Multi-Objective Generation Scheduling with Hybrid Energy Resources

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MULTI-OBJECTIVE GENERATION SCHEDULING WITH HYBRID ENERGY RESOURCES

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ABSTRACT

In economic dispatch (ED) of electric power generation, the committed generating units are scheduled to meet the load demand at minimum operating cost with satisfying all unit and system equality and inequality constraints. Generation of electricity from the fossil fuel releases several contaminants into the atmosphere. So the economic dispatch objective can no longer be considered alone due to the environmental concerns that arise from the emissions produced by fossil fueled electric power plants. This research is proposing the concept of environmental/economic generation scheduling with traditional and renewable energy sources. Environmental/economic dispatch (EED) is a multi-objective problem with conflicting objectives since emission minimization is conflicting with fuel cost minimization.

Production and consumption of fossil fuel and nuclear energy are closely related to environmental degradation. This causes negative effects to human health and the quality of life. Depletion of the fossil fuel resources will also be challenging for the presently employed energy systems to cope with future energy requirements. On the other hand, renewable energy sources such as hydro and wind are abundant, inexhaustible and widely available. These sources use native resources and have the capacity to meet the present and the future energy demands of the world with almost nil emissions of air pollutants and greenhouse gases. The costs of fossil fuel and renewable energy are also heading in

opposite directions. The economic policies needed to support the widespread and sustainable markets for renewable energy sources are rapidly evolving.

The contribution of this research centers on solving the economic dispatch problem of a system with hybrid energy resources under environmental restrictions. It suggests an effective solution of renewable energy to the existing fossil fueled and nuclear electric utilities for the cheaper and cleaner production of electricity with hourly emission targets. Since minimizing the emissions and fuel cost are conflicting objectives, a practical approach based on multi-objective optimization is applied to obtain compromised solutions in a single simulation run using genetic algorithm. These solutions are known as non-inferior or Pareto-optimal solutions, graphically illustrated by the trade-off curves between criterions fuel cost and pollutant emission. The efficacy of the proposed approach is illustrated with the help of different sample test cases. This research would be useful for society, electric utilities, consultants, regulatory bodies, policy makers and planners.

DEDICATION

To my family for their support, guidance, patience and continuous encouragement.

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CHAPTER ONE

INTRODUCTION

1.1 Classical Economic Dispatch: An Overview and Solution Techniques

Electric power systems are highly complex interconnected networks. They transfer large amounts of the electric power over wide geographical areas. Scheduling of available generating resources to meet the load demand is an important job of a power system operator. This generation - load balance should be achieved in minimum operating cost to receive the maximum benefits. The generation scheduling problem consists of determining the optimal operation strategy for the next scheduling period, subject to a variety of constraints [1]. Economic operation is very important for any power system to achieve the profits on the capital investment. The importance of conservation of fossil fuels puts pressure on the power companies to achieve the maximum possible fuel efficiency by which cost of kilowatt - hour to the consumers and the delivering company can be minimized as the prices of fuel are continuously rising [2, 3].

Economic dispatch is an important optimization task in power system operations for allocating generation among the committed units such that all the constraints imposed are satisfied with minimizing the operating fuel cost. Improvements in the scheduling of unit outputs can lead to significant cost saving [4]. Previous efforts at economic dispatch have applied various mathematical programming methods and optimization techniques [5]. These methods represent the dispatch problem with quadratic fuel cost function and solve it by deterministic optimization techniques such as the lambda iteration method, the gradient method [6] and the dynamic programming method [7]. These methods require continuously increasing fuel cost curves to find the global optimal solution. Gradient techniques perform well in their narrow class of problems, but it works inefficiently elsewhere. Later, Lagrangian methods [8] have been increasingly used since they have the capability of including inequality constraints. These methods are based on the equal incremental cost criterion. It is desirable that the solution of power system problems be globally optimal, but solution searched by mathematical optimization is normally locally optimal. These facts make it difficult to deal effectively with many power system problems through strict mathematical formulation alone [9].

Despite remarkable advancement in mathematical optimization techniques, conventional mathematical methods have yet to achieve fast and reliable real time applications in power systems. Considerable efforts are required to avoid mathematical traps such as ill-conditioning and convergence difficulties [10]. Since most classical methods used the point by point approach where one solution gets updated to a new solution in one iteration, the parallel programming techniques can not be exploited in solving the problem. Deregulation of power system has also introduced some new issues into the existing problems [11]. These problems are difficult to handle with strict mathematical formulations alone. Artificial intelligence techniques, such as ANN, fuzzy logic and evolutionary algorithms have become a strong candidate for many optimization applications due to their flexibility, efficiency and robustness. These techniques can be applied to solve the earlier stated problems [1, 12]. Genetic Algorithm (GA), which is a part of evolutionary algorithms, uses stochastic operators instead of deterministic rules to search the optimal solution. It works with the population of the solution candidates and searches many optimum points in parallel. Thus, allowing it to escape from the local optimal and gives higher probability to obtain global optimal solution [13].

1.1.1 Popular Optimization Techniques: Summary

Various approaches to the solution of the generation scheduling problem have been proposed. They ranged from simple to complicated methods. The method adopted by different power system entities depends on their mix of units and operating constraints. Several optimization techniques [1, 9, 10, 12] have been proposed to solve GS problem. They can be categorized into two main groups: (i) mathematical methods, which include dynamic programming, branch and bound methods and Lagrangian relaxation (ii) artificial intelligent methods, like expert system, artificial neural networks, fuzzy logic, genetic algorithm, simulated annealing and tabu search.

1.2 Energy Sources: Characteristics and Use in Classical Economic Dispatch

1.2.1 Thermal Energy Source

In conventional economic dispatch the coefficients are assumed to be deterministic, but in real-world situations, these data are subjected to inaccuracies and uncertainties. These deviations are attributed to (i) inaccuracies in the process of measuring and forecasting of input data and (ii) changes of unit performance during the period between measuring and operation [14]. Economic dispatch calculates the cost of generation based on data relating fuel cost and power output. To simplify the problem, the highly nonlinear fuel cost function is approximated by a quadratic equation with cost coefficients. Thus, the operating point in practice will differ from the planned operating point and will thus affect the actual fuel cost. Approximation of the fuel cost function is shown in Fig.1.1.

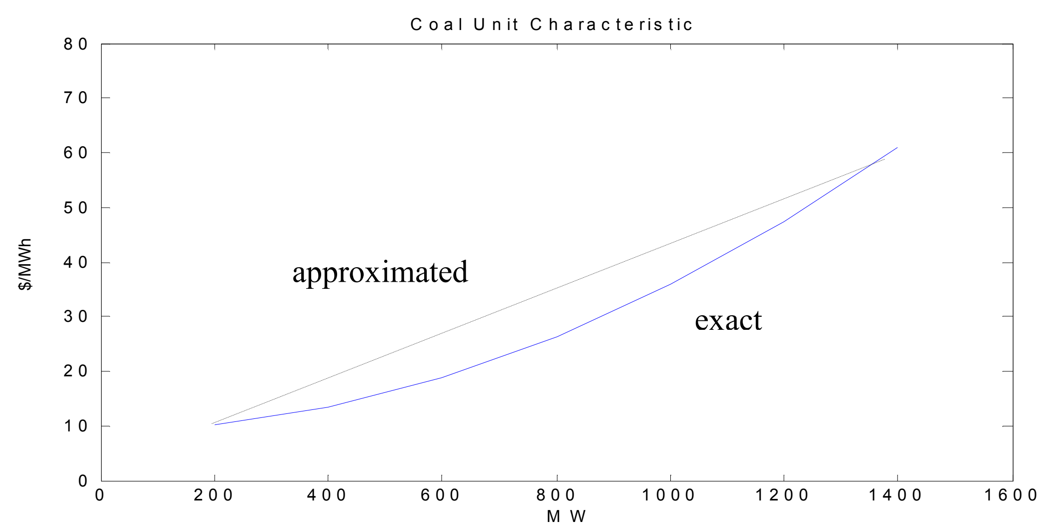

Fig.1.1 Incremental Cost Curve for Coal Unit [2]

Initially, the well-known Kuhn-Tucker conditions [6, 15] introduced optimality requirements for economic dispatch. Once these conditions are satisfied, all thermal units except those efficient units which have been loaded to their maximum capacities will be operated at the same incremental fuel cost. Based on these conditions, several methods have been developed [9]. For systems consisting of thermal units only, the lambda iteration method and the gradient method [6] are commonly used for performing the dispatch. For a large scale economic dispatch problem the fuel cost functions of different generating units are first approximated by piece-wise linear functions and then linear optimization techniques [16] are used to solve the problem. A branch and bound method for the scheduling of the thermal units has been presented in [17]. Lagrangian relaxation (LR) methods have been used to solve the problem with improved computational efficiency. To solve the different problems faced in applying the mathematical techniques, the artificial intelligence techniques have been recently applied in solving the economic dispatch problem. Different methods based on genetic algorithm [5, 18-21] have been used to solve small as well as large-scale dispatch problems. A method based on particle swarm optimization, which is a type of modern heuristic algorithms, has been presented in [22]. A method, based on variable scaling hybrid differential evolution [23] has been used to solve the economic dispatch problem in large-scale systems to overcome the drawback of the fixed and random scaling factor used in earlier methods.

The results from the different methods have shown that the classical deterministic methods take lot of computational time for the large-scale systems. The accuracy of the piece-wise linear approximation method is compromised with its computational time. The branch and bound method is considered a time consuming process due to successive elimination of a set of inappropriate solutions. Compared to the branch and bound method the LR method provides improved computational efficiency. However, adjusting the multipliers properly in each iteration is the big problem with the LR methods. These mathematical methods are also inefficient in solving the higher order fuel cost functions. On the other hand, the heuristic approaches and the artificial methods are more robust and have given better performance for stochastic models. These methods do not depend on the exact mathematical formulation, so are more effective in solving the higher order functions and more complex scheduling problems with more constraints. These methods have also shown their capability to obtain a global optimal solution for a complex problem in considerable computational time [9].

1.2.2 Hydro Energy Source

In hydro units, the limited energy storage capability of water reservoirs, along with the stochastic nature of their availability, makes its solution more difficult to estimate. The well-timed allocation of hydro energy resources is a complicated task that requires probabilistic analysis and long-term considerations, as the water availability depends on the reservoir water level and the utility's rules and regulations. So if water is used in the present period, it may not be available in the next period. This may increase the future operational cost of a system [24]. Tradeoff between immediate and future operating cost is illustrated in Fig.1.2.

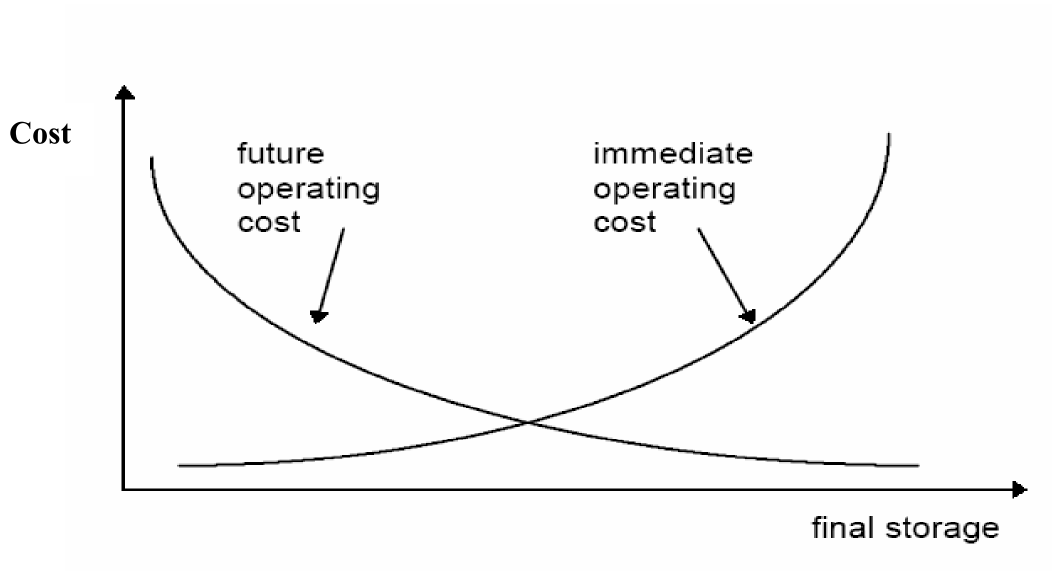

Fig.1.2 Optimal Hydro Scheduling [25]

Lagrange method, linear programming method, goal programming, non-linear programming method, Kuhn-Tucker conditions and dynamic programming methods are some of the important optimization techniques for optimal use of hydro power have been described in [26]. A linear programming based technique to solve the short-term scheduling problem for a large-scale cascaded hydro system was presented in [27]. Application of genetic based fuzzy systems to hydroelectric generation scheduling was presented in [28]. If hydro units are also considered with thermal units in the scheduling of the power generation, either the lambda iteration method or the gradient method [6] should be included in a gradient search loop, which determines the level of generation of fuel-constrained and hydro units in different scheduling periods. However, such non-linear methods require long computation time for large-scale systems.

1.2.3 Nuclear Energy Source

The fuel cost function of the nuclear units contains the stochastic nature. So, it is achieved by the estimated curve drawn between the thermal power of the heat produced in the reactor and the cost associated with this heat [29]. Due to the incremental cost characteristic shown in Fig.1.3, the nuclear unit operates at its peak generating limit to get maximum economic benefits. It is also desired to operate the nuclear power plant at the base load without any fluctuations.

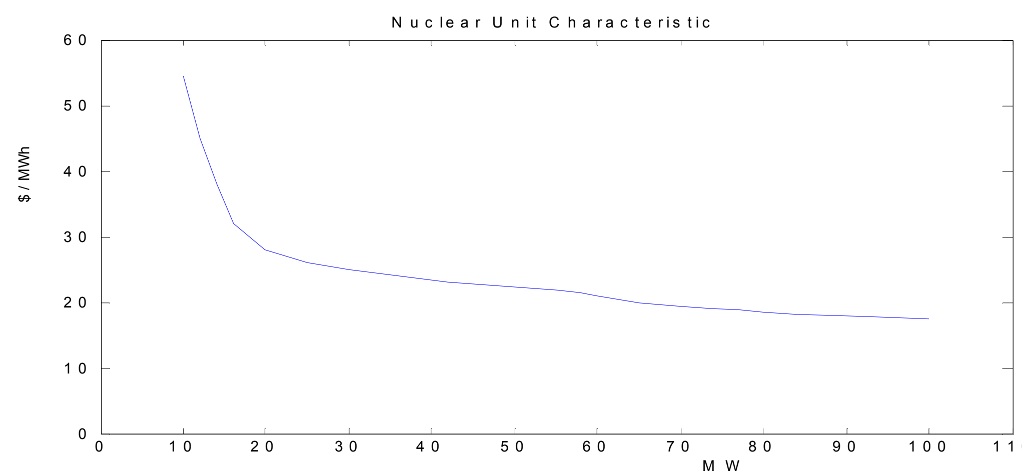

Fig.1.3 Estimated Incremental Cost Curve for Nuclear Unit

1.2.4 Wind Energy Source

A wind generating system could operate effectively in reducing the operating cost and the emissions of the system if the wind availability can be predicted intelligently. The intermittent nature of the wind makes its prediction difficult. Statistical methods can be used to predict wind speeds using historical wind speed data [30-34]. The relationship between the wind speed and the power output from the wind turbine was estimated by the Fig.1.4.

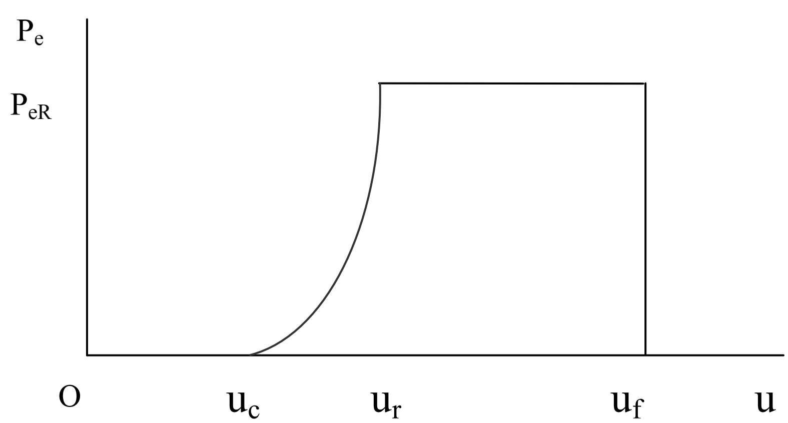

Fig.1.4 Wind Turbine Output versus Wind Speed Plot [35]

The output power from a wind turbine can be expressed by the following equation [35, 36]:

$$P_m = C_P \left(\frac{1}{2}\rho A u^3\right) \text{ watt}$$

Where

P_e = Electric Power Output

P_{eR} = Rated Electric Power Output

u = Wind Speed

u_c = Cut – in Wind Speed

u_R = Rated Wind Speed

u_f = Furling or Shut down Wind Speed

P_m = Mechanical Power Output

C_P = Coefficient of Performance

ρ = Air Density

A = Cross Sectional Area

The impacts of wind generation on the generation schedules of a system have been evaluated by using a dynamic programming technique [30]. The Monte Carlo simulation method was applied to assess the wind generation role in future generation portfolios [37]. The wind power planning was studied to assess long term social benefits in [32]. This approach used probabilistic load duration curves to account for the stochastic interaction between wind power availability, electricity demand and conventional generator dispatch. The wind generation impact on conventional plant's emissions was analyzed with linear programming approach [31]. In other research approach the effect of large-scale wind power on a thermal system operation was studied with a simulation model SIVAEL [38]. This model was used for hourly power and heat dispatch planning purposes.

