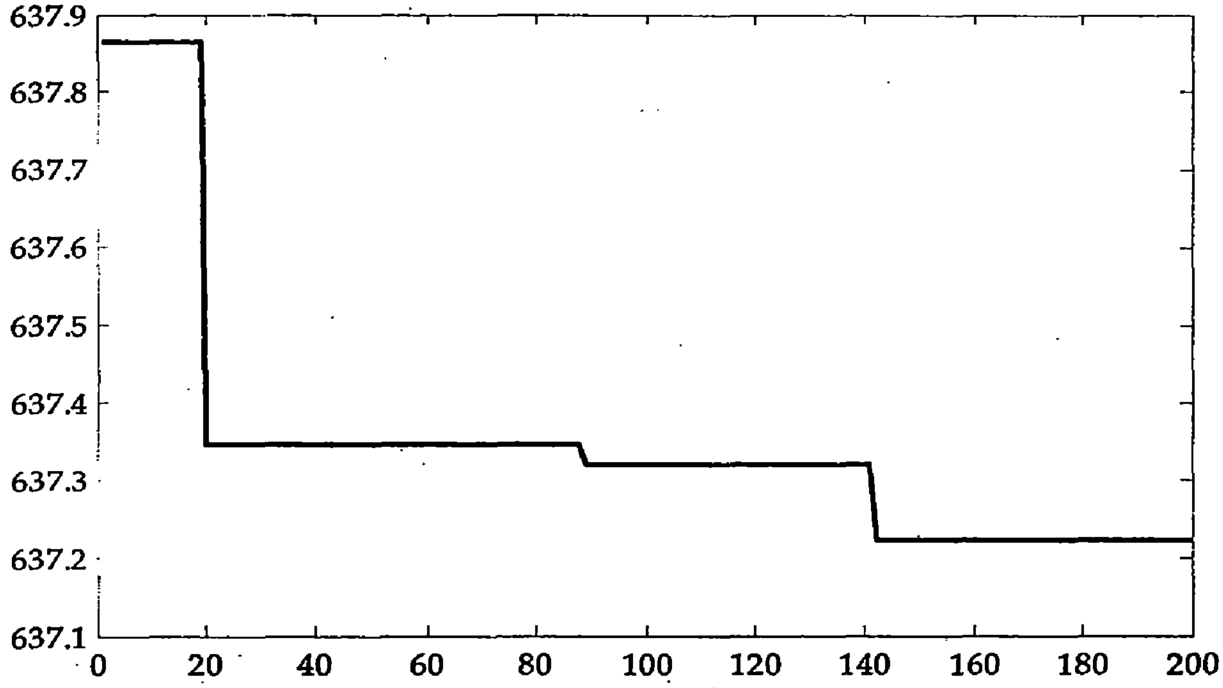

Figure-7.21: Convergence Curve of GA (case7, condition2)