1.2.5 Hybrid Energy Sources

There are many types of energy sources other than the ones mentioned in the previous sections such as solar energy. This type of energy can not be expressed by a certain function since it depends on their availability. Thus, for the hybrid energy systems, the limited energy capability of some sources, along with the stochastic nature of their availability, makes its solution more difficult to estimate than for single energy systems. Different operating properties of energy sources can be exploited in the optimal way by combining the sources to solve the generation scheduling problem more efficiently. An electric grid with the hybrid energy resources has been shown in Fig.1.5.

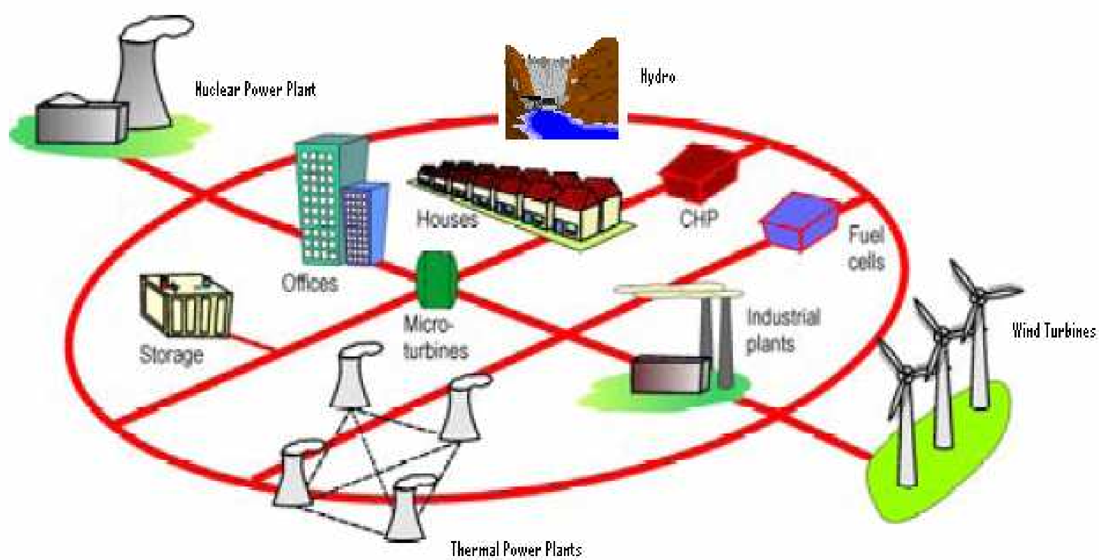

Fig.1.5 Electric Grid with Hybrid Energy Resources [39]

Hydrothermal generation scheduling problem was solved with multi-pass dynamic programming method [40]. In another approach of dynamic programming, a two-stage algorithm [41] was used to solve the scheduling problem. However, direct application of the dynamic programming methods are impractical due to dimensionality that leads to excessive computational times. To minimize some of the difficulties faced in earlier methods, dynamic programming was coupled with the Lagrangian Relaxation method [42, 43]. In these methods, the sub-gradient algorithm was used to update the multiplier in the iterations. The Lagrangian relaxation (LR) methods were used to solve the hydrothermal scheduling problem [8, 44-53]. In these methods, the LR technique was applied to solve the dual problem rather than original problem. To update the multipliers accurately in each iteration is a big problem and also makes the slow convergence which is caused by non-differentiable characteristics of dual functions. The Hopfield neural network approach was presented in [54] to solve the hydrothermal generation scheduling problem. Recently different artificial neural network-based techniques [55, 56] and a genetic-embedded fuzzy system approach [57] have been applied to solve the hydroelectric generation scheduling. These methods are time consuming for scheduling of more than one type of energy sources together. The genetic algorithm based techniques [58-60] have been used effectively to solve the hydrothermal scheduling problem. A functional analytic optimization technique was described to solve the hydro-thermal-nuclear generation scheduling in [61, 62]. This technique employs minimum norm formulation to solve the problem. Addition of wind energy with the hydropower of the Nordic electricity market was studied using the EMPS model [63], which is a stochastic model for optimal scheduling and system performance. Economic and operational impacts on the energy cost due to incorporating wind energy on hydro, thermal, and nuclear system were analyzed in [64]. The Lagrange method was then applied to solve the dispatch problem.

1.3 Multi-Objective Generation Scheduling

1.3.1 Introduction and Background

In economic dispatch (ED) of electric power generation, the committed generating units are scheduled to meet the load demand at minimum operating cost with satisfying all unit and system equality and inequality constraints. Generation of electricity from the fossil fuel releases several contaminants into the atmosphere. So the economic dispatch objective can no longer be considered alone due to the environmental concerns that arise from the emissions produced by fossil fueled electric power plants. Due to Clean Air Act [65] Amendments 1990 and the increasing public awareness for the environmental protection, the electric utilities have been forced to change their operational strategies to reduce the pollution and the atmospheric emissions of the thermal power plants. A concept of environmental/economic generation scheduling with traditional and renewable energy sources is applied in this dissertation. Environmental/economic dispatch is a multi-objective problem with conflicting objectives since emission minimization conflicts with fuel cost minimization.

Energy conversion from the fossil fuel into electric energy provides the backbone of the electricity generation system worldwide. This conversion is obtained in power plants operating with low efficiency cycles. Coal has been the most abundant and cheapest fossil fuel with sufficient resources to sustain our long run needs of energy for centuries, but combustion of coal in old coal-fired power plants discharges significant quantities of ash, nitrogen, sulfur oxides, mercury and greenhouse gases such as carbon dioxide into the atmosphere. This discharge is one of the main causes for the enhanced greenhouse effect, which is believed to be responsible for the climate change of our environment. Consequently the governments are regulating the greenhouse gas emissions due to growing environmental concern [66]. Deregulation of electric utilities also causes negative impact on environmental quality. It affects the increase in airborne emissions almost proportionally with the increased power generation with the fossil fuels. The increasing competition in electricity markets may reduce the electric prices by using cheap fuel sources but it will increase the emissions.

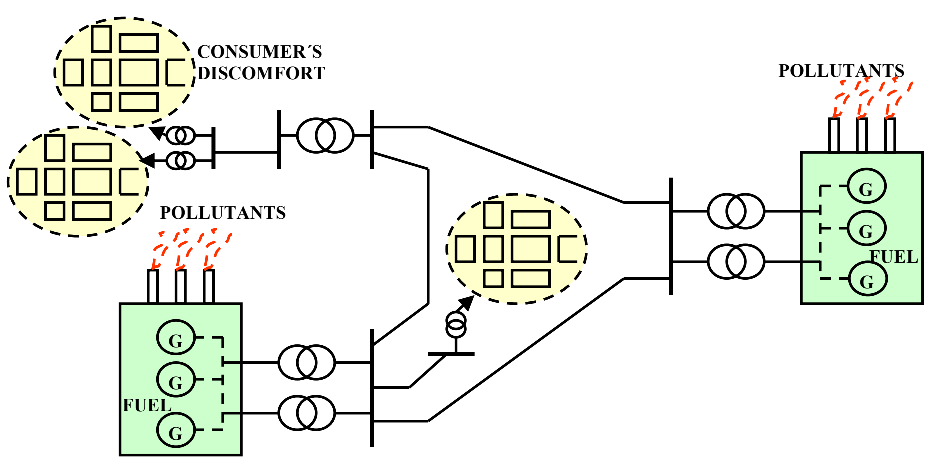

Fig.1.6 Schematic of Multi-Objective Environmental/Economic Dispatch Problem [67]

Energy generation from fossil fuels produces particulate, SO_2, NO_x and CO_2 emissions, mercury and other heavy metal emissions. Dust particles, which return from the atmosphere with the rain or snow give rise to streams of polluted water, disseminating the particles over the land. The polluted water changes the proper biological conditions of soil, which affects the agriculture, creates deforestation and causes the land erosion The social costs of SO_2 and NO_x emissions include environmental damage from acidic and nitrogen deposition in lake, forest, and estuary ecosystems and negative effects on human health from summertime ground-level ozone formation. CO_2 emissions contribute to atmospheric concentrations of the greenhouse gases and the associated social cost of global climate change. Mercury emissions impose social costs due to the negative health effects of human exposure to mercury deposition in water [68].

Production and consumption of the fossil fuel and the nuclear energy are closely related to the environmental degradation. This causes negative effects to the human health and the quality of life. Depletion of the fossil fuel resources will also be challenging for the presently employed energy systems to cope with future energy requirements. On the other hand, the renewable energy sources, such as the hydro and the wind are abundant, inexhaustible and widely available. These sources use native resources and have the capacity to meet the present and the future energy demands of the world with almost nil emissions of air pollutants and greenhouse gases. The fossil fuel and renewable energy prices, and social and environmental costs of each are also heading in opposite directions.

The economic policies needed to support the widespread and sustainable markets for renewable energy sources are rapidly evolving [69].

In summary, the advantages of using hybrid energy resources are as follows:

- Provide cheaper and reliable energy to the consumers;
- Increase the quality and efficiency of output power;
- Provide a cleaner environment by efficient use of renewable energy sources;
- Reduce global warming due to minimized fuel emissions;
- Reduce the depletion of fossil fuel reserves.

1.3.2 Literature Review

Relation to Present State of Knowledge in the Field

Environmental/economic dispatch is a multi-objective problem with conflicting objectives since pollution minimization competes with minimum generation cost. Various strategies have been proposed [70, 71] in the literature to reduce the atmospheric emission. One of the first approaches to solve the environmental/economic dispatch problem considering multi-objective optimization was goal programming techniques [72]. Different approaches [73, 76] have been described in the literature related to environmental/economic dispatch (EED) problem. In [73], the problem was reduced to single objective problem with taking the emission as a constraint with limits. This method does not give the trade-off relations between cost and emission. A linear programming-based optimization approach was reported in [74], where different objectives were considered one at a time. Since the EED problem is highly non-linear in nature, classical optimization methods which use derivatives and gradients do not give certainty to locate the global optimum solution. The ε- constraint multi-objective approach was presented in [75, 76]. In this approach the most preferred objective was optimized by taking other objectives as constraints. This technique is time consuming and it gives weak information about the trade-off relationship between different objectives.

In some research approaches, the EED problem was taken as a single objective problem with adding different objectives linearly by giving weights [77, 78]. A Hopfield neural network technique was proposed in [79], where the emission function of SO_2 and NO_x were weighted and added to the fuel cost objective function. This technique was extended in [80] by taking the Hopfield neural network and using the Tabu search with linear combination of the objectives. It was observed that the selection of weighting factor for different objectives is a complicated process as each weighting factor affects the other. Moreover, these techniques are time consuming as they require multiple runs to get the desired Pareto optimal solutions. Recently fuzzy logic based multi-objective optimization techniques [81-83] were proposed to solve the EED problem. However, the techniques were computationally complex, time consuming and don't provide the Pareto optimal front in single simulation run.

During the last decade, different evolutionary algorithms [84-89] have been proposed to find the diverse Pareto-optimal front. These can be efficiently used to avoid the shortcomings of classical methods [90]. The ability of the genetic algorithm to find multiple Pareto-optimal solutions in single simulation run makes it an attractive tool to solve problems with multiple and conflicting objectives.

1.4 Overview of the Dissertation

The main objective of the work done in this dissertation is to develop a technique to solve the environmental/economic dispatch problem with hybrid energy resources. More specifically, the technique will help to reduce the operating fuel cost and the fuel emissions simultaneously by efficient use of traditional and renewable energy sources. The main emphasis is on to develop efficient computational technique to solve this problem.

Chapter 1 provides the background information about the classical economic dispatch, hybrid energy resources and the environmental/economic dispatch problem. It also discusses the important techniques used earlier to solve the generation scheduling problems.

Chapter 2 presents the classical economic dispatch problem and the derivation of transmission loss equation to include in the dispatch problem. By including the transmission loss equation, we enhance the chances to get more accurate results. Additionally, an algorithm based on the Lagrangian relaxation method is also presented to solve the hydro-thermal and the hydro-thermal-nuclear generation scheduling problems. This algorithm is efficient for a single objective problem with small generating units and less coupling constraints.

Chapter 3 is focused on the different methods to solve the single objective generation scheduling problem with hybrid energy resources. Minimization of the fuel cost is the only objective to achieve in solving the scheduling problem. Two methods are presented to solve the problem. The first one is a mathematical method applied to solve the higher order fuel cost function problem. The second method is based on the genetic algorithm. This method is first used to solve the highly non-linear, non-convex fuel cost function of the thermal units with the valve-point effects. Then it was applied to solve a long-term generation scheduling problem with the hybrid energy resources. Due to probabilistic nature of the GA, it is suitable to solve a stochastic generation scheduling problem using available energy resources efficiently.

Chapter 4 presents a genetic algorithm based technique to solve the multi-objective generation scheduling problem with the hybrid energy resources. In this problem, two conflicting objectives, fuel emission minimization and fuel cost minimization have been considered to achieve simultaneously. The genetic algorithm based algorithm has been applied on different test cases to show its general nature. It was efficient in solving the highly non-linear multi-objective generation scheduling problem with different combinations of available energy sources. The multiple optimal solutions have been obtained as a trade-off curve known as Pareto-optimal front. A fuzzy-based technique has been used to extract the best compromised solution from the obtained trade-off curve.

Chapter 5 summarizes the research work and discusses the areas for the future work.

CHAPTER TWO

ECONOMIC OPERATION ANALYSIS USING HYBRID ENERGY RESOURCES

The electric power industry all over the world has been undergoing radical changes in its market structure and the regulatory laws. A basic trend in this restructuring process has been the replacement of traditional expansion planning and operation procedures based on centralized decisions by market oriented approaches. The optimum generation scheduling of the hybrid energy resources has become very important in this competitive electric market. This chapter presents the short-term hydro-thermal-nuclear coordination problem. This is a large scale nonlinear problem. A method for scheduling hydro-thermal-nuclear power systems based on the Lagrangian relaxation technique has also been provided in this chapter. It describes a procedure that determines the optimal allocation of energy subject to the availability of the source during a time period so that the expected benefits are maximized. The proposed method fulfills two objectives, to distribute the non-conventional energy optimally according to economic criterion and at the same time to minimize the production cost of the system.

In general, the generation scheduling problem consists in minimizing an objective function subject to a variety of system and unit constraints. The objective function is usually non-convex and represents the total cost of producing electricity. The total load balance is the main system constraint of the problem. The unit constraints include all operational limitations of the generating units, such as minimum stable generation and the maximum capacity of the unit.

Notations

The list of symbols used is summarized as follows:

i = thermal unit index

H= hydro system

S = thermal system

Nu = nuclear system

N = total number of thermal units

F_T = total fuel cost (in \$/hr) of N units

F_{sk} = thermal fuel cost during the k^{th} interval

P_{sk} = thermal output power during the k^{th} interval

q_{k} = discharge rate during the k^{th} interval

P_{lossk} = transmission losses during the k^{th} interval

P_i = output of the i-th thermal unit (MW)

P_{load} = total load

$d F_i (P_i) / d P_i$ = incremental cost rate (\$/MWh)

j = the interval = 1, 2, 3… j_{max}

n_j = length of the j^{th} interval

F_j = fuel cost during the j^{th} interval

V_j = storage volume at the end of jth interval

q_j = discharge rate during the j^{th} interval

$\varepsilon_{1=}$ the tolerance for the load balance

$\varepsilon_{2\,=}$ the tolerance for the water balance

P_{Hk} = hydro output during the k^{th} interval

$q_{tot\,=}$ total water discharge

Psj = steam generation during the j^{th} interval

P_{lossj} = transmission losses during the j^{th} interval

P_{loadj} = received power during the j^{th} interval (load)

Psj = thermal generation during the j^{th} hour

$P_{Hj\,=}$ hydro generation during the j^{th} hour

T_{max} = sum of total time of all intervals

Operational economics involving power generation and delivery can be subdivided into two parts: one dealing with the minimum cost of power production called economic dispatch and the other dealing with the minimum loss delivery of the generated power to the loads [2].

2.1 Classical Economic Dispatch Problem

Economic dispatch determines the power output of each generating unit within the plant for a specific load condition to minimize the total fuel cost needed to satisfy the load. So, the economic dispatch focuses upon coordinating the production costs of the generating units operating on the power system.

The objective function, F_T, is given by the total cost for supplying the load. The problem is to minimize F_T subject to the constraint that the sum of the powers generated must be equal to the received load. Initially the transmission losses are neglected and no operating limits are stated to formulate this problem. The objective function can be written as:

$$F_T = F_1 + F_2 + F_3 + F_4 + \ldots\ldots\ldots + F_N$$

$$= \sum_{i=1}^{N} F_i(P_i) \tag{2.1}$$

and,

$$\phi = 0 = P_{load} - \sum_{i=1}^{N} P_i \tag{2.2}$$

Here ϕ is the symbol for the load balance constraint. In the practical case, since the sum of the power generated must be equal to the sum of the total load and the total transmission losses, the new constraint with the transmission losses can be written as follows:

$$\phi = 0 = P_{load} + P_{loss} - \sum_{i=1}^{N} P_i \tag{2.3}$$

In order to establish the necessary conditions for an extreme value of the objective function, the constraint function has been multiplied by an undetermined multiplier and added to the objective function. This is known as the Lagrange function and is shown below:

$$L = F_T + \lambda \phi \tag{2.4}$$

Where λ is known as the Lagrange multiplier.

The necessary conditions for an extreme value of the objective function can be obtained by taking the first derivative of the Lagrange function with respect to each of the independent variables and equating the derivatives to zero. So, the minimum operating cost condition can be written as follows [6]:

$$\frac{dL}{dP_i} = \frac{dF_i(P_i)}{dP_i} - \lambda\left(1 - \frac{dP_{loss}}{dP_i}\right) = 0 \tag{2.5}$$

Or

$$\frac{dF_i(P_i)}{dP_i} + \lambda \frac{dP_{loss}}{dP_i} = \lambda \tag{2.6}$$

The necessary condition for the existence of a minimum cost operating condition is given by:

$$\lambda = \frac{\frac{dF_i(P_i)}{dP_i}}{(1 - \frac{dP_{loss}}{dP_i})} \tag{2.7}$$

This equation can be written in the following form:

$$\lambda = L_{n_i}(\frac{dF_i(P_i)}{dP_i}) \tag{2.8}$$

Where L_{n_i} is called the penalty factor of plant i and is given by:

$$L_{n_i} = \frac{1}{(1 - (\frac{dP_{loss}}{dP_i}))} \tag{2.9}$$

2.2 Transmission Loss Equation

To derive the transmission loss equation in terms of the power output of the plants, the bus impedance matrix of the network is obtained. The derivation is carried out in two stages. In the first stage, a power invariant transformation is applied to Zbus of the system in order to express the system loss in terms of only the generator currents. In the second stage, the generator currents are transformed into the power outputs of the plants, which lead to the desired form of the loss equation for a system with any number of sources [2]. Derivation of the loss equation is shown in Appendix A.

The general form of the derived loss equation can be written as below:

$$P_{loss} = \sum_{i=1}^{k} \sum_{j=1}^{k} P_{g_i} B_{ij} P_{g_j} + \sum_{i=1}^{k} B_{i_o} P_{g_i} + B_{oo} \qquad (2.10)$$

Where

B_{ij} = square matrix of loss coefficients

B_{i_o} = vector of loss coefficients

B_{oo} = constant

The coefficients for the loss function are obtained from the network parameters and by running the power flow solution. The power flow solution can only be used once to calculate the coefficients for a specific network and set of loads. It is assumed that the network does not change and hence the changes in the coefficients will be due to changes in load at different intervals [91].

2.3 Hydro-thermal Scheduling Problem

2.3.1 Introduction and Lagrangian Approach

The problem of hydro-thermal generation scheduling is one of the most challenging large-scale optimization problems in power system analysis. The thermal scheduling sub-problem consists in minimizing the cost of thermal generation corresponding to a given hydro scheduling. The basic idea of the Lagrangian relaxation (LR) technique in solving the hydro-thermal scheduling problem is to relax the coupling of the system-wide constraints on demand by using the Lagrange multipliers. The method decomposes the problem into the scheduling of individual units. Intuitively, the hard system constraints are converted into the soft prices, with the Lagrange multipliers acting as the prices to regulate the coordination between hydro and thermal units, and the generation of each unit [44]. A more general and basic hydro-thermal scheduling problem requires that a given amount of water should be used in such a way to minimize the cost of running the thermal units. It is assumed in this problem that the hydro plant is not sufficient to supply all the load demands at a certain period and there is a maximum total volume of water that may be discharged throughout the period of T_{max} hours. The loads are assumed to be constant in each interval of the scheduling [6]. An illustration of a hydro-thermal system serving a common load is shown in Fig.2.1.

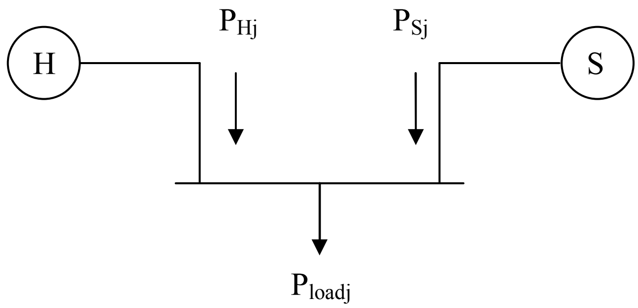

Fig.2.1 Hydro-thermal System [6]

The objective of hydro-thermal coordination is to minimize the total operating cost of the system. It can be shown as follows:

$$\text{Min } F_T = \sum_{j=1}^{j_{max}} n_j F_j \tag{2.11}$$

The constraints to be considered are as follows:

(a) Load balance constraint:

Total given load at a particular time should be equal to the sum of power outputs from all the generating units.

$$P_{load_j} - P_{H_j} - P_{S_j} = 0 \tag{2.12}$$

(b) Total water discharge constraint:

Total water discharge in a time period should be equal to the available water in the reservoir.

$$\sum_{j=1}^{j_{max}} n_j q_j = q_{tot} \tag{2.13}$$

(c) Time interval constraint:

Sum of all the time intervals should be equal to the total scheduling time period.

$$\sum_{j=1}^{j_{max}} n_j = T_{max} \tag{2.14}$$

Using the cost function and the constraints, the Lagrangian is formulated as the following:

$$L = \sum_{j=1}^{j_{max}} [n_j F(P_{S_j}) + \lambda_j (P_{load_j} - P_{H_j} - P_{S_j})] + \gamma [\sum n_j q_j (P_{H_j}) - q_{tot}] = 0 \tag{2.15}$$

Where λ and γ are the Lagrange multipliers associated with the power balance and the water discharge constraints.

For a specific interval j = k,

Differentiation of the Lagrange function with respect to (wrt) P_{sk} gives,

$$\frac{\partial L}{\partial P_{sk}} = 0 \tag{2.16}$$

$$n(\frac{dF_{sk}}{dP_{sk}}) = \lambda_k \tag{2.17}$$

Differentiation of the Lagrange function with respect to (wrt) P_{Hk} gives,

$$\frac{\partial L}{\partial P_{Hk}} = 0 \tag{2.18}$$

$$\gamma\, n_k (\frac{d_{q_k}}{d_{P_{Hk}}}) = \lambda_k \tag{2.19}$$

Adding the network losses in Eq. (2.12) for each hour gives,

$$P_{load_j} + P_{loss_j} - P_{H_j} - P_{S_j} = 0 \tag{2.20}$$

Using Eq. (2.20) in Eq. (2.15), the Lagrange function is then given by,

$$L = \sum_{j=1}^{j_{max}} [n_j F(P_{S_j}) + \lambda_j (P_{load_j} + P_{loss_j} - P_{H_j} - P_{S_j})] + \gamma[\sum n_j q_j (P_{H_j}) - q_{tot}] = 0 \quad (2.21)$$

The resulting coordination equations at hour k are given by,

$$n_k \left(\frac{dF(P_{sk})}{dP_{sk}}\right) + \lambda_k \left(\frac{dP_{lossk}}{dP_{sk}}\right) = \lambda_k \quad (2.22)$$

$$\gamma n_k \left(\frac{dq(P_{Hk})}{dP_{Hk}}\right) + \lambda_k \left(\frac{dP_{lossk}}{dP_{Hk}}\right) = \lambda_k \quad (2.23)$$

The determination of the economical schedule for the thermal generating units, which satisfies all the operating constraints, is regarded as one of the power system's major operating problems. The scheduling of the generating units in a hydro-thermal power system brings additional difficulties because it requires a long-term forecast of the availability of water and a co-ordination between the hydro-thermal problems.

2.3.2 A $\lambda - \gamma$ Iteration Algorithm for Generation Scheduling with Losses

The proposed algorithm is summarized as follows:

1. Initialize the schedules for all the thermal, nuclear units and the multipliers λ and γ.
2. Solve the coordination equations for the hydro schedules.
3. Find the network losses by using the loss equation.

4. Update the multiplier λ according to the power balance constraint.
5. Find the water discharge by using the hydro schedule.
6. Update the time interval j according to the time interval constraint.
7. Update the multiplier γ according to water discharge constraint.
8. Obtain the output schedules until there is no more constraint violation.

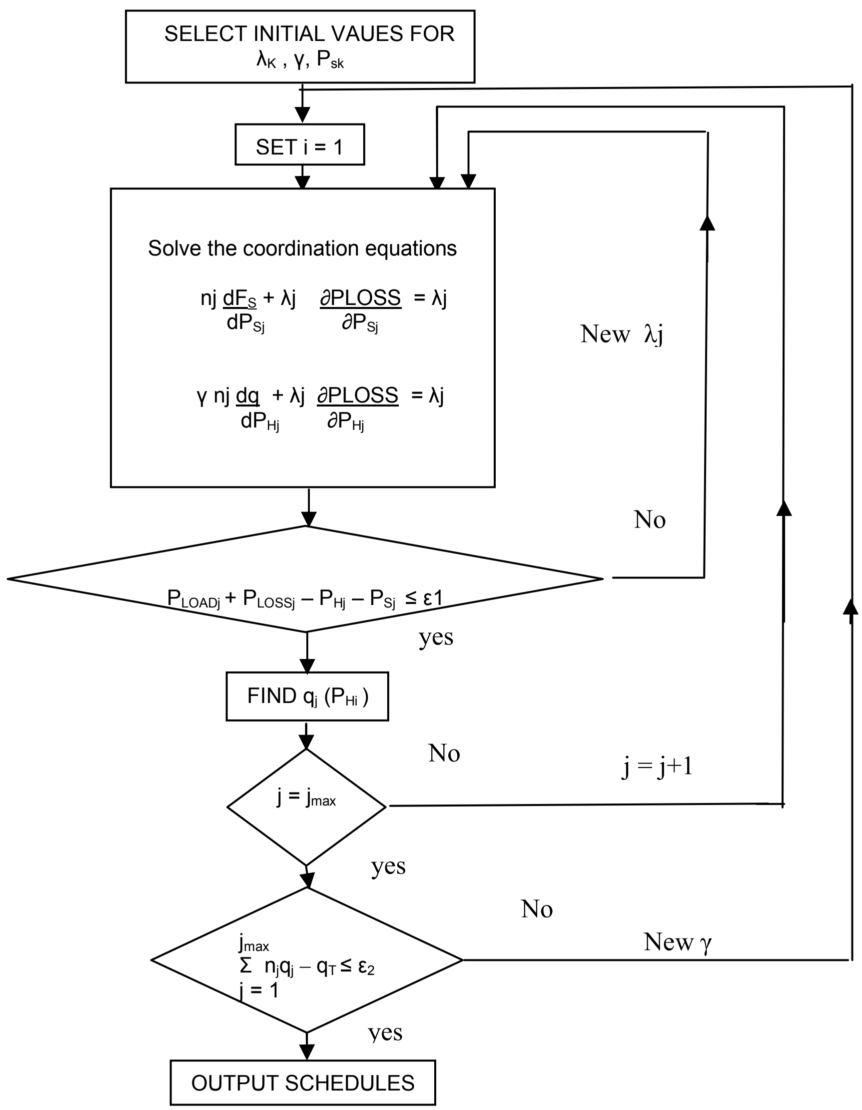

Fig.2.2 A λ – γ Iteration Scheme for Hydro-Thermal Scheduling with Losses [6]

2.3.3 Numerical Results and Discussions of Sample Test Cases

The algorithm was implemented in MATLAB. It has been tested for a generation schedule using the IEEE 14-bus system [Appendix B] for the following two cases:

Case 1: Two thermal and two hydro units.

Case 2: Three thermal and one hydro unit.

The fuel cost functions for the thermal systems with their maximum and minimum capacities are the following:

$$\begin{array}{ll} 1)\ F_1 = 575 + 5.9P_{s1} + 0.00455P_{s1}^2 & 50\,\text{MW} \le P_{s1} \le 900\,\text{MW} \\ 2)\ F_2 = 330 + 6P_{s2} + 0.0046P_{s2}^2 & 100\,\text{MW} \le P_{s2} \le 1200\,\text{MW} \\ 3)\ F_3 = 800 + 5.9P_{s3} + 0.0045P_{s3}^2 & 30\,\text{MW} \le P_{s3} \le 600\,\text{MW} \end{array}$$

The discharge rates for the hydro systems with their maximum and minimum capacities are the following:

$$\begin{array}{ll} 1)\ q_1 = 290 + 4.8P_{H1} & 0 \le P_{H1} \le 800\,\text{MW} \\ 2)\ q_2 = 320 + 4.9P_{H2} & 0 \le P_{H2} \le 1000\,\text{MW} \end{array}$$

The maximum water discharge for the two hydro systems are given for the entire time periods:

$$q_{t1} = 8050 \text{ acre-ft} \quad , q_{t2} = 8060 \text{ acre-ft}$$

The additional equality constraint for the balance of generation, load and losses is:

$$P_{s1} + P_{s2} + P_{H1} + P_{H2} - P_{Load} - P_{Loss} = 0 \qquad (2.24)$$

The load pattern is assumed to be as follows:

Load for first 12 hours of the day = 800 MW

Load for next 12 hours of the day = 900 MW

<u>Case 1</u>

In this case, two thermal units (1, 2) and two hydro units are considered in the scheduling algorithm. The optimal schedules found by the program for the above load pattern is shown in Table 2.1.

Table 2.1 Generation Schedules for 2 Thermal (1, 2) and 2 Hydro Units

	First 12 hours	Second 12 hours
First Thermal	204.92 MW	190.66 MW
Second Thermal	186.10 MW	244.42 MW
First Hydro	156.76 MW	117.66 MW
Second Hydro	269.97 MW	367.71 MW

Case 2

In case 2, all the thermal units (1, 2, 3) and the second hydro unit (2) have been considered in the scheduling algorithm. The optimal schedules found by the program for the same load pattern is shown in Table 2.2.

Table 2.2 Generation Schedules for 3 Thermal and 1 Hydro (2) Unit

	First 12 hours	Second 12 hours
First Thermal	194.79 MW	183.30 MW
Second Thermal	292.15 MW	350.16 MW
Third Thermal	79.38 MW	48.58 MW
Hydro	249.54 MW	336.72 MW

2.3.4 Analysis of Results

From the results it can be seen that as the load increases in the second time interval, the hydro units serve most of the increased load demand. As seen in the results for case 1, the schedule of the first hydro unit has decreased from 156.76 MW to 117.66 MW in the second time interval due to the maximum water discharge constraint and its water discharge characteristic. As a result, the cheaper thermal units bear a greater part of the increased load demand at peak load time. The dispatch for thermal unit 2 increases from 186.10 MW to 244.42 MW. On the other hand, the scheduling algorithm allocates lesser generation for the more expensive thermal units. This is seen for the first thermal unit whose dispatch has decreased from 204.92 MW to 190.66 MW. Similarly in case 2 the hydro unit's schedule increases from 249.54 MW to 336.72 MW in the second time interval and bears most of the increased load. The dispatch for the second thermal unit, which is the cheapest among the three units, increases from 292.15 MW in the first time period to 350.16 MW in the second time period. As in case 1, the dispatch for the most expensive thermal unit (unit 3) decreases from 79.38 MW to 48.58 MW.

2.4. Hydro-Thermal-Nuclear Scheduling Problem

2.4.1 Sample Test Case Data and Results

In this sample test problem, two thermal units, one nuclear unit and one hydro unit have been considered. The algorithm presented in Fig.2.2 has been applied with the presence of the nuclear unit to solve this scheduling problem. The algorithm has been implemented using IEEE -14 bus system [Appendix B]. The fuel cost functions used for the thermal systems with their maximum and minimum capacities are the following:

$$1)\ F_1 = 700 + 21.1P_{s1} + 0.00456P_{s1}^2 \qquad 50\,\mathrm{MW} \le P_{s1} \le 300\,\mathrm{MW}$$
$$2)\ F_2 = 500 + 21.15P_{s2} + 0.00465P_{s2}^2 \qquad 80\,\mathrm{MW} \le P_{s2} \le 400\,\mathrm{MW}$$

The fuel cost function of the nuclear unit is achieved by the estimated curve drawn between the thermal power of the heat produced in the reactor and the cost associated with this heat. This curve is shown in Fig.1.3 and the cost function can be written as step-wise linear functions with their maximum and minimum limits as follows:

F (Pnu) =	-7.45*Pnu + 61	10 < Pnu < 16 MW
	-3*Pnu + 34.667	16 < Pnu < 25 MW
	-1.0486*Pnu + 26.72	25 < Pnu < 60 MW
	-0.34*Pnu + 20.68	60 < Pnu < 100 MW

The discharge rate for the hydro system with its maximum and minimum capacity is as follows:

$$q = 785 + 11.74 P_H \qquad 0 \le P_H \le 600 \text{MW}$$

The maximum water discharge for the two hydro systems are given for the entire period:

$$q_t = 22500 \text{ acre-ft}$$

The additional equality constraint for the balance of generation, load and losses is:

$$P_{s1} + P_{s2} + P_{Nu} + P_H - P_{Load} - P_{Loss} = 0 \tag{2.25}$$

The load pattern is assumed to be as follows:

Load for first 12 hours of the day = 500 MW

Load for next 12 hours of the day = 600 MW

Table 2.3 Generation Scheduling for Hydro Thermal Nuclear Units

	First 12 hours	Second 12 hours
First Thermal	81.15 MW	66.08 MW
Second Thermal	98.41 MW	179.83 MW
Nuclear	100 MW	100 MW
Hydro	226.88 MW	263.53 MW

2.4.2 Analysis of Results

It can be deduced from the obtained results that as the load increased in the second period, the hydro unit serves a large part of the increased load demand. Schedules of the hydro unit depend on the maximum water discharge constraint and its water discharge characteristic. As a result, the cheaper thermal unit bears a greater part of the increased load demand at peak load time. The dispatch of thermal unit 1 decreases from 81.15 MW to 66.08 MW. On the other hand, the algorithm allocates more generation for the less expensive thermal unit. It can be seen for the second thermal unit whose dispatch has increased from 98.41MW to 179.83MW. For the nuclear unit, as the generation increases its fuel cost reduces due to its fuel cost curve characteristic. So, the dispatch for the nuclear unit is constant at 100 MW, its maximum generation capacity in both the time periods.