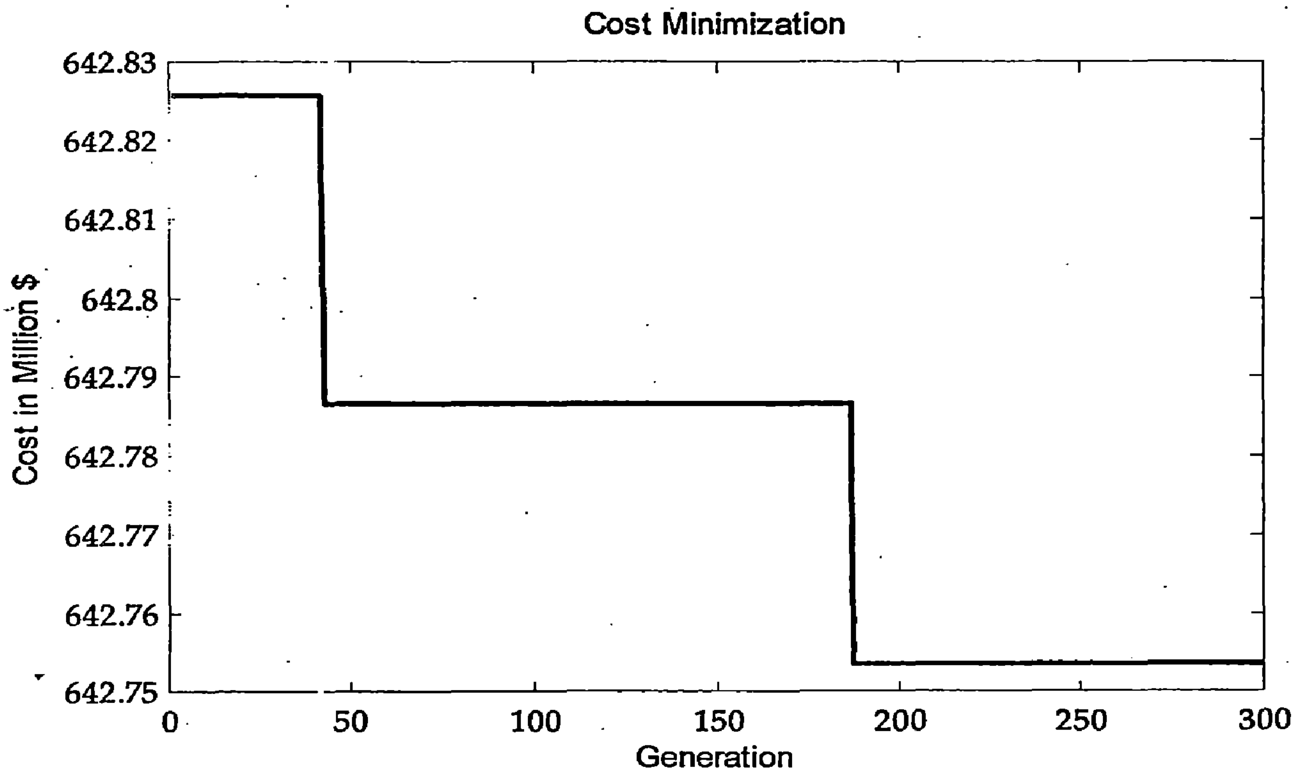

Figure-7.22: Convergence Curve of GA (case8, condition2)

Table-7.11: Energy Generation and Reliability Indices in condition-1

Cases	Nuclear (GWh)			Base IPP (GWh)	Coal (GWh)			Middle IPP (GWh)	Oil (GWh)				Peak IPP (GWh)	Gas (GWh)				LOLP	EENS
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17		
1	6307	6307	0	6723	0	0	3357	3544	1125	595	0	0	378	0	0	0	0	0.0679	159590
2	6307	6307	0	6723	0	0	3357	3544	1125	595	0	0	378	0	0	0	0	0.0679	159590
3	6307	6307	0	6723	0	3357	2976	577	1127	595	0	0	371	0	0	0	0	0.0661	155284
4	6307	6307	0	6723	0	3357	2976	577	1127	595	0	0	371	0	0	0	0	0.0661	155284
5	6307	6307	0	0	3381	3377	3357	3561	1138	594	0	0	351	0	0	0	0	0.0564	121510
6	6307	6307	0	0	3381	3377	3357	3561	1138	594	0	0	351	0	0	0	0	0.0564	121510
7	6307	6307	0	4204	3376	3332	2747	0	1142	599	0	0	357	0	0	0	0	0.0574	124170
8	6307	6307	0	4204	3376	3332	2747	0	1142	599	0	0	357	0	0	0	0	0.0574	124170

Table-7.12: Energy Generation and Reliability Indices in condition-2

Cases	Nuclear (GWh)			Base IPP (GWh)	Coal (GWh)			Middle IPP (GWh)	Oil (GWh)				Peak IPP (GWh)	Gas (GWh)				LOLP	EENS
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17		
1	6307	6307	0	6723	0	0	3357	3544	1125	595	0	0	378	86	41	18	0	0.007	14892
2	6307	6307	0	6723	0	0	3357	3544	1125	595	0	0	378	86	41	18	0	0.007	14892
3	6307	6307	0	6723	0	3357	2976	577	1127	595	0	0	371	84	40	17	0	0.0066	13935
4	6307	6307	0	6723	0	3357	2976	577	1127	595	0	0	371	84	40	17	0	0.0066	13935
5	6307	6307	0	0	3381	3377	3357	3561	1138	594	0	0	351	68	31	0	0	0.0117	22184
6	6307	6307	0	0	3381	3377	3357	3561	1138	594	0	0	351	68	31	0	0	0.0117	22184
7	6307	6307	0	4204	3376	3332	2747	0	1142	599	0	0	357	69	32	14	0	0.0052	9210
8	6307	6307	0	4204	3376	3332	2747	0	1142	599	0	0	357	69	32	14	0	0.0052	9210