2.5 Conclusions

A hydro-thermal-nuclear scheduling based on the Lagrangian relaxation approach for the hydro-thermal-nuclear coordination problem of a practical system under important operating constraints has been presented in this chapter. This method maximizes the production profits of the hydro-thermal-nuclear power system. It also minimizes the total operating cost of thermal and nuclear units by efficient use of hydro energy, subject to system-wide demand and individual unit constraints. The proposed method is proved to be accurate since losses are included in the algorithm. One of the advantages of using Lagrange multipliers is to relax complicating demand. The method decomposes the problem into the scheduling of the individual units. Good coordination of the hydro, thermal and nuclear units is achieved through Lagrange multipliers. The schedules of the hydro units depend on the maximum total volume of water that may be discharged throughout the period. Numerical results for the IEEE 14-bus system show that this approach is efficient and provides near-optimal solutions. The problem which is supposed to be handled by the LR algorithm, with only the thermal units, is simple and does not require a long computation time. However, if hydro units are considered, various coupling constraints will be involved in this problem and the dispatch process will demand vast computer resources (CPU time and memory space). Hence, the search process suggested earlier is not very efficient for the scheduling.

CHAPTER THREE

SINGLE OBJECTIVE GENERATION SCHEDULING WITH HYBRID ENERGY RESOURCES

In chapter 2, the Lagrangian relaxation (LR) method for the generation scheduling problem requires vast computer resources. It takes a long time to provide the results due to the coupling constraints of the different units. To update the multipliers accurately in each iteration is a big problem. This method does not solve the scheduling problem with higher order fuel cost functions. Generally, the fuel cost function of generating units is approximated to a quadratic function. So, we do not obtain accurate dispatch results due to this function approximation. Therefore, the fuel cost curve of a generator should not be overly simplified in practical operations of the power system. As we increase the accuracy of the fuel cost function, we end up getting a highly non-linear, non-smooth, non-convex function, which can not be efficiently solved by classical or gradient based methods [92]. To improve drawbacks of the LR method this chapter aims to solve the generation scheduling problem with higher order and highly non-linear fuel cost functions of the generation units. Sequential quadratic programming (SQP) and the genetic algorithm methods have been used to achieve the goal mentioned above. These methods solve the highly non-linear problem efficiently to minimize the fuel cost of a system. This chapter also includes the application of the genetic algorithm to solve a long-term scheduling problem with the hybrid energy resources by efficient use of available sources to achieve the maximum profits.

3.1 Sequential Quadratic Programming Method

The sequential quadratic programming (SQP) method is considered to be one of the most efficient non-linear programming methods for the constrained optimization. The performance of this method is better than all the other non-linear programming methods in terms of efficiency, accuracy and providing optimal solution for a large number of test problems. This method is similar to Newton’s method for constrained optimization. In this method, an approximation is made of the Hessian of the Lagrangian function in each iteration using a Broyden–Fletcher–Goldfarb–Shanno (BFGS) quasi-Newton updating method. The result of this approximation is then used to generate a quadratic programming (QP) sub-problem. The solution of the QP is used to form a search direction for a line search procedure [93]. The SQP routine in this work is adopted from Matlab optimization toolbox (fmincon routine). The function fmincon is the optimization program written in Matlab. It attempts to find a constrained minimum of a scalar function of several variables starting at an initial estimate. This is generally referred to as constrained non-linear optimization or non-linear programming. Function fmincon uses a sequential quadratic programming (SQP) method. In this method, the function solves a quadratic programming (QP) sub-problem at each iteration. An estimate of the Hessian of the Lagrangian is updated at each iteration using the BFGS formula. A line search is performed using a merit function similar to that proposed by references [94-96]. The QP sub problem is solved using an active set strategy similar to that described in [97].

3.1.1 Sample Test Case

The SQP method has been tested for a generation scheduling problem which has two thermal units, one hydro unit and one nuclear unit. The method was implemented in Matlab. Third order fuel cost functions for the thermal generating units have been considered to show the effectiveness of the method in solving higher order fuel cost function problems. An estimated step-wise linear fuel cost curve for the nuclear unit has been considered. A non linear water discharge characteristic of the hydro unit has been included in the scheduling problem.

First Thermal Unit

$F(Ps1) = 0.00184*Ps1^3 + Ps1^2 + 9.2*Ps1 + 575 \qquad 150 < Ps1 < 1500$ MW

Second Thermal Unit

$F(Ps2) = 0.00158*Ps2^3 + Ps2^2 + 8.8*Ps2 + 700 \qquad 100 < Ps2 < 1200$ MW

Nuclear Unit

$F(Pnu) =$	$-37.25*Pnu + 305$	$50 < Pnu < 80$ MW
	$-15*Pnu + 173.335$	$80 < Pnu < 125$ MW
	$-5.243*Pnu + 133.6$	$125 < Pnu < 300$ MW

$-1.7*Pnu + 103.4 \qquad 300 < Pnu < 500$ MW

Hydro Unit

$q(Ph) = 330 + 4.97*Ph \qquad 0 < Ph < 1000$ MW

$q(Ph) = 5300 + 12*(Ph - 1000) + 0.05*(Ph - 1000)^2 \qquad 1000 < Ph < 1100$ MW

The maximum water discharge for the hydro unit is given for the entire period:

$$q_t = 100000 \text{ acre-ft}$$

The load pattern for a day has been assumed as follows:

Load for first 12 hours of the day = 2200 MW

Load for next 12 hours of the day = 2500 MW

Table 3.1 Generation Schedules for 2 Thermal, 1 Hydro and 1 Nuclear Unit

	First 12 hours	Second 12 hours
First Thermal	591.459 MW	591.425 MW
Second Thermal	647.313 MW	648.824 MW
Nuclear	500 MW	500 MW
Hydro	604 MW	939.930 MW

3.1.2 Analysis of Results

From the results it can be seen that as the load increases in the second time interval, the hydro unit serves almost all of the increased load demand. Schedules of the hydro unit depend on the maximum water discharge constraint and its water discharge characteristic. Since in this particular case the maximum water available for the hydro unit is in good quantity, the hydro unit bears an almost entire increased load during the second time interval. Due to this reason, both the thermal units are bearing an almost constant load at both the time intervals. This is the favorable condition for the thermal units for their long life. For the nuclear unit, as the generation increases, its fuel cost reduces due to its fuel cost curve characteristic. So the dispatch for the nuclear unit is constant at its maximum generation capacity in both the time intervals.

3.2 Genetic Algorithms

3.2.1 Principles of Genetic Algorithm

Genetic Algorithms (GAs) follow the principles of natural genetics and natural selection to constitute search and optimization procedures. These are computerized search and optimization algorithms to work on the principle of survival of the fittest. Genetic algorithms (GAs), unlike strict mathematical methods, have the apparent ability to adapt nonlinearities and discontinuities commonly found in power systems [13]. They operate on string structures, typically a concatenated list of binary digits representing a coding of the parameters for a given problem. Many such structures are considered simultaneously, with the most fit of these structures receiving exponentially increasing opportunities to pass on genetically important material to successive generations of string structures. In this way, GAs search from many points in the search space at once, and yet continually narrow the focus of the search to the areas of the observed best performance. The only information that GAs require to work is: given two solutions, the designer has to come up with metrics that can rank the two solutions in order of their suitability. The suitability of a solution is termed as fitness of a solution. Thus, a fitter solution wins (and therefore survives) when compared to a solution with smaller fitness value (if fitness is to be maximized). GAs differ from more traditional optimization techniques in the following important ways:

- GAs use objective function information to guide the search, not derivative or other auxiliary information.

- GAs use a coding of the parameters used to calculate the objective function in guiding the search, not the parameter themselves.
- GAs search through many points in the solution space at one time, not a single point.
- GAs use probabilistic rules, not deterministic rules, in moving from one set of solutions (a population) to the next.
- GAs are ideally suited for handling multi-objective problems.

The three important GA operators, which are commonly used, are as follows:

- Reproduction or selection
- Crossover
- Mutation

The functions of the GA operators can be described as follows:

3.2.2 Reproduction

This is usually the first operator that is applied to an existing population to create progenies. Reproduction first selects good parent solutions or strings to form the mating pool. The essential idea in reproduction is to select strings of above – average fitness from the existing population and insert their multiple copies in the mating pool, in a probabilistic manner. This results in a selection of existing solutions with better than average fitness to act as parents for the next generation [98].

3.2.3 Crossover

Crossover is also known as recombination. In the crossover operation, we exchange the information among the parent strings present in the mating pool. In this way crossover creates new string solutions. Single point crossover is the most common implementation of the crossover. In this type of the crossover a crossing point is randomly chosen along the string length and all the bits to the right side of this crossing site are exchanged between the two parent strings. It is expected that if good substrings from the parents get combined by crossover, the children are likely to have improved fitness. It has been found that the effect of crossover can be detrimental or beneficial. Therefore, to preserve some of the good strings in the mating pool, not all the strings in the mating pool are used in crossover. A crossover probability (P_c) is used to decide whether a given member of the mating pool will be crossed [98].

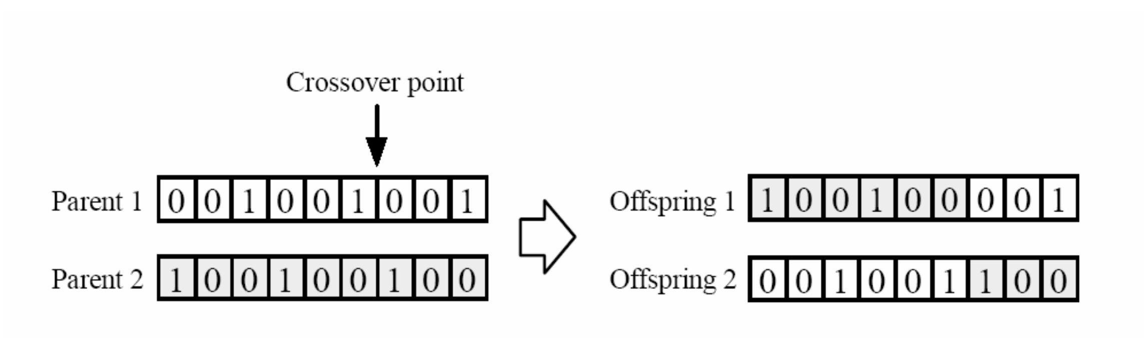

Fig.3.1 The standard one point crossover for binary strings [99]

3.2.4 Mutation

The crossover operator attempts to produce new strings of superior fitness by effecting large changes in a strings structure (this is similar to large jumps in search of the optimum in the solution space); we also need a local search around a current solution. This is accomplished by a GA operator known as mutation. Mutation gives emphasis to maintain diversity in the population. It creates a new solution in the neighborhood of a current solution by introducing a small change in some form of the current solution. Crossover aims at recombining parts of good substrings from good parent strings to hopefully create a better offspring. Mutation, on the other hand, alters a single child string locally to hopefully create a superior child string [98].

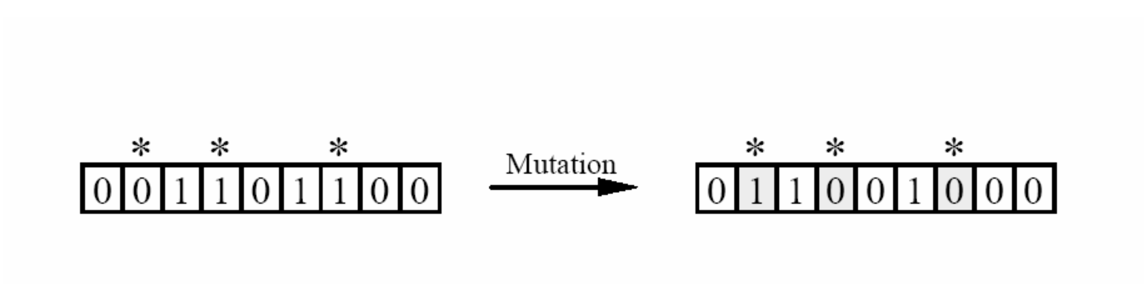

Fig.3.2 A mutation for binary strings [99]

The genetic operations such as crossover and mutation mimic the process of heredity of genes to create new offsprings at each generation. The evolution operation such as selection mimics the process of Darwinian evolution to create populations from generation to generation. Selection is the process by which strings with better fitness values receive correspondingly better copies in the new generation. That is the more fitness string solutions should have more chances to be copied to the next generation population. The task of crossover is the creation of new individuals (children), out of two individuals (parents) of the current population. Mutation is a background operator, which produces spontaneous random changes in various chromosomes. A simple way to achieve mutation would be to alter one or more genes. In genetic algorithms, mutation serves the crucial role of either replacing the genes lost from the population during the selection process so that they can be tried in a new context or providing the genes that were not present in the initial population. In the GA terminology, a solution is often referred to as an individual and a group of solutions is called a population. The design variables are called genotypes and the objectives and constraints are called phenotypes [100]. The logical flow of a simple genetic algorithm can be written as follows:

3.3 Logical Flow of Simple Genetic Algorithm [101]

Begin

t := 0;

Initialize P (t);

Evaluate P (t);

While (! termination criterion) do

P' (t): = selection (P (t));

P'' (t): = variation (P' (t));

Evaluate (P'' (t));

P (t+1): = Survivor (P (t), P’’ (t));

t: = t+1;

od

End

The stepwise flowchart for these logics can be shown in Fig.3.3.

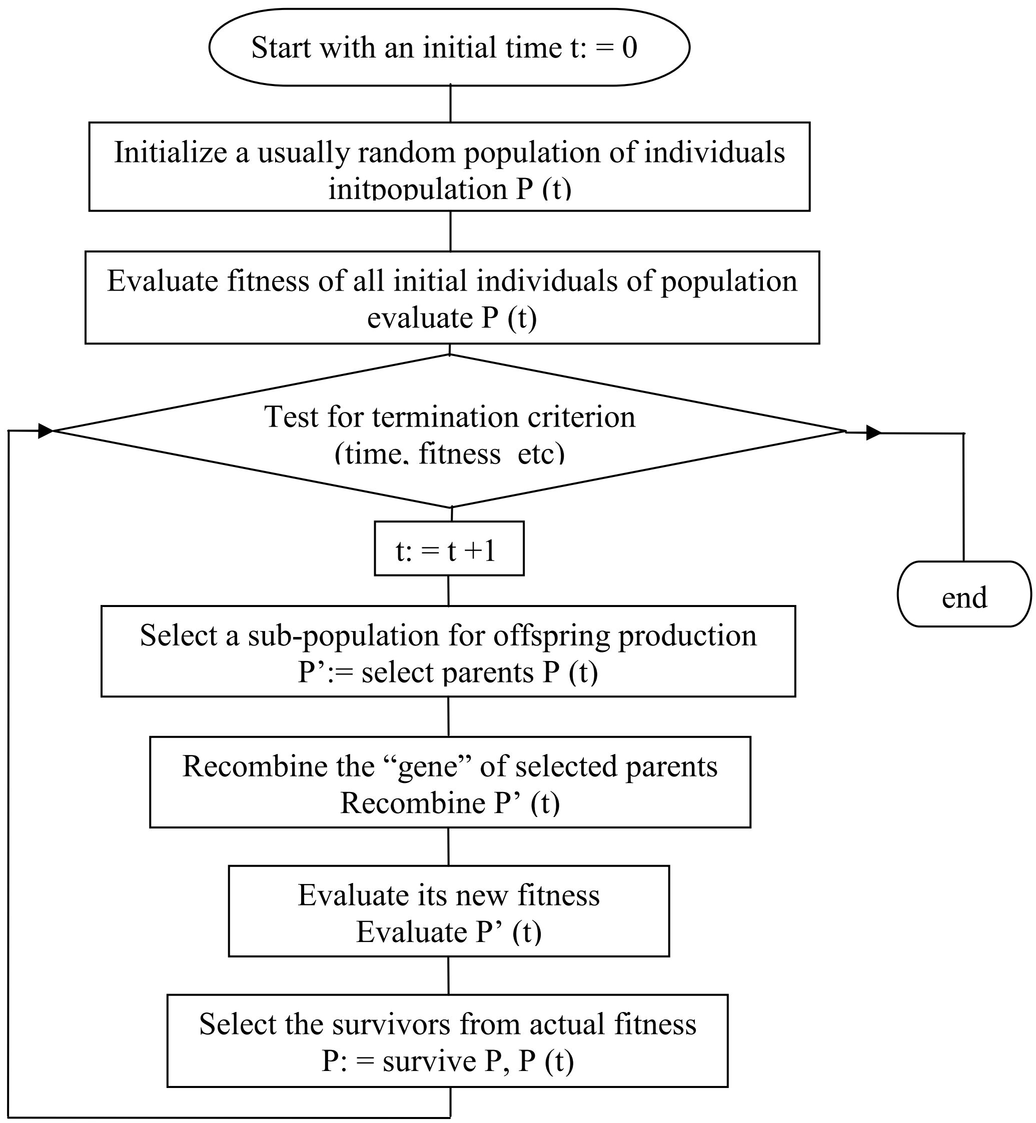

Fig.3.3 Flowchart of Simple Genetic Algorithm [102]

3.4 Generation Scheduling with Valve-Point Effects

The main objective of the economic dispatch (ED) problem is to determine the optimal combination of power outputs of all the generating units to meet the required load demand at minimum operating cost with satisfying equality and inequality constraints of the system as well as the generating units. In the classical ED problem, the fuel cost function for each generating unit has been approximately represented by a quadratic function. This function is solved by optimization techniques based on mathematical programming methods such as lambda-iteration method and the gradient-based method [6]. These mathematical methods require incremental or marginal fuel cost curves which should be monotonically increasing to find the global optimal solution. The fuel cost functions of the generating units can be modeled in a more practical fashion by including the valve-point effects. The valve-point effects cause ripples in the fuel cost function; so the number of local optima is increased. Therefore, the practical and the real life ED problem is represented as a non-smooth and non-convex optimization problem with the equality and inequality constraints, which cannot be efficiently solved by the classical mathematical methods [103]. To solve the problem with irregular search space (after including valve-point effects), we require highly robust algorithms to avoid premature convergence. Stochastic search algorithms, such as genetic algorithms (GAs), may prove to be very effective in solving non-linear economic dispatch problem without any restrictions in the shape of the fuel cost curves. These artificial intelligence methods use probabilistic rules to update their individual's positions in the solution space. These methods do not guarantee to find the global optimal solution in the definite time period, but most of the time they provide the near optimal and reasonable solution while solving the highly non-linear economic dispatch problem [104].

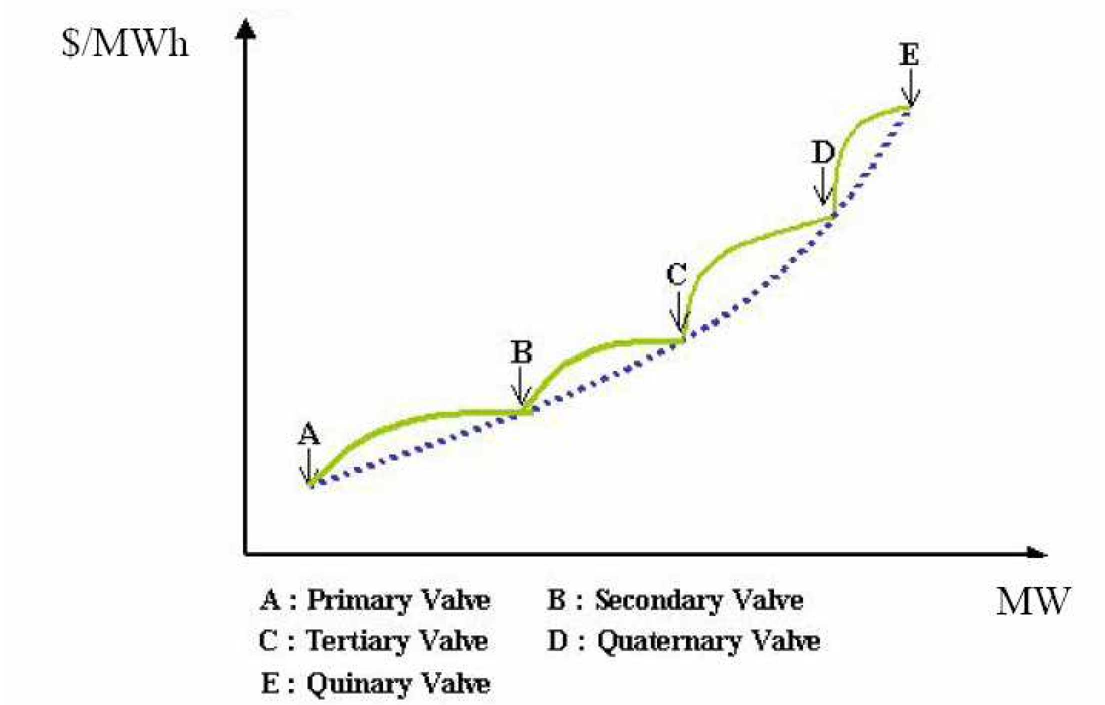

Fig.3.4 Incremental Cost Curve for Coal Unit with Valve Point Effects [103]

3.4.1 Objective Function with valve-point effects

The generating units with multi valve steam turbines exhibit a greater variation in the fuel cost functions. Since the valve-point results in the ripples in the heat rate curve as shown in Fig.3.4, a cost function contains higher order nonlinearity. Therefore, the fuel cost function in the objective of the economic dispatch problem should be replaced with consideration of the valve-point effects. So, after adding sinusoidal terms to the quadratic cost functions, the new fuel cost function can be written as follows [105]:

$$F_i(P_i) = a_i + b_i P_i + c_i P_i^2 + \left| e_i \times \sin(f_i \times (P_{i,min} - P_i)) \right| \tag{3.1}$$

Where a_i, b_i, c_i are the coefficients of the cost curve of the i-th generator and e_i, f_i are the coefficients of the valve point effects. The cost function of the generating units exhibits the non-convex characteristics, as the valve-point effects are modeled and imposed as sinusoidal components**.**

3.4.2 Sample Test Case

To demonstrate the effectiveness of the proposed method, the numerical studies have been performed for a sample system. This case study consisted of 13 thermal units of generation with the effects of valve-point loading, as given in the Table 3.2. It is a large system with many local minimum points. The total load demand is 1800 MW in this example. The population size used for the GA is 20 individuals. The probability of crossover and mutation were set at 0.98 and 0.076 respectively. The program was run for 2000 generations and the results are shown in the Table 3.3.

Table 3.2 Unit fuel cost functions data with valve point loadings [105]

Unit	$P_{L,\,min}$ (MW)	$P_{L,\,max}$ (MW)	a	b	c	e	f
1	0	680	0.00028	8.1	550	300	0.035
2	0	360	0.00056	8.1	309	200	0.042
3	0	360	0.00056	8.1	307	200	0.042
4	60	180	0.00324	7.74	240	150	0.063
5	60	180	0.00324	7.74	240	150	0.063
6	60	180	0.00324	7.74	240	150	0.063
7	60	180	0.00324	7.74	240	150	0.063
8	60	180	0.00324	7.74	240	150	0.063
9	60	180	0.00324	7.74	240	150	0.063
10	40	120	0.00284	8.6	126	100	0.084
11	40	120	0.00284	8.6	126	100	0.084
12	55	120	0.00284	8.6	126	100	0.084
13	55	120	0.00284	8.6	126	100	0.084

3.4.3 Simulation Results

Table 3.3 Minimum Fuel Cost Dispatch

$P_{L,1}$ (MW)	358.99
$P_{L,2}$ (MW)	299.06
$P_{L,3}$ (MW)	224.35
$P_{L,4}$ (MW)	109.86
$P_{L,5}$ (MW)	109.86
$P_{L,6}$ (MW)	109.86
$P_{L,7}$ (MW)	109.86
$P_{L,8}$ (MW)	159.73
$P_{L,9}$ (MW)	60.00
$P_{L,10}$ (MW)	76.97
$P_{L,11}$ (MW)	71.41
$P_{L,12}$ (MW)	55.00
$P_{L,13}$ (MW)	55.00
Total Load Demand (MW)	1800
Total Fuel Cost ($/hr)	18049.26

3.4.4 Analysis of Results

In this sample case the economic dispatch with valve-point effects has been presented. A genetic algorithm-based technique has been used to solve this highly non-linear problem. This technique shows its capability for solving more complicated power economic dispatch problems. It may prove to be promising in terms of production cost and computational time. The results show that the technique is effective, robust and applicable to the large-scale real-world economic dispatch problem.

3.5 Long-Term Generation Scheduling with Hybrid Energy Resources

In this sample test case three thermal units, one nuclear unit, one hydro unit and one wind unit have been considered for a long-term economic dispatch problem. The main objective is to use the available energy resources efficiently for long-term profit maximization which leads to minimizing the operating cost of the system. The fuel cost functions for the thermal and nuclear units have been estimated on the basis of the fuel cost curve shown on Fig.1.3 and Fig.1.4 respectively. Third order fuel cost functions for the thermal units with their maximum and minimum generation capacities are as follows:

First Thermal Unit

$$F(Ps1) = 96.0 + 8.8*x1(i) + 0.00072*x1(i)\,\hat{}2 + 8.52e\text{-}6*x1(i)\,\hat{}3$$

$$200 < Ps1 < 1500 \text{ MW}$$

Second Thermal Unit

$$F(Ps2) = 366.82 + 7.74*x2(i) + 0.0009*x2(i)^2 + 5.73e\text{-}8*x2(i)^3 \qquad 150 < Ps2 < 1200 \text{ MW}$$

Third Thermal Unit

$$F(Ps3) = 109.54 + 8.63*x3(i) + 0.0033*x3(i)^2 + 6.01e\text{-}5*x3(i)^3 \qquad 120 < Ps2 < 1000 \text{ MW}$$

The fuel cost function of the nuclear unit is achieved by the estimated curve drawn between the thermal power of the heat produced in the reactor and the cost associated with this heat. It is shown as step-wise linear curves with their maximum and minimum limits as follows:

Nuclear Unit

F (Pnu)	=	-37.25*Pnu + 305	50 < Pnu < 80 MW
		-15*Pnu + 173.335	80 < Pnu < 125 MW
		-5.243*Pnu + 133.6	125 < Pnu < 300 MW
		-1.7*Pnu + 103.4	300 < Pnu < 500 MW

The discharge rate for the hydro system with its maximum and minimum capacity is as follows [6]:

Hydro Unit

$$q(Ph) = 330 + 4.97*Ph \qquad 0 < Ph < 1000 \text{ MW}$$

q (Ph) = 5300 + 12*(Ph - 1000) + 0.05*(Ph - 1000) ^2 1000 < Ph < 1100 MW

The additional equality constraint for the balance of generation, load and losses is:

$$P_{s1}+P_{s2}+P_{s3}+P_{Nu}+P_{H}+P_{W}-P_{Load}-P_{Loss}=0 \tag{3.2}$$

Since there was no possible way to get the exact data for the water available in the hydro reservoir and the power available from the wind energy source, the data used in this sample test case has been assumed on the basis of the data given in [6] and [30]. The available water in the reservoir for three different days of a year has been shown in table 3.4. The predicted wind penetration in MW for the same three days in 4 hr time intervals has been shown in the following table:

Table 3.4: Available hydro and wind energy resources for three different days of a year

Day of a Year		Nov 15						July 15						Feb 15					
Water Available in Reservoir (in Acre-ft)		100000						60000						20000					
Wind Energy Available	Time Duration (in Hrs)	0-4	4-8	8-12	12-16	16-20	20-24	0-4	4-8	8-12	12-16	16-20	20-24	0-4	4-8	8-12	12-16	16-20	20-24
	Power (in MW)	225	200	160	140	180	170	250	220	200	170	150	190	200	170	160	190	140	180

3.5.1 Simulation Results

Case 1

The load duration curve for a day of the month November has been shown below:

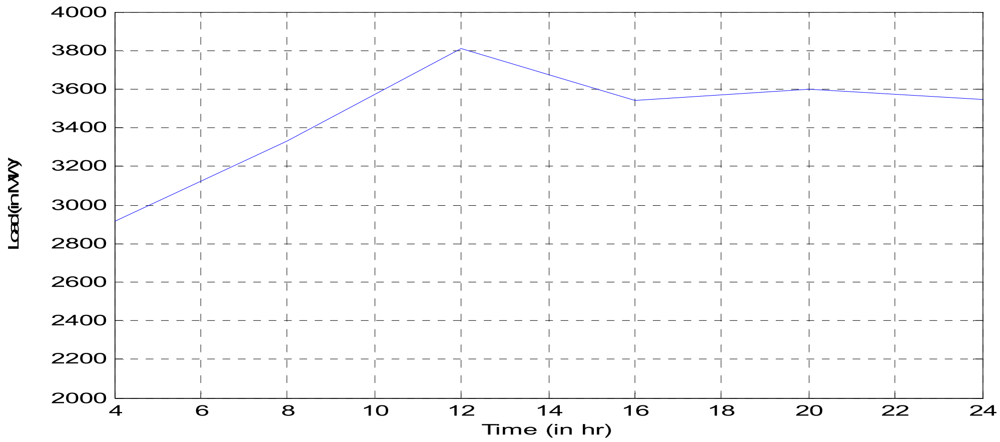

Fig.3.5 Sample Load Duration Curve of a day in November

The simulation results obtained for this case has been shown in bar chart form to give visual understanding about the generation of different units for the given load duration curve.

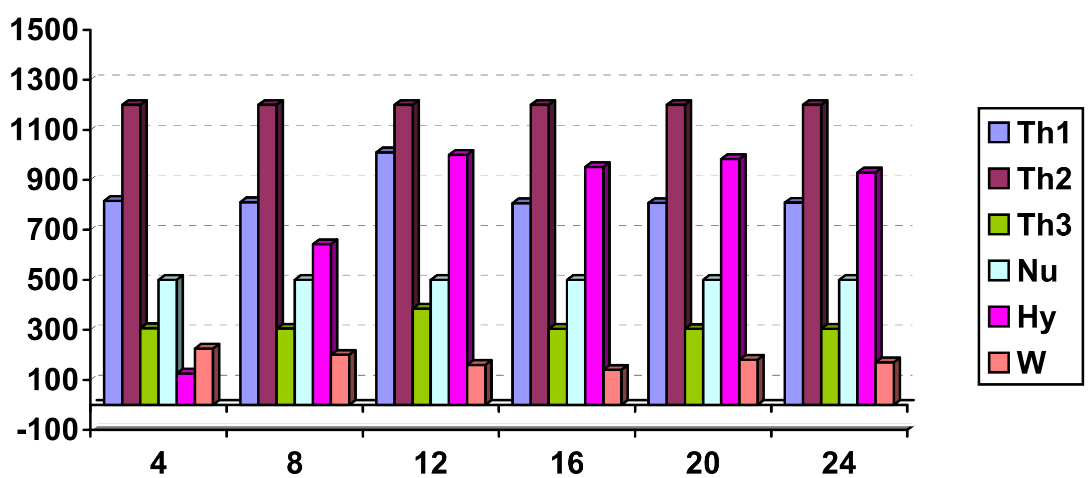

Fig.3.6 Simulation Results of Case One

Case 2

The load duration curve for a day of the month July has been shown below:

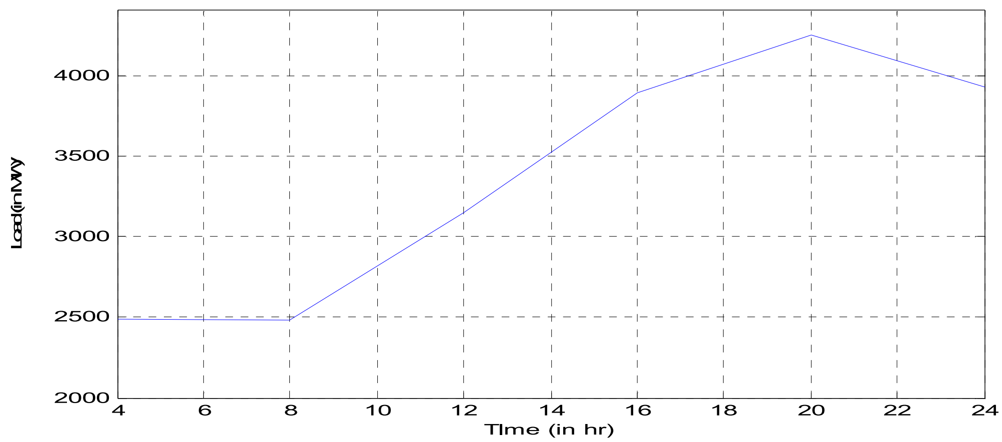

Fig.3.7 Sample Load Duration Curve of a day in July

The simulation results obtained for this case has been shown in bar chart form to give visual understanding about the generation of different units for the given load duration curve.