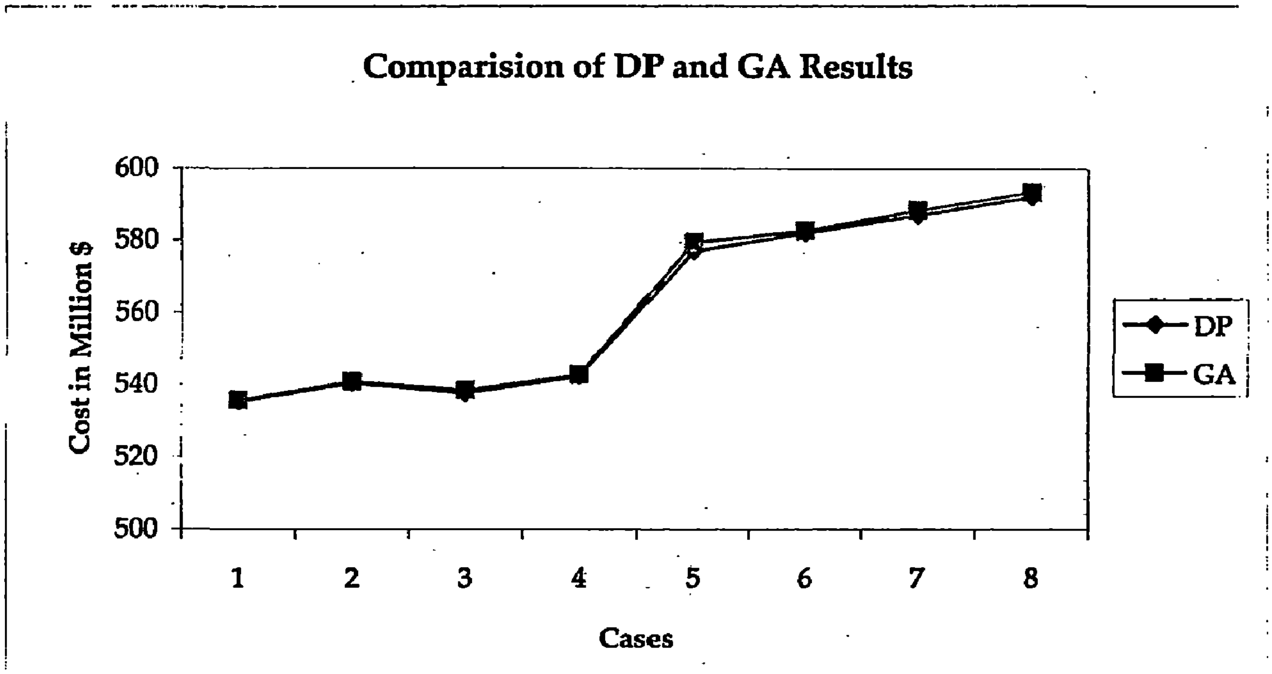

Figure-23: Comparison Results of Condition-1

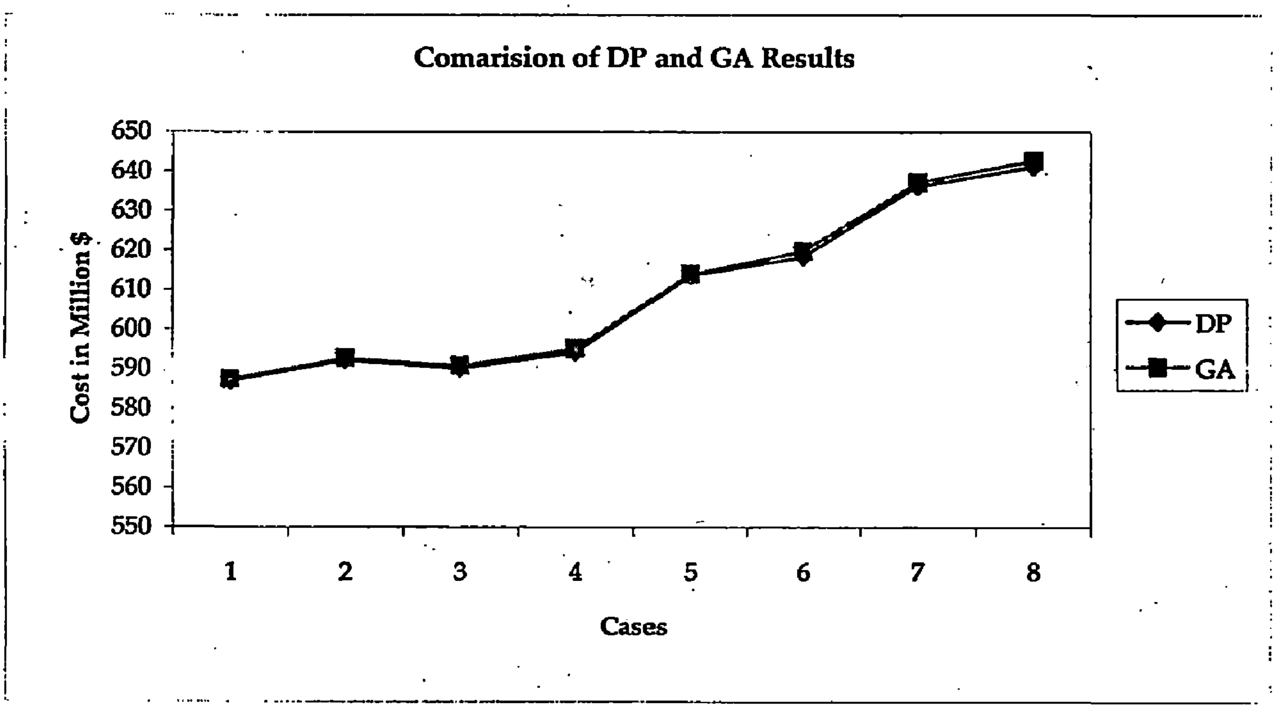

Figure-7.24: Comparison Results of Condition-2

CHAPTER EIGHT

CONCLUSION

In the recent years, the deregulation of power sector is a new trend in developing countries to increase private participation, encourage competition and promote efficient energy use and conservation. The performance of existing power systems in developing countries (especially in south Asia) is very poor and also the addition of new generating plant is very costly. The government owned electric power industry has not sufficient budget for generation expansion and these countries are mostly dependent upon the donor agencies for development of new infrastructure. In such case, the generation expansion can not be cost economic and it suffers from the price escalation depending upon the foreign currency exchange rate. So, the developing countries are making tremendous efforts to pen their markets to become more competitive and to attract the private participation and foreign capital in power sector. The electricity market reform or deregulation of power sector is a major priority of the developing countries for the future.

The entry of independent power producers (IPPs) in a competing environment in the electric power market is a part of deregulation. Most of the Asian developing countries have already introduced some degree of competition in generation by allowing IPPs to sell electricity to government owned utilities. Till the recent time, participation of IPPs in public supply systems was generally discouraged. On the other side, the IPPs were also not serious in low cost supply and tried to get maximum benefit by selling electricity at higher rates. They invariably failed to provide reliable and low cost power supply.

Keeping in view of these above factors, the generation expansion in deregulated market has been studied and the generation expansion including the participation of IPPs is presented in this dissertation. The following conclusion can be drawn from the study.