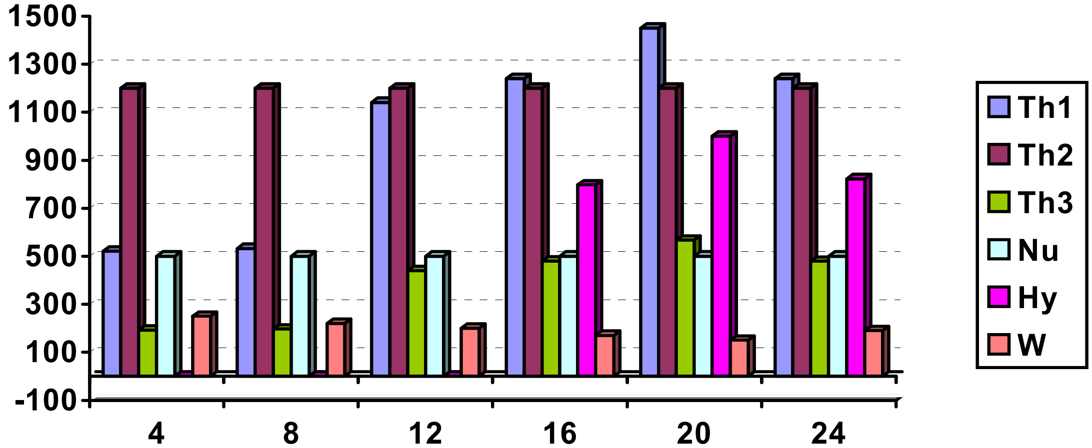

Fig.3.8 Simulation Results of Case Two

Case 3

The load duration curve for a day of the month February has been shown below:

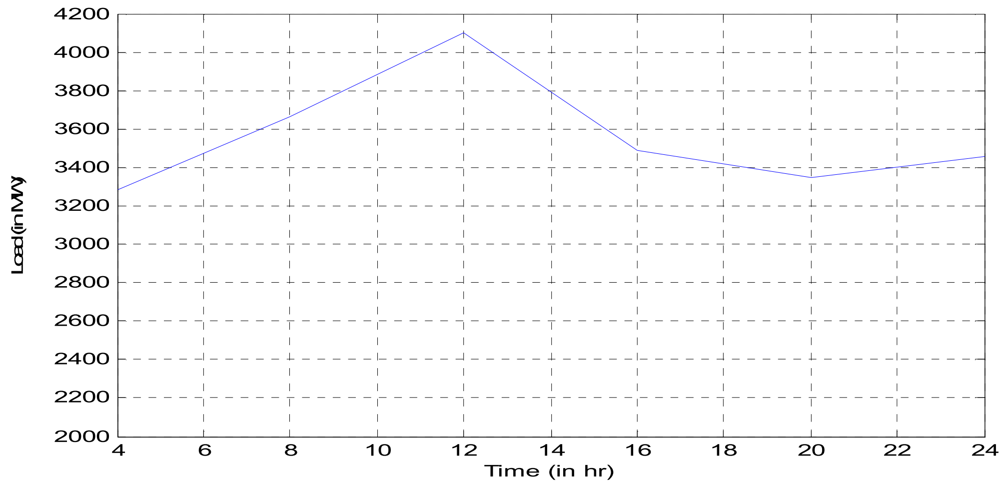

Fig.3.9 Sample Load Duration Curve of a day in February

The simulation results obtained for this case has been shown in bar chart form to give visual understanding about the generation of different units for the given load duration curve.

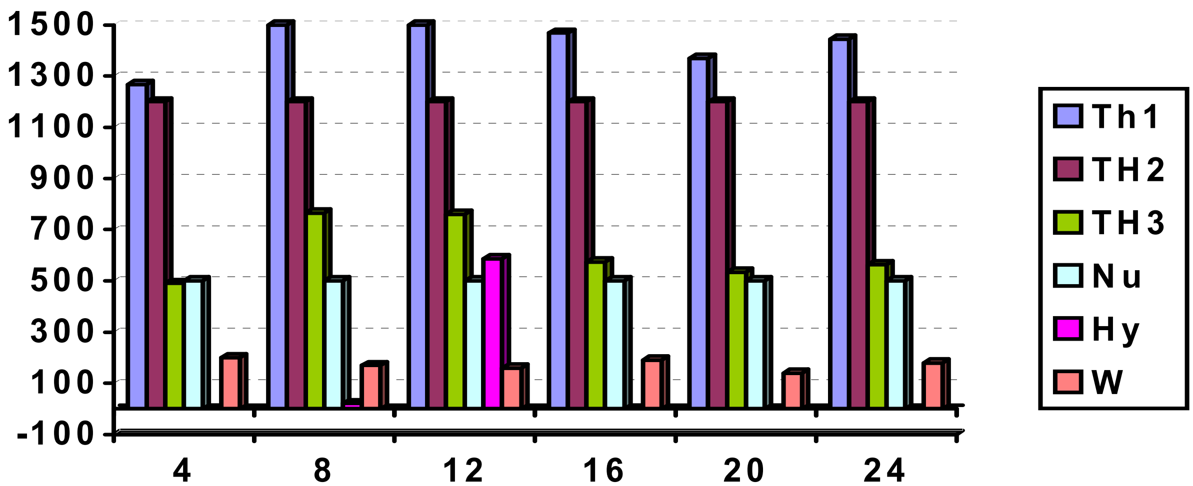

Fig.3.10 Simulation Results of Case Three

3.5.2 Analysis of Results

From all the simulation results, it has been found that the cheapest thermal unit bears most of the load. So the second thermal unit has been allocated the maximum generation at its maximum generation capacity. Since the third thermal unit is the most expensive unit, the first thermal unit bears more than the third thermal unit. Due to the fuel cost characteristic of the nuclear unit, it has been allocated at its maximum generation capacity at all the time intervals. It can be observed from the results of test case one that as the load fluctuates between minimum to maximum value, the hydro unit bears most of these fluctuations. This is a desired condition for the thermal units for their less wear and tear chances. In the second test case, the total water available in the reservoir for the entire day is lesser but the wind energy penetrations in different time intervals are a bit more than the first case. It was found that in this case the fuel cost for the entire day was more than the fuel cost of case one due to less availability of the energy resources and higher loads during the day. In the third and final case, the total water available in the reservoir for the entire day is least and the wind energy penetrations in different time intervals are also very low as compared to two earlier cases. It can be seen from the load duration curve that the load demand on this day is higher as related to other cases. It was found that in this case, the fuel cost for the entire day was highest among all the three cases due to less availability of water and the wind energy resources and higher loads during the day. For all the three cases, total available water for a day in the reservoir has been used in an optimum way to achieve maximum benefits by reducing the total operational fuel cost. It has also been found in all the three cases, that the total available wind power has been efficiently used during the entire day to minimize the total fuel cost. In summary, the algorithm was able to find optimal solution for the generation scheduling during three different days of a year with using all the available energy sources to minimize the fuel cost of the system. So, the algorithm can be used efficiently to solve and analyze the long-term generation scheduling problem with hybrid energy resources.

3.6 Conclusions

This chapter presented one mathematical and one artificial intelligence technique to solve the highly non-linear generation scheduling problems with different combinations of hybrid energy resources. Important physical and technical operating constraints have been considered while solving the different cases. First, the sequential quadratic programming technique was applied to solve the hydro-thermal-nuclear coordination problem with third order fuel cost functions for the thermal units. This technique gives good results if the fuel cost functions are continuous. This technique cannot be applied if the function to be minimized or the constraints are discontinuous. It might only give local solutions for these types of problems. The method is sensitive to the initial point. It guarantees local optima as it follows a gradient search direction from the starting point towards the optimal point.

In the second part of this chapter, the genetic algorithm has been described with its important characteristics suitable to solve the complex generation scheduling problem. Genetic algorithm is a powerful strategy to improve the global searching capability and escape from local minima. It has been shown that the genetic algorithm approach is suitable to solve the economic dispatch problems with the valve-point effect. The results show that the proposed algorithm is very effective and promising for solving scheduling problem with highly non-linear and discontinuous fuel cost functions. Moreover, the proposed approach is robust, requires a small population and is applicable to large-scale systems.

A general algorithm has been developed for generation scheduling in power systems with hybrid energy resources. The algorithm has been applied successfully to solve the hydro-thermal-nuclear-wind coordination problem of the power system with different constraints. The proposed method determines the optimal allocation of energy resulting from random availability of source during different sub-periods of a year so that the expected benefits are maximized. This algorithm has been successfully tested for generation scheduling of three different days of a year using the IEEE 14 – bus system. The method maximizes the production profits of the hybrid energy power system by efficient use of the available hydro and wind energy.

CHAPTER FOUR

MULTI-OBJECTIVE GENERATION SCHEDULING WITH HYBRID ENERGY RESOURCES USING GENETIC ALGORITHM

This chapter presents a genetic algorithm based technique to solve the multi-objective generation scheduling problem with hybrid energy resources. This problem has two conflicting objectives, emission minimization and fuel cost minimization. Both the objectives have to be solved simultaneously and in a single simulation run to obtain fast and informative trade-off results. In chapter 3, the sequential quadratic programming method was used to solve the single objective generation scheduling problem with higher order fuel cost functions. This method has its limitations while solving the multi-objective problem in single simulation run. So, Pareto-optimal solutions for the trade-off information between the conflicting objectives can not be obtained. A simple genetic algorithm was used and applied to solve the single objective scheduling problem earlier. The same algorithm has been used to solve the multi-objective problem in this chapter with different combinations of energy sources. The results show that the applied algorithm is efficient in solving the multi-objective environmental/economic dispatch problem in a single simulation run. Thus, the trade-off solutions between the conflicting objectives can be obtained. By using different sample test problems with different combinations of energy sources, the versatile nature of the algorithm has been illustrated. The results show that the proposed multi-objective genetic algorithm efficiently solves all the problems found in earlier chapters.

4.1 Multi-Objective Optimization

Optimization of the conflicting objectives is one of the important problems faced in power system planning. Simultaneous minimization of the emission and the fuel cost is an interesting power system optimization problem due to their conflicting nature. In general, if the functions $f_1(x)$ and $f_2(x)$ are conflicting each other, a trade-off relationship can be shown as in the following Fig 4.1:

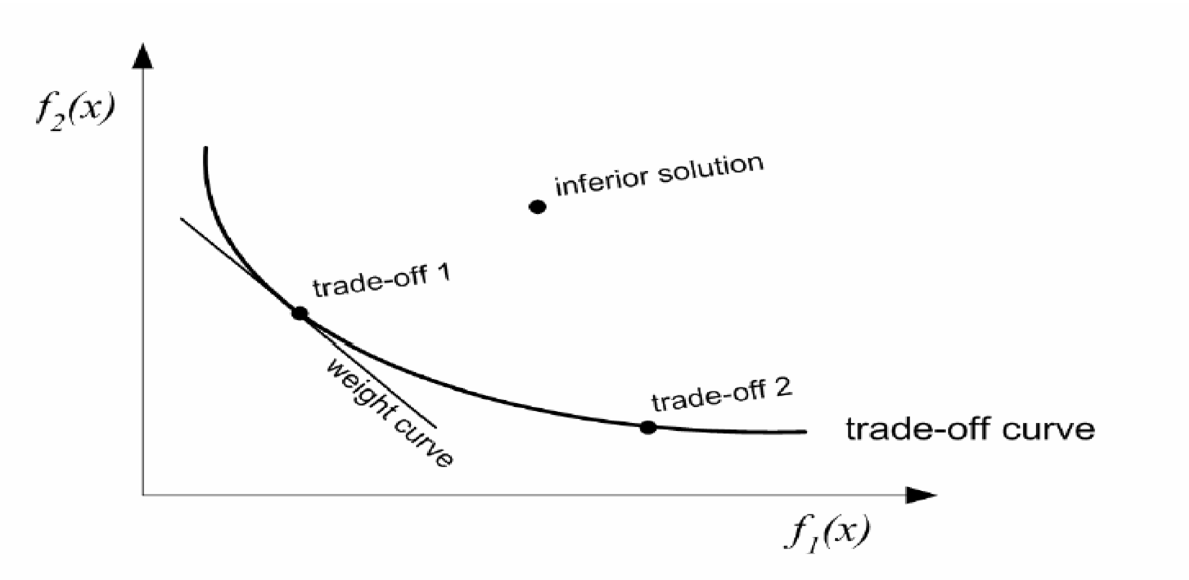

Fig.4.1 Trade-off curve and relation to weighted multi-objective Optimization [106]

The trade-off curve is comprised of all the non-dominated solutions of a problem. The curve above also shows the weighted single objective solution. Most of the planning problems have the objective to minimize the cost or to search an economic optimal solution. In the environmental/economic dispatch problem, the emissions can be included as a constraint in a single objective optimization problem. The total cost function with multiple conflicting cost components can also be obtained. By adding all these components, the single objective problem can be solved. In single objective problem results, the weights given to different components will affect the total cost of the objective. Since all the cost components have to be converted to monitory units, it is difficult to convert some objectives, like fuel emissions, into the exact equivalent cost unit. By solving the single objective problem, the trade-off information also cannot be obtained. So, to avoid the problems in a single objective conversion with the weight factors, a multi-objective optimization technique should be applied. Multi-objective optimization technique is performed to give the accurate results to the planner. By this, all the objectives are optimized without assigning weights to them [106, 107].

4.1.1 Principles of Multi-Objective Optimization

Many real-world problems involve simultaneous optimization of several functions. Generally, these functions are non-commensurable and often competing and conflicting objectives. Multi-objective optimization with such conflicting objective functions gives rise to a set of optimal solutions, instead of one optimal solution. The reason of the optimality of many solutions is that no one can be considered to be better than any other with respect to all objective functions. These optimal solutions are known as Pareto-optimal solutions [108].

A general multi-objective optimization problem consists of a number of objectives to be optimized simultaneously and is associated with a number of equality and inequality constraints. It can be formulated as follows:

$$\underset{x}{\text{Minimize}}\ f_i(x) \quad i = 1,\ldots,N_{obj} \tag{4.1}$$

$$\text{Subject to:} \quad g_j(x) = 0 \quad j = 1,\ldots,M \tag{4.2}$$

$$h_k(x) \le 0 \quad k = 1,\ldots,K \tag{4.3}$$

Where f_i is the i-th objective function, x is a decision vector that represents a solution and N_{obj} is the number of objectives.

For a multi-objective optimization problem, any two solutions x^1 and x^2 can have one of two possibilities: one dominates or covers the other or none dominates the other. In a minimization problem, without loss of generality, a solution x^1 covers or dominates x^2 if the following two conditions are satisfied:

$$1.\ \forall\, i \in \{1,2,\ldots,N_{obj}\}: f_i(x^1) \le f_i(x^2) \tag{4.4}$$

$$2.\ \exists\, j \in \{1,2,\ldots,N_{obj}\}: f_j(x^1) < f_j(x^2) \tag{4.5}$$

If any of the above conditions is violated, the solution x^1 does not dominate the solution x^2. If x^1 dominates the solution x^2, x^1 is called the non-dominated solution. The solutions that are non-dominated within the entire search space are denoted as Pareto-optimal and constitute the Pareto-optimal set. This set is also known as Pareto-optimal front [109].

4.2 Environmental/Economic Dispatch Problem

4.2.1 Problem Objectives

Fuel Cost Objective: The classical economic dispatch problem minimizes the total fuel cost while satisfying the required quantity of power. The dispatch problem can be stated mathematically as follows:

$$C = \sum_{i=1}^{n} (a_i + b_i P_{G_i} + c_i P_{G_i}^{2}) \tag{4.6}$$

Where C is the total fuel cost (\$/hr), n is the number of generators, $a_{i,} b_i, c_i$ are cost coefficients of the i-th generator, and P_{G_i} is the real power output of the i-th generator.

Emission Objectives: In general, the atmospheric pollutants such as SO_2 and NO_x caused by fossil-fueled thermal units can be modeled using second order polynomial functions. The functions can be written as follows [80]:

SO_2 Emission Objective

$$E_{SO_2} = \sum_{i=1}^{n} (a_{iS} P_{G_i}^{\ 2} + b_{iS} P_{G_i} + c_{iS}) \qquad (4.7)$$

Where, $a_{iS,} b_{iS}, c_{iS}$ are SO_2 Emission coefficients of the i-th generator.

NO_x Emission Objective

$$E_{NO_x} = \sum_{i=1}^{n} (a_{iN} P_{G_i}^{\ 2} + b_{iN} P_{G_i} + c_{iN}) \qquad (4.8)$$

Where, $a_{iN,} b_{iN}, c_{iN}$ are NO_x Emission coefficients of the i-th generator

Units of E_{SO_2} and E_{NO_x} are in ton/hr.

4.2.2 Objective Constraints

The optimization problem is bounded by the following constraints:

Power balance constraint: The total power generation must cover the total demand (P_D) and the real power loss in transmission lines (P_{loss}). Hence,

$$\sum_{i=1}^{n} P_i - P_D - P_{loss} = 0 \qquad (4.9)$$

The transmission losses can be represented as

$$P_{loss} = \sum_{i=1}^{n} \sum_{j=1}^{n} P_{G_i} B_{ij} P_{G_j} \tag{4.10}$$

4.2.3 Problem Formulation

The non-linear constrained multi-objective optimization problem can be summarized as follows.

$$\text{Minimize} \quad [C, E_{SO_2}, E_{NO_2}] \tag{4.11}$$

$$\text{Subject to:} \quad h(P_{G_i}) = 0 \tag{4.12}$$

$$P_{G_{imin}} \leq P_{G_i} \leq P_{G_{imax}} \tag{4.13}$$

Where h is the problem constraint.