1. The generation expansion problem has been totally redirected from the cost minimization to profit maximization through competition and deregulation of electricity market.

2. The entry of Independent Power Producers (IPPs) in generation has become almost a necessity in the transition of electricity sectors from monopoly to competition. This helps to attract investment and provides an opportunity in bringing new technologies in developing countries.

3. The new capacities can be added in power generation through the competitive bidding among the IPPs in various forms of organization such as Built, Lease and Transfer (BLT), Built, Own, Operate, and Transfer (BOOT), or Built, Own and Operate (BOO).

4. The IPPs can be classified as Base_type, Middle_type and Peak_type depending upon their duration hours of generation. They can compete with each other to replace similar type of Utility's generation technologies.

5. The inclusion of IPPs in generation expansion can reduce the burden on the state promoted utilities.

6. The Utility can get more profit or lower its generation cost/sale price when the Base_type and Middle_ type IPPs bid at lower price. In a competitive market, reduced cost would translate into reduced prices to end-users.

7. In case of Peak_type IPP, the Utility can lower its generation cost by introducing Peak_type IPP at both higher and lower rates. If the Peak_type IPP bids at lower price, the Utility can prefer to introduce the large amount of Peak_type IPP generation.

8. The introduction of Independent Power Producers (IPPs) in power sector can be an immediate and timely solution to meet the high demand growth of developing countries. It can also be the solution to end infinite growth of public expenditure in power sector and promise of freedom from rigidity, inefficiency of the state owned Utilities in developing countries.

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```
% Genetic Algorithm Program

nvals = input('Enter the number of variables: ');

for n = 1:nvals

    a(n) = input('Enter the Lower limit of variables: ');
    bb(n) = input('Enter the Upper limit of variables: ');
    fr(n) = input('Enter the FOR: ');
    b (n) = bb(n)*(1-fr(n)/100);

end


popsize = 100;
stringlength = 12 * size(a,2);
gen =500;

tic
res = zeros(1,size(a,2)+4);
pow = 0;
c = zeros(1,gen);
c(1) = 0.5;
oper = 0;
bf = zeros(1,gen);


%Initialisation
 [pop1] = pop_sel(popsize,stringlength,@gaf_ap24,a,b);
  pop = pop1;
  newpop = pop;

for g = 1:gen

% Improved Genetic Algorithm Process
   k1 = 7.5;
   k2 = 7.8;
   pr = rand;
  if pr > c(g)

% Selection of Chromosomes for Crossover and Crossover

   oper(g) =1;
```

```
  x1 = zeros(1,popsize/2);
  y1 = zeros(1,popsize/2);
  jj =1;

 for ii = 1:popsize/2
     x = round(rand*((popsize)-1));
     y = round(rand*((popsize)-1));
    if x ~= y1 & y ~= x1 & x ~= y & x ~= x1 & y ~= y1
      pare1 = newpop(x+1,1:(stringlength+size(a,2)+4));
      pare2 = newpop(y+1,1:(stringlength+size(a,2)+4));
      [child1,child2] = t_crossover(pare1,pare2,pr,@gaf_ap24,a,b);

      newpop(x+1,1:stringlength+size(a,2)+3) =
child1(1:stringlength+size(a,2)+3);
      newpop(y+1,1:stringlength+size(a,2)+3) =
child2(1:stringlength+size(a,2)+3);
      jj = jj + 1;
     x1(jj) = x;
    y1(jj) = y;

  end

 end

for ii = 1:popsize
   newpop(ii,stringlength+size(a,2)+4) =
(max(newpop(:,stringlength+size(a,2)+3)) ...
                                                                        +
                                   min(newpop(:,stringlength+size(a,2)+3))) ...
                                                  -
newpop(ii,stringlength+size(a,2)+3);

end

 else
% Selection of Chromosome for Mutation and Mutation

  oper(g) = 2;
  z1 = zeros(1,popsize);
  ii=1;

 for jj = 1:popsize
    z = round(rand*(popsize-1));
```

```
    if z ~= z1
      pare = newpop(z+1,1:(stringlength+size(a,2)+4));
      [child] = t_mutation(pare,pr,@gaf_ap24,a,b);
      newpop1(z+1,1:stringlength+size(a,2)+3) =
child(1:stringlength+size(a,2)+3);
      z1(ii) = z;
      ii = ii+1;

   end

 end

for jj = 1:popsize
    newpop(jj,stringlength1+size(a,2)+4) =

                                   (max(newpop(:,stringlength+size(a,2)+3)) ...
                                              +
                                   min(newpop(:,stringlength+size(a,2)+3))) ...
                                        -
                                   newpop(jj,stringlength+size(a,2)+3);
 end
 end


% Changing of population
    oldpop1 = pop1;
    pop = newpop;

% Checking of minimum fitness value
if c(g)>= 0.1 && c(g)<= 0.95
    f_min1 = min(oldpop(:,stringlength1+size(a,2)+4));
    f_min2 = min(newpop(:,stringlength1+size(a,2)+4));
    if g > 1
     if f_min1 > f_min2 && oper(g) == 1      % from crossover
       c(g+1) = c(g) - k1/gen;
     elseif f_min1 > f_min2 && oper(g) == 2  % from mutation
         c(g+1) = c(g) + k1/gen;
     elseif f_min1 <= f_min2 && c(g) > c(g-1)    % control parameters need to
hold back
         c(g+1) = c(g) - k2/gen;
       elseif  f_min1 <= f_min2 && c(g) <= c(g-1)
         c(g+1) = c(g) + k2/gen;
     end
```

```
    else
        c(g+1) = c(1);
    end
else
    c(g) = 0.5;
end



 % Elite Selection
   en = 4;
   [epop,eind] = elite_sel(oldpop,pop1,en);

 % Selection considering Elite individuals

 [z,j] = sort(epop(:,end),'descend');
  epop1 = epop(j,:);
  newpop1 = elit_roulette(epop1,en,a);

   for k = 1:en
      newpop((popsize1-en)+k,:) = eind(k,:);
   end

    % Result

      [m,n] = min(newpop(:,stringlength+size(a,2)+3));
      res = newpop(n,(stringlength+1):(stringlength+size(a,2)+4));

 yy = round(res(1:size(a,2)));
 pow = sum(yy);

  bf(g) = min(newpop(:,stringlength+size(a,2)+3));

end
g = 1:gen;
 plot(g,bf(g),'k');

 xlabel('Generation');
 ylabel('Cost in Million $');
 title('Cost Minimization');

toc
```

```
% Initialization of population in GA program
% Selection of population within the constraints range.

function [spop,v1,v2,pf]=pop_sel(popsize1, stringlength, fun,a,b);

 k = 1;
 popsize = 100;
s = zeros(1,popsize);
nobjf = zeros(1,popsize);
pop = zeros(popsize,stringlength+size(a,2)+4);
spop = zeros(popsize1,stringlength+size(a,2)+4);

while k <= popsize1
    pop = round(rand(popsize, stringlength+size(a,2)+4));

   for i = 1:popsize1
      for j = 1:size(a,2)
         substr1 = (((j-1)*stringlength)/size(a,2))+1;
         substr2 = j*stringlength/size(a,2);
         bin = 2.^(size(pop(:,substr1:substr2),2)-1:-1:0);
         s(i) = sum(bin * transpose(pop(i,substr1:substr2)));
         x(j) = round(s(i) * (b(j)-a(j))/(2.^(stringlength/size(a,2))-1)+a(j));
         pop(i,stringlength+j) = (x(j));
         temp(j) = pop(i,stringlength+j);
      end

    if (sum(x)) >= c1
         spop(k,:) =  pop(i,:);
         pf(k) = pen_cost1(x,c1,c2);        % c1 & c2 constraint limits
         spop(k,stringlength+size(a,2)+1) = fun(temp);
         spop(k,stringlength+size(a,2)+2) = pf(k);
         nobjf(k) = fun(temp)*(1+10*pf(k));
         spop(k,stringlength+size(a,2)+3) = nobjf(k);
         v1(k)= sum(x);
         k = k + 1;
         if k  > 100
            break;
         end
    end

   end
end
   for ii = 1:(k-1)
      spop(ii,stringlength+size(a,2)+4) = (max(nobjf)+min(nobjf))- nobjf(ii);
   end
```

er function of Genetic Algorithm Program

```
ion [child1, child2,pf] = crossover(parent1, parent2, pc,fun,a,b);

stringlength = size(parent1,2)-size(a,2)-4;
rdm = rand;
cpoint = 0;
 child1(:,1:stringlength) = 0;
 child2(:,1:stringlength) = 0;
 nobjf1 = 0;
 nobjf2 = 0;
if rdm < pc
   cpoint=round(rand*(stringlength-2))+1;
   child1 = [parent1(:,1:cpoint) parent2(:,cpoint+1:stringlength)];
   child2 = [parent2(:,1:cpoint) parent1(:,cpoint+1:stringlength)];

      for j = 1:size(a,2)
         substr1 = (((j-1)*stringlength)/size(a,2))+1;
         substr2 = j*stringlength/size(a,2);
         ch1(j) = round(sum(2.^(size(child1(:,substr1:substr2),2)-1:-1:0)...
 *transpose(child1(:,substr1:substr2)))*(b(j)-(j))/(2.^(stringlength/size(a,2))-
1)+a(j));
         child1(:, stringlength+j) = ch1(j);
         ch2(j) = round(sum(2.^(size(child2(:,substr1:substr2),2)-1:-1:0)...
*transpose(child2(:,substr1:substr2)))*(b(j)-a(j))/(2.^(stringlength/size(a,2))-
)+a(j));
         child2(:, stringlength+j) = ch2(j);
```

```
    end

    pf1 = pen_cost1(ch1,c1,c2);                      % c1 & c2 constraint limits
    child1(:,stringlength+size(a,2)+1) = fun(ch1);
    child1(:,stringlength+size(a,2)+2) = pf1;
    nobjf1 = fun(ch1)*(1+10*pf1);
    child1(:,stringlength+size(a,2)+3) = nobjf1;

    pf2 = pen_cost1(ch2,c1,c2);                                % c1 & c2 constraint
limits
    child2(:,stringlength+size(a,2)+1) = fun(ch2);
    child2(:,stringlength+size(a,2)+2) = pf2;
    nobjf2 = fun(ch2)*(1+10*pf2);
    child2(:,stringlength+size(a,2)+3) = nobjf2;
    pf = pf1+pf2;
else
  pf = 0;
  child1=parent1;
  child2=parent2;
end
```

% Mutation Function for Genetic Algorithm Program