4.3 Multi-Objective Genetic Algorithm [110]

Step 1: Initialize the population P_o of size N with iteration counter t = 0.

Step 2: Decode strings to solutions in the phenotype world. Next calculate the values of the n objectives for each solution. Then, update the tentative set of non dominated solutions.

Step 3: Operate constrained binary tournament selection operations to select two parent solutions.

Step 4: Apply a simulated binary crossover operator to each of the selected pairs in step 3 with crossover probability P_c.

Step 5: Apply a polynomial mutation operator to each of the generated strings with mutation probability P_m.

Step 6: The populations of parent and offspring solutions are combined and then ranked from best class of solutions to worst by elite preservation.

Step 7: Continue the iterations until it reaches a pre specified termination criterion (maximum number of generations).

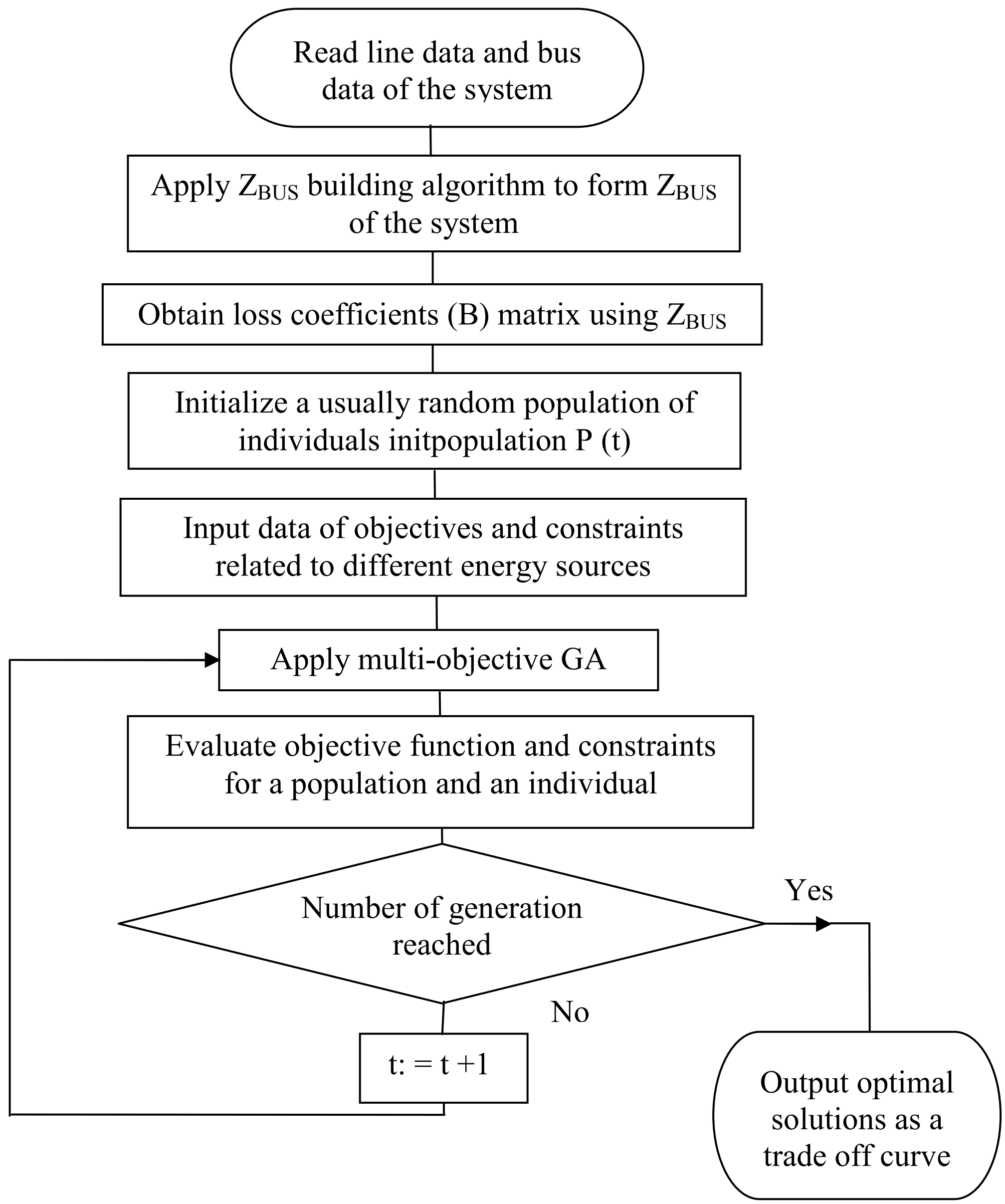

Fig.4.2 Multi-Objective Generation Scheduling Flowchart

4.4 Best Compromise Solution

The applied algorithm generates the Pareto-optimal set of non-dominated solutions. The following approach presents one solution as the best compromise solution to the decision maker. Due to indefinite nature of the decision maker's judgment, each objective function of the i-th solution is represented by a membership function μ_i defined as:

$$\mu_i = \begin{cases} 1 & F_i \le F_i^{min} \qquad (4.14) \\ \dfrac{F_i^{max} - F_i}{F_i^{max} - F_i^{min}} & F_i^{min} \le F_i \le F_i^{max} \qquad (4.15) \\ 0 & F_i \le F_i^{max} \qquad (4.16) \end{cases}$$

The normalized membership function μ^k can be calculated for each non-dominated solution k as follows:

$$\mu^k = \frac{\sum_{i=1}^{N_{obj}} \mu_i^k}{\sum_{k=1}^{M} \sum_{i=1}^{N_{obj}} \mu_i^k} \qquad (4.17)$$

Where M is the number of non-dominated solutions. Maximum value of μ^k gives the best compromise solution [84].

4.5 Simulation Results

4.5.1 Sample Test Case 1

In order to validate the concept of this genetic algorithm based approach, it has been applied to a 3- thermal unit test system [6] to solve the environmental/economic multi-objective dispatch problem. The proposed approach minimizes three conflicting objectives, while allocating the electricity demand among the committed generating units subject to physical and technological constraints. Operating cost, SO_2 emission and NO_x emission are the objectives undertaken to be minimized simultaneously. Fuzzy set theory is applied to extract the best compromise non-dominated solution. Simulation results for a 3 generator sample power system have been presented to illustrate the performance and applicability of the applied method. The data of the sample test system is given in Table 4.1. The system demand is 850 MW in all the simulations.

Table 4.1 Fuel Cost Coefficients

Unit i	a_i	b_i	c_i	$P_{G_{i_{min}}}$	$P_{G_{i_{max}}}$
1	561.0	7.92	0.001562	150.0	600.0
2	310.0	7.85	0.00194	100.0	400.0
3	78.0	7.97	0.00482	50.0	200.0

The system transmission loss is calculated by using a simplified loss expression [6]:

$$P_{loss} = 0.00003\,P_{G_1}{}^2 + 0.00009\,P_{G_2}{}^2 + 0.00012\,P_{G_3}{}^2 \qquad (4.18)$$

The SO_2 and NO_x emission function coefficients [80] are given in Tables 4.2 and 4.3 respectively.

Table 4.2 SO_2 Emission Coefficients

Unit i	a_{iS}	b_{iS}	c_{iS}
1	1.6103e-6	0.00816466	0.5783298
2	2.1999e-6	0.00891174	0.3515338
3	5.4658e-6	0.00903782	0.0884504

Table 4.3 NO_x Emission Coefficients

Unit i	a_{iN}	b_{iN}	c_{iN}
1	1.4721848e-7	-9.4868099e-5	0.04373254
2	3.0207577e-7	-9.7252878e-5	0.055821713
3	1.9338531e-6	-3.5373734e-4	0.027731524

In all the simulations, the population size was chosen as 200 individuals; crossover and mutation probabilities were 0.9 and 0.5 respectively. The distribution index for crossover and mutation were set at 10 and 50 respectively. The simulations were run for 20 generations. The algorithm is implemented to optimize the power dispatch for a 3-objective problem: fuel cost (f1), SO_2 emission (f2) and NO_x emission (f3). The results are shown in Figs.4.3 - 4.5.

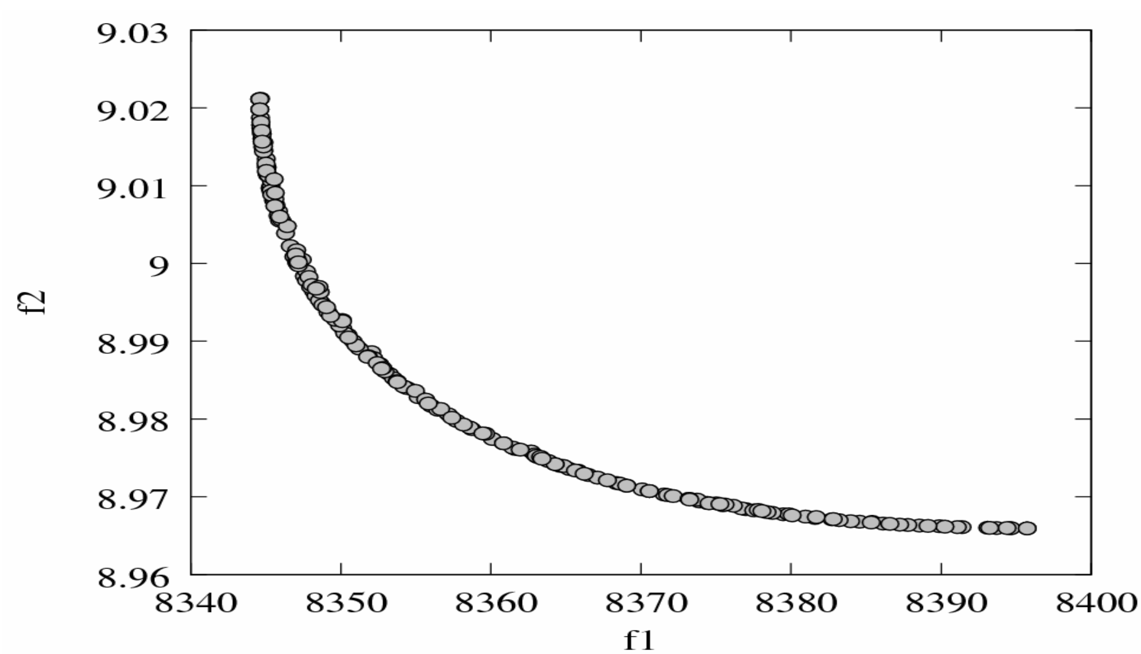

Fig.4.3 Pareto-optimal front for fuel cost and SO_2 emission

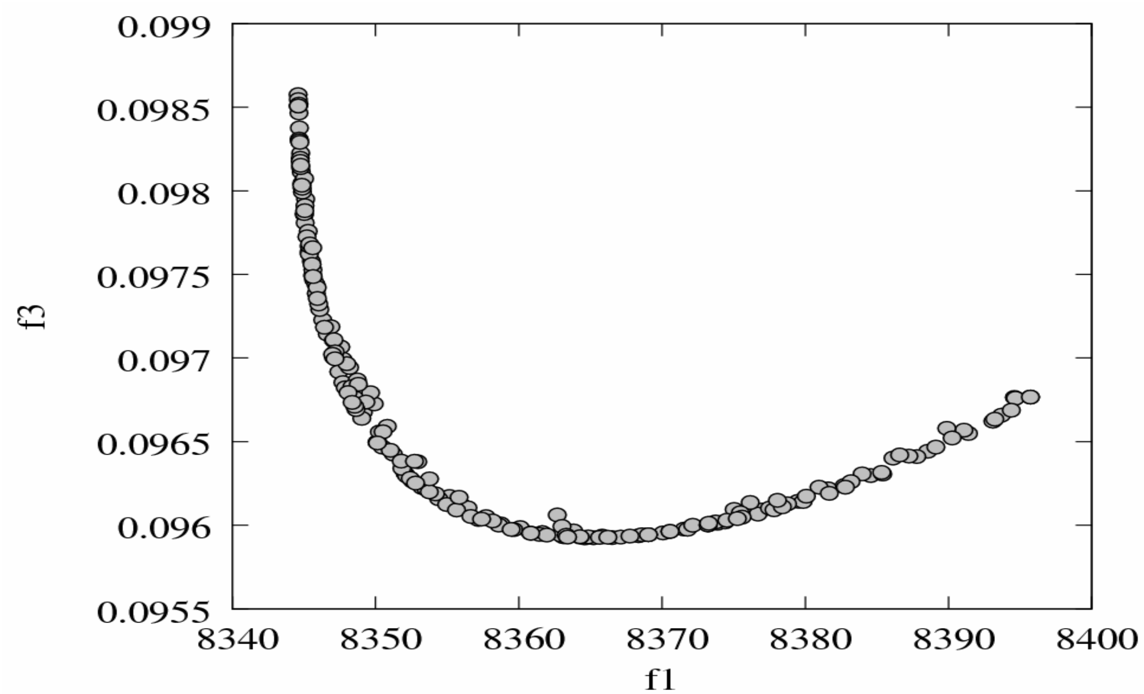

Fig.4.4 Pareto-optimal front for fuel cost and NO_x emission

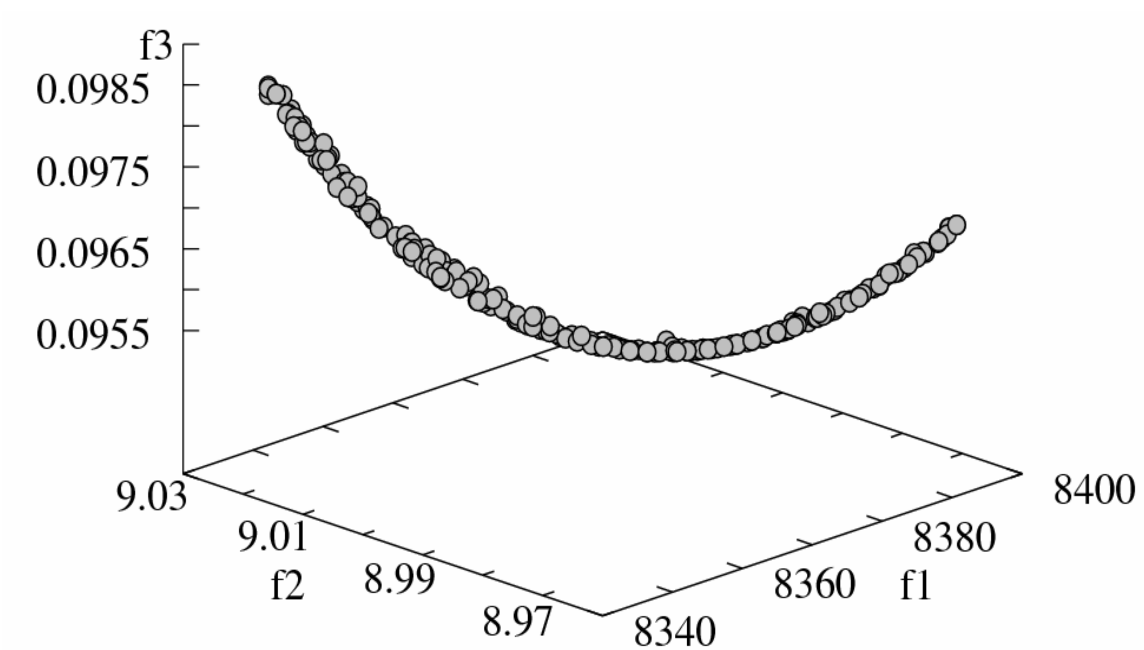

Fig.4.5 Pareto-optimal front for fuel cost, SO_2 and NO_x emission

Tables 4.4, 4.5 and 4.6 show the simulation results for best fuel cost, best SO_2 emission and best NO_x emission dispatch.

Table 4.4 Minimum Fuel Cost Dispatch

Cost ($/hr)	8344.600
Emission SO_2 (ton/hr)	9.021121
Emission NO_x (ton/hr)	0.098575
Losses P_{loss} (MW)	15.364

Table 4.5 Minimum SO_2 Emission Dispatch

Cost ($/hr)	8395.726
Emission SO_2 (ton/hr)	8.965
Emission NO_x (ton/hr)	0.09676
Losses P_{loss} (MW)	14.486

Table 4.6 Minimum NO_x Emission Dispatch

Cost ($/hr)	8364.624
Emission SO_2 (ton/hr)	8.973
Emission NO_x (ton/hr)	0.0959
Losses P_{loss} (MW)	14.0276

The best compromise solution is selected by using fuzzy set theory and is shown in Table 4.7

Table 4.7 Best Compromise Solution for 3 Objectives

Cost ($/hr)	8352.1
Emission SO_2 (ton/hr)	8.9878
Emission NO_x (ton/hr)	0.0962
Losses P_{loss} (MW)	14.7761

4.5.2 Sample Test Case 2

In order to show the applicability of the algorithm in solving more complex problems with highly non-linear functions with different technical and physical constraints of the system, the environmental/economic dispatch was applied to the standard IEEE 30 bus , 6 generators test system [84]. The data for the fuel cost and the fuel emission coefficients are given in Table 4.8 and Table 4.9.