```
function [child,pf] = mutation(parent,pm,fun,a,b)

stringlength = size(parent,2)-size(a,2)-4;
ch = zeros(1,size(a,2));
nobjf = 0;

if rand < pm
   mpoint=round(rand*(stringlength-1))+1;
   child(:,1:stringlength) = parent(:,1:stringlength);
   child(mpoint) = abs(parent(mpoint)-1);

    for j = 1:size(a,2)
       substr1 = (((j-1)*stringlength)/size(a,2))+1;
       substr2 = j*stringlength/size(a,2);
       b2d = 2.^ (size(child(:,substr1:substr2),2)-1:-1:0);
       trm = transpose(child(:,substr1:substr2));
       ch(j) =  round((sum(b2d * trm)*(b(j)-a(j))/ (2.^(stringlength/size(a,2))-
1)+a(j)));
       child(:, stringlength+j) = ch(j);
    end

    pf = pen_cost1(ch,c1,c2);            % c1 & c2 constraint limits
    child(:,stringlength+size(a,2)+1) = fun(ch);
    child(:,stringlength+size(a,2)+2) = pf;
    nobjf = fun(ch)*(1+10*pf);
    child(:,stringlength+size(a,2)+3) = nobjf;

else
   pf = 0;
   child = parent;

end
```

% Elitism Selection Function for IGA

```
function [epop,eind] = elite_sel(oldpop,newpop,en);

popsize = 100;
tpop = zeros(2*popsize,size(oldpop,2));
epop = zeros(2*popsize-en,size(oldpop,2));
eind = zeros(en,size(oldpop,2));
tpop(1:popsize,:) = oldpop;
tpop(popsize+1:end,:) = newpop;
[z,j] = sort(tpop(:,end));
tpop = tpop(j,:);

for k = 1:en
   eind(k,:) = tpop(2*popsize-(k-1),:);
end

epop = tpop(1:(2*popsize-en),:);
```

```
% Roulette-Wheel Selection Function for program testing

function [newpop] = elit_roulette(oldpop,en,a);

popsize = 100;
stringlength = size(oldpop,2)-size(a,2)-4;
totalfit = sum(oldpop(:,stringlength+size(a,2)+4));
prob = oldpop(:,stringlength+size(a,2)+4) / totalfit;
prob = cumsum(prob);
rns = sort(rand(popsize,1));
fitin = 1; newin = 1;

while newin <= (popsize-en)
        if rns(newin) < prob(fitin)
          newpop(newin,:) = oldpop(fitin,:);
          newin = newin + 1;
          fitin = 1;
        else
          fitin = fitin+1;
        end
end
```

Summary Results of last few trials of Genetic Algorithm for case-4, condition-1

Serial No	Nuclear			Base IPP		Coal		Middle IPP		Oil			Peak IPP	Gas				f(x)	c	F(x)
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17			
1	720	720	0	750	0	386	385	138	242	240	0	0	370	0	0	0	0	549.7	0.0000	549.7
2	720	719	0	750	0	386	385	138	241	242	0	0	370	0	0	0	0	549.65	0.0000	549.65
3	720	720	0	754	0	385	386	123	240	241	0	0	379	0	0	0	0	546.41	0.0005	549.177
4	720	720	0	754	0	386	386	130	240	243	0	0	373	0	0	0	0	548.437	0.0000	548.437
5	720	720	0	754	0	386	386	130	240	243	0	0	373	0	0	0	0	548.437	0.0000	548.437
6	720	719	0	754	0	385	386	123	243	243	0	0	380	0	0	0	0	546.947	0.0000	546.947
7	720	720	0	760	0	385	386	116	243	243	0	0	379	0	0	0	0	546.156	0.0000	546.156
8	720	719	0	760	0	385	386	116	243	242	0	0	379	0	0	0	0	546.03	0.0000	546.03
9	720	720	0	754	0	386	386	115	243	244	0	0	385	0	0	0	0	545.046	0.0000	545.046
10	720	720	0	754	0	386	386	115	243	244	0	0	385	0	0	0	0	545.046	0.0000	545.046
11	720	720	0	767	0	386	386	105	240	244	0	0	385	0	0	0	0	544.64	0.0000	544.64
12	720	720	0	767	0	382	386	99	244	244	0	0	387	0	0	0	0	542.869	0.0003	544.243
13	720	720	0	767	0	382	386	99	244	244	0	0	387	0	0	0	0	542.869	0.0003	544.243
14	720	720	0	768	0	386	386	99	244	244	0	0	386	0	0	0	0	543.559	0.0000	543.559
15	720	720	0	767	0	386	386	99	244	244	0	0	387	0	0	0	0	543.394	0.0000	543.394
16	720	720	0	767	0	386	386	99	244	244	0	0	387	0	0	0	0	543.394	0.0000	543.394
17	720	720	0	766	0	386	386	99	244	244	0	0	387	0	0	0	0	542.806	0.0000	542.806
18	720	720	0	766	0	386	386	99	244	244	0	0	387	0	0	0	0	542.7766	0.0000	542.7766
19	720	720	0	766	0	386	386	99	244	244	0	0	387	0	0	0	0	542.7766	0.0000	542.7766
20	720	720	0	766	0	386	386	99	244	244	0	0	387	0	0	0	0	542.7766	0.0000	542.7766

Summary Results of last few trials of Genetic Algorithm for case-2, condition-2

Serial No	Nuclear			Base IPP		Coal		Middle IPP		Oil			Peak IPP	Gas				f(x)	c	F(x)
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17			
1	720	720	0	756	0	0	386	510	240	240	0	0	382	194	196	196	0	595.593	0.0000	595.593
2	720	720	0	756	0	0	386	509	240	240	0	0	385	196	196	192	0	595.559	0.0000	595.559
3	720	720	0	758	0	0	386	506	244	242	0	0	376	196	196	196	0	595.107	0.0000	595.107
4	720	720	0	756	0	0	386	507	243	240	0	0	382	195	195	196	0	595.104	0.0000	595.104
5	720	720	0	756	0	0	386	507	243	240	0	0	382	194	196	196	0	595.096	0.0000	595.096
6	720	720	0	758	0	0	386	505	244	243	0	0	376	196	196	196	0	594.881	0.0000	594.881
7	720	720	0	758	0	0	386	505	244	243	0	0	376	196	196	196	0	594.881	0.0000	594.881
8	720	720	0	758	0	0	386	505	244	243	0	0	376	196	196	196	0	594.881	0.0000	594.881
9	720	720	0	756	0	0	386	506	243	240	0	0	382	195	196	196	0	594.820	0.0000	594.820
10	720	720	0	756	0	0	386	506	243	240	0	0	382	195	196	196	0	594.820	0.0000	594.820
11	720	720	0	756	0	0	386	506	243	240	0	0	382	195	196	196	0	594.820	0.0000	594.820
12	720	720	0	756	0	0	386	506	242	240	0	0	382	196	196	196	0	594.710	0.0000	594.710
13	720	720	0	757	0	0	386	505	244	244	0	0	376	196	196	196	0	594.705	0.0000	594.705
14	720	720	0	757	0	0	386	504	244	244	0	0	377	196	196	196	0	594.492	0.0000	594.492
15	720	720	0	757	0	0	386	504	244	244	0	0	377	196	196	196	0	594.492	0.0000	594.492
16	720	720	0	760	0	0	386	493	244	243	0	0	385	196	196	196	0	592.570	0.0002	593.876
17	720	720	0	760	0	0	386	493	244	243	0	0	385	196	196	196	0	592.570	0.0002	593.876
18	720	720	0	766	0	0	386	489	244	244	0	0	383	196	196	196	0	592.717	0.0000	592.717
19	720	720	0	760	0	0	386	493	244	244	0	0	385	196	196	196	0	592.611	0.0000	592.61[illegible]
20	720	720	0	760	0	0	386	493	244	244	0	0	385	196	196	196	0	592.611	0.0000	592.[illegible]

% Output of Dynamic Programming

Enter Transaction Price for Base IPP: 27.74

Enter minimum capacity for Base IPP: 0

Enter Transaction Price for Middle IPP: 40.94

Enter minimum capacity for Middle IPP: 0

Enter Transaction Price for Peak IPP: 68.14

Enter minimum capacity for Peak IPP: 0

Enter the Required Capacity: 4100

Do You want to include Gas Unit(y/n): 'n'

Nuclear	Base IPP	Coal	Middle IPP	Oil	Peak IPP	Gas	Total Cost
1500	800	400	500	500	400	0	535.333

% Output of Dynamic Programming

Enter Transaction Price for Middle IPP: 40.94

Enter minimum capacity for Middle IPP: 0

Enter Transaction Price for Peak IPP: 68.14

Enter minimum capacity for Peak IPP: 0

Enter the Required Capacity: 4700

Do You want to include Gas Unit(y/n): 'y'

Enter the number of Gas Units: 3

Nuclear	Base IPP	Coal	Middle IPP	Oil	Peak IPP	Gas	Total Cost
1500	800	400	500	500	400	600	587.104

```
% Probability Production Simulation Program
% Equivalent Energy Function Method
% calculation of Energy of Generating Units & Reliability
Indices

function [lolp,eens,t_eng] = reliabfun(x,fr)

plant = x;
nvals = input('Enter the number of values: ');

for val = 1:nvals

    ld = input('Enter the Load Data in ascending order: ');
    hrs = input('Enter the hours in ascending order: ');
end

nplant = length(plant);
nhr = dsort(hrs);
max_dem = max(ld);
tot_cap = sum(plant);
deltax = gcd(plant(1),plant(2));

for i = 3:length(plant)
    deltax = gcd(deltax,plant(i));
end

lw = lw_lim(min(ld),deltax);
upp = up_lim(max_dem,deltax);
y = (upp - lw)/deltax;
c = zeros(1,y);

for n = 1:y
    for m = 1:length(ld)
        if (lw+deltax*(n-1)) <= ld(m) & (lw+deltax*n) >= ld(m)
            c(m) = lw+deltax*n;
        end
    end
end