4.5.2.1 Problem Formulation

Fuel Cost Minimization:

The fuel cost curves for the generators can be represented by a quadratic function as shown in Eq. (4.6).

Fuel Emission Minimization:

The combined fuel emission function for the sulphur oxides SO_x and nitrogen oxides NO_x, which is caused by the thermal generating units can be expressed as follows [84]:

$$E = \sum_{i=1}^{N} 10^{-2}(\alpha_i + \beta_i P_{G_i} + \gamma_i P_{G_i})^2 + \zeta_i \exp(\lambda_i P_{G_i}) \qquad (4.19)$$

Where $\alpha_i, \beta_i, \gamma_i, \zeta_i, \lambda_i$ are the emission coefficients of the ith generator. Unit of fuel emission is ton/hr.

While solving the problem, power balance constraint and the generator maximum and minimum operating limits have been taken into account.

Table 4.8 Fuel Cost Coefficients

Unit i	a_i	b_i	c_i	$P_{G_{i_{min}}}$	$P_{G_{i_{max}}}$
1	10	200	100	5	50
2	10	150	120	5	60
3	20	180	40	5	100
4	10	100	60	5	120
5	20	180	40	5	100
6	10	150	100	5	60

The emission function coefficients [84] are given in Table 4.9.

Table 4.9 Fuel Emission Coefficients

Unit i	α_i	β_i	γ_i	ζ_i	λ_i
1	4.091	-5.554	6.490	2.0E-4	2.857
2	2.543	-6.047	5.638	5.0E-4	3.333
3	4.258	-5.094	4.586	1.0E-6	8.000
4	5.426	-3.550	3.380	2.0E-3	2.000
5	4.258	-5.094	4.586	1.0E-6	8.000
6	6.131	-5.555	5.151	1.0E-5	6.667

In all the simulations, the population size was chosen as 60 individuals; crossover and mutation probabilities were 0.9 and 0.15, respectively. The distribution index for crossover and mutation were set at 10 and 50, respectively. The simulations were run for 60 generations. The algorithm is implemented to optimize the power dispatch for a 2-objective problem: fuel cost (f1) and fuel emissions (f2). The result is shown in the Fig. 4.6.

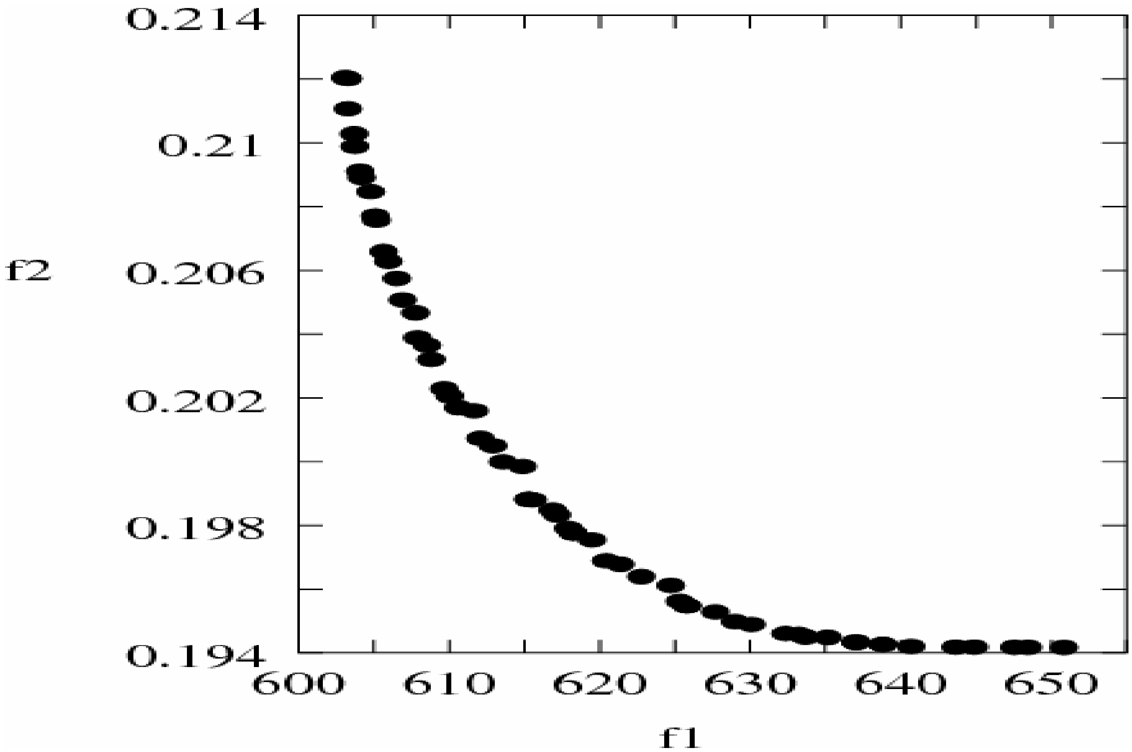

Fig.4.6 Pareto-optimal front for fuel cost and fuel emission

Table 4.10 Minimum Fuel Cost Dispatch

P_{Th1} (MW)	13.0369
P_{Th2} (MW)	35.5404
P_{Th3} (MW)	56.2026
P_{Th4} (MW)	87.6944
P_{Th5} (MW)	51.8599
P_{Th6} (MW)	39.6145
Cost ($/hr)	603.0981
Emission SO_2 (ton/hr)	0.2120

Table 4.11 Minimum Emission Dispatch

P_{Th1} (MW)	41.3518
P_{Th2} (MW)	46.6391
P_{Th3} (MW)	54.8444
P_{Th4} (MW)	39.4672
P_{Th5} (MW)	54.8308
P_{Th6} (MW)	51.8659
Cost ($/hr)	650.8507
Emission SO_2 (ton/hr)	0.1941

Table 4.12 Best Compromise Solution for two objectives

P_{Th1} (MW)	32.2198
P_{Th2} (MW)	40.1092
P_{Th3} (MW)	50.3380
P_{Th4} (MW)	63.2587
P_{Th5} (MW)	53.6502
P_{Th6} (MW)	44.9137
Cost ($/hr)	617.9297
Emission SO_2 (ton/hr)	0.1979

4.5.3 Sample Test Case 3

This sample test case presents application of the algorithm to solve the multi-objective hydro-thermal generation scheduling problem. The proposed approach minimizes two conflicting objectives while allocating the electricity demand among the committed generating units subject to physical and technological constraints. Operating cost and SO_2 emissions are the objectives undertaken to be minimized simultaneously. Fuzzy set theory is applied to extract the best compromise non-dominated solution. Simulation results for the one hydro and three thermal generator sample power system have been presented to illustrate the performance and applicability of the proposed method. Effects of the hydro unit on the fuel cost and the SO_2 emissions have been studied by the simulation results.

4.5.3.1 Problem Objectives

Fuel Cost Objective: The classical economic dispatch problem minimizes the total fuel cost while satisfying the required quantity of power. The fuel cost function considered in this sample case is shown in Eq. (4.6).

Emission Objective: The atmospheric pollutants such as SO_2 caused by fossil-fueled thermal units can be modeled using second order polynomial functions. The emission function is shown in Eq. (4.7).

4.5.3.2 Objective Constraints

The optimization problem is bounded by the following constraints:

Power balance constraint*:* The total power generation must cover the total system demand P_D, since transmission losses do not affect the final decision significantly,

Hence,

$$\sum_{i=1}^{n} P_i - P_D \simeq 0 \tag{4.20}$$

Operational limits of generating units:

$$P_{G_{imin}} \leq P_{G_i} \leq P_{G_{imax}} \tag{4.21}$$

Water balance constraint:

$$n\,q = q_t \tag{4.22}$$

Where n is the entire period of dispatch in hrs, q is the water discharge rate in acre-ft/hr and q_t is the volume of maximum water discharge for the hydro system in acre-ft.

4.5.3.3 Problem Formulation

The non-linear constrained multi-objective optimization problem can be summarized as follows.

$$\text{Minimize} \quad [C, E_{SO_2}] \tag{4.23}$$

$$\text{Subject to:} \quad h(P_{G_i}) = 0 \tag{4.24}$$

$$P_{G_{imin}} \leq P_{G_i} \leq P_{G_{imax}} \tag{4.25}$$

$$n\,q = q_t \tag{4.26}$$

Where h is the problem constraint.

In order to validate the proposed algorithm, the environmental/economic dispatch was applied to a test system of three thermal units and one hydro unit [6]. The fuel cost function coefficients and SO_2 emission function coefficients of the three thermal units are given in Table 4.1 and Table 4.2 respectively. The operational limits of the units and the system demand are assumed in the simulations. The system demand is 1500 MW in all simulations for one day. The algorithm is implanted in C programming language and, to show the effects of the hydro unit, it has been tested for the following two cases:

Case 3a: Three thermal units.

Case 3b: Three thermal and one hydro unit.

The discharge rate for the hydro system with its maximum and minimum capacities is as follows [6]:

$q = 330 + 4.97P_H \qquad 0 < P_H \leq 600$

$q = 5300 +12 (P_H - 600) + 0.5 (P_H - 600)$ ^2 $\qquad 600 < P_H \leq 700$

Unit of the q is acre-ft/hr

The maximum water discharge for the hydro system is given for the whole time period:

$$q_t = 200000 \text{ acre-ft}$$

In all simulations, the population size was chosen as 60 individuals; crossover and mutation probabilities were 0.9 and 0.25, respectively. The distribution index for crossover and mutation were set at 10 and 50, respectively. The simulations were run for 20000 generations. The algorithm is implemented to optimize the power dispatch for the 2-objective problem: fuel cost (f1) in \$/hr and SO_2 emissions (f2) in ton/hr.

Case 3a:

In this case, three thermal units are considered in the scheduling algorithm. The Pareto-optimal front obtained is shown in Fig.4.7. Tables 4.13 and 4.14 show the simulation results for the best fuel cost dispatch and the best SO_2 emission dispatch.

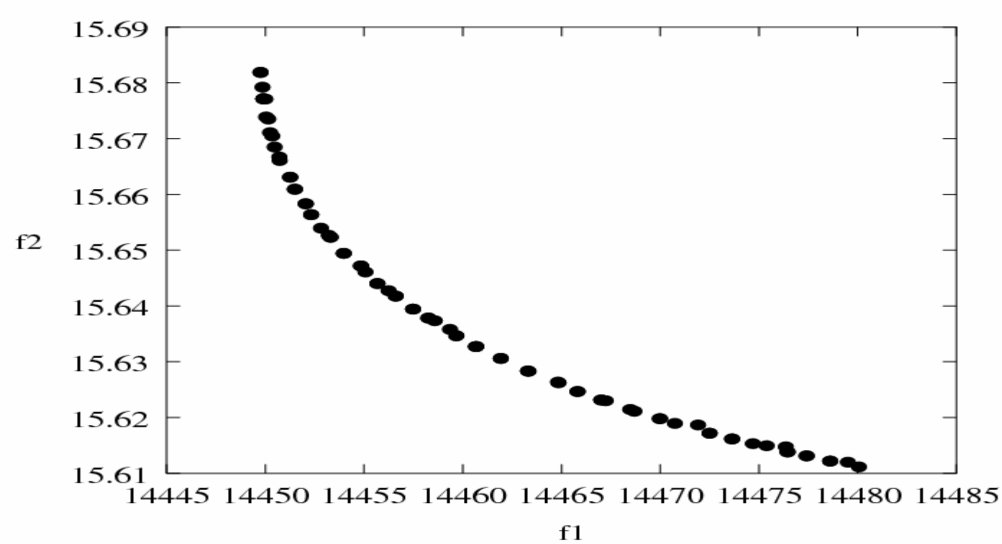

Fig.4.7 Pareto-optimal front for fuel cost (f1) and SO_2 emission (f2) without hydro unit

Table 4.13 Minimum Fuel Cost Dispatch

P_{Th1} (MW)	701.3390
P_{Th2} (MW)	575.1287
P_{Th3} (MW)	223.4329
Cost ($/hr)	14449.76
Emission SO_2 (ton/hr)	15.68185

Table 4.14 Minimum SO_2 Emission Dispatch

P_{Th1} (MW)	799.9880
P_{Th2} (MW)	508.2253
P_{Th3} (MW)	191.6869
Cost ($/hr)	14480.06
Emission SO_2 (ton/hr)	15.61116

The best compromise solution is selected by using Fuzzy set theory and is shown in Table 4.15.

Table 4.15 Best Compromise Solution for 2 objectives

P_{Th1} (MW)	752.1019
P_{Th2} (MW)	541.8491
P_{Th3} (MW)	205.9590
Cost ($/hr)	14458.26
Emission SO_2 (ton/hr)	15.63783

Case 3b:

In this case, three thermal units and one hydro unit have been considered in the scheduling algorithm. The Pareto-optimal front obtained is shown in Fig.4.8. Tables 4.16 and 4.17 show the simulation results for the best fuel cost dispatch and the best SO_2 emission dispatch.

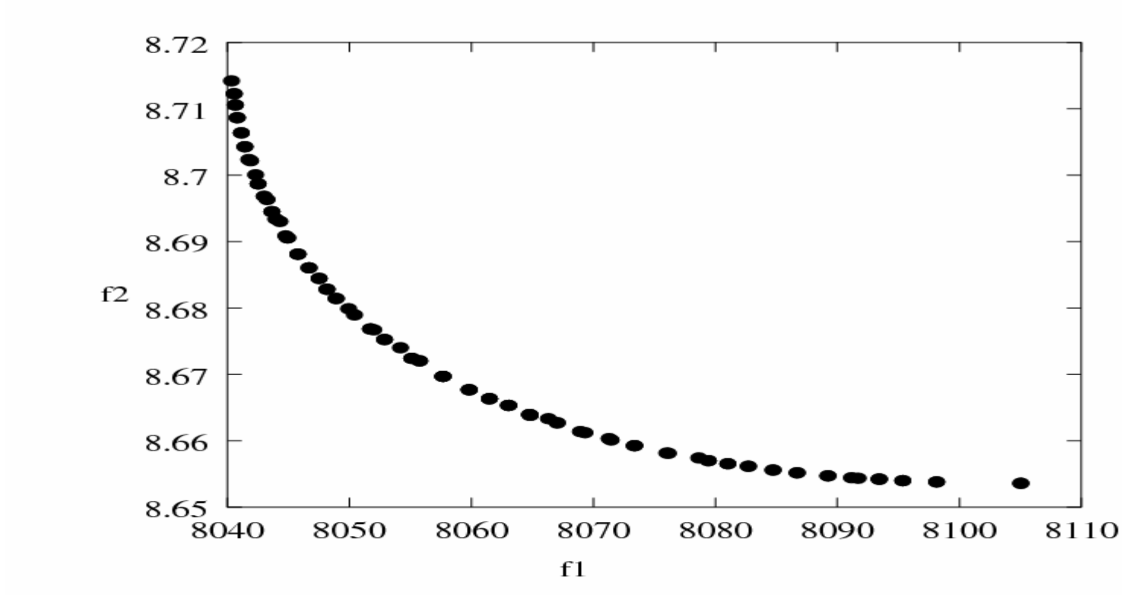

Fig.4.8 Pareto-optimal front for fuel cost (f1) and SO_2 emission (f2) with hydro unit

Table 4.16 Minimum Fuel Cost Dispatch

P_{Th1} (MW)	396.1630
P_{Th2} (MW)	316.8428
P_{Th3} (MW)	120.0872
P_H (MW)	666.8078
Cost ($/hr)	8040.335
Emission SO_2 (ton/hr)	8.714196

Table 4.17 Minimum SO_2 Emission Dispatch

P_{Th1} (MW)	533.8703
P_{Th2} (MW)	224.0564
P_{Th3} (MW)	75.17238
P_H (MW)	666.8077
Cost (\$/hr)	8105.044
Emission SO_2 (ton/hr)	8.653598

The best compromise solution is selected by using Fuzzy set theory and is shown in Table 4.18.

Table 4.18 Best Compromise Solution for 2 objectives

P_{Th1} (MW)	462.8887
P_{Th2} (MW)	272.3847
P_{Th3} (MW)	97.82047
P_H (MW)	666.8077
Cost (\$/hr)	8057.668
Emission SO_2 (ton/hr)	8.669701

4.5.4 Sample Test Case 4

In this case, the algorithm has been applied to solve the multi-objective generation scheduling problem for a three thermal and a wind unit test system. The proposed approach minimizes two conflicting objectives while allocating the electricity demand among the committed generating units subject to physical and technological constraints. Operating cost and SO_2 emissions are the objectives undertaken to be minimized simultaneously. Fuzzy set theory is applied to extract the best compromise non-dominated solution. Simulation results for the three thermal generator and one wind unit sample power system have been presented to illustrate the performance and applicability of the proposed method. Effects of the wind unit on the fuel cost and the SO_2 emissions have been studied by the simulation results. The fuel cost function and SO_2 emission function have been shown in Eq. (4.6) and Eq. (4.7). All the data related to thermal units is given in Table 4.1 and Table 4.2. The system demand is 850 MW in all the simulations. The system transmission loss is calculated by using a simplified loss expression as shown in Eq. (4.18).

In all the simulations