% The discrete value corresponding to the system unit's total
capacity
% The discrete value corresponding to the maximum load

jn = tot_cap/deltax;
ne = round((max_dem/deltax)+1);

n = 0;
q = fr/100;
p = 1-q;
e = zeros(1,jn+ne);
e1 = zeros(nplant,jn+ne);

range = zeros(1,y);

pp = 1;
```

```
% Finding of range of sections

for i = 1:(y+1)
    r = 0;
    for j = 1:length(ld)
          temp = (lw+deltax*(i));
        if temp == c(j)
           r = r + 1;
           range(i) = r;
          break;
        end

    end
end

% Calculation of Primary Energy Eo(J)

u = 1;

while (deltax*u) <= lw

    e(u) = deltax * nhr(1);
    u = u + 1;
end

u = u - 1;
ld(length(ld)+1) = 0;
nhr(length(nhr)+1) = 0;
eng = [ld(1)-lw]*nhr(1);

 for i = 1:y
     n = n+range(i);
     for j = pp:n
         if(lw+deltax*i)>=ld(j+1)
             dif = ld(j+1)-ld(j);
             if dif <= 0
                 dif = 0;
             end
            e(i+u) = dif * nhr(j+1);
            ld(j) = lw+deltax*i;
            eng = eng + e(i+u);
         else
             e(i+u)=[(lw+deltax*i)-ld(j)]*nhr(j+1);
             ld(j) = lw+deltax*i;
             eng = eng + e(i+u);
         end
     end

         pp = n;
         e(i+u) = eng;
         eng = 0;
 end


 pe = 0;
```

```
for k = 1:ne
    pe = pe + e(k);
end

% Loading of Generating Units

v = zeros(nplant,jn+ne);
tcap = 0;
z = zeros(1,nplant);
kk = zeros(1,nplant);

for ii = 1:nplant
    m = 1;
    plant(ii) = plant(ii);
    tcap = tcap + plant(ii);
    z = plant(ii)/deltax;
    kk(ii) = tcap/deltax;
        if ii == 1
            for jj = 1:(ne+kk(ii))
                if jj-kk(ii) < 0;
                   v(ii,jj) = 0;
                elseif jj-kk(ii) ==0
                   v(ii,jj) = e(1);
                else
                   v(ii,jj) = e(m);
                   m = m + 1;
                end
            end
           for f = kk(ii):(ne+kk(ii))
               e1(ii,f) = p(ii)*e(f)+q(ii)*v(1,f);
           end
        else
            for jj = 1:(ne+kk(ii))
                if jj-kk(ii) < 0;
                   v(ii,jj) = 0;
                else
                   v(ii,jj) = e1(ii-1,jj-z);
                end
            end
            for f = kk(ii):(ne+kk(ii))
                e1(ii,f) = p(ii)*e1(ii-1,f)+q(ii)*v(ii,f);
            end
        end
end

% Total Energy generated by Units

t_eng = zeros(1,nplant);
eng = 0;
cap(1) = plant(1);

for n = 1:(cap(1)/deltax)
    eng = eng+e(1,n);
end
t_eng(1) = p(1) * eng;
```

```
 for i = 1:(nplant-1)
     eng = 0;
     cap(i+1) = cap(i) + plant(i+1);
     for n = ((cap(i)/deltax)+1):(cap(i+1)/deltax)
         eng = eng + e1(i,n);
     end
     t_eng(i+1) = eng * p(i+1);
 end

% Printing the result

tv = transpose(v);
te1 = transpose(e1);

% Energy Output of Each Generator Units

 for i = 1:nplant

    fprintf('\nEnergy output of Generator%d',i);
    fprintf('%10d\n',round(t_eng(i)));

 end

 % Calculation of EENS

 eens = 0;
 for i = (jn+1):(jn+ne)
     eens = eens + round(te1(i,end));
 end

 % Calculation of LOLP

 lolp = (te1(jn,end)+te1(jn+1,end))/(2*8760*deltax);

% Printing EENS and LOLP

% fprintf('\n Reliablity Indices: ');
% fprintf('\n ---------------------\n');
%    fprintf('\n        LOLP:  %0.5f\n',lolp);
%    fprintf('\n        EENS: %8d\n',eens);
% fprintf('\n ---------------------\n');
```

```
>> [LOLP,EENS,energy] = reliabfun(x,fr)

Output of (EEF) Production Simulation Program
------------------------------------------------------------------------------------
Energy output of Generator1  6307200

Energy output of Generator2  6307200

Energy output of Generator3        0

Energy output of Generator4  6723355

Energy output of Generator5        0

Energy output of Generator6        0

Energy output of Generator7  3357012

Energy output of Generator8  3544388

Energy output of Generator9  1125054

Energy output of Generator10   594550

Energy output of Generator11        0

Energy output of Generator12        0

Energy output of Generator13   377798

Energy output of Generator14        0

Energy output of Generator15        0

Energy output of Generator16        0

Energy output of Generator17        0
------------------------------------------------------------------------------------

 Reliability Indices:
 --------------------------

     LOLP:  0.06788

     EENS:   159590

--------------------------
```

```
>> [LOLP,EENS,energy] = reliabfun(x,fr)

Output of (EEF) Production Simulation Program
--------------------------------------------------------------------------------
Energy output of Generator1   6307200

Energy output of Generator2   6307200

Energy output of Generator3         0

Energy output of Generator4   6723355

Energy output of Generator5         0

Energy output of Generator6         0

Energy output of Generator7   3357012

Energy output of Generator8   3544388

Energy output of Generator9   1125054

Energy output of Generator10   594550

Energy output of Generator11        0

Energy output of Generator12        0

Energy output of Generator13   377798

Energy output of Generator14    85834

Energy output of Generator15    40913

Energy output of Generator16    17952

Energy output of Generator17        0
--------------------------------------------------------------------------------

Reliablity Indices:
-------------------------

    LOLP:  0.00704

    EENS:    14892

-------------------------
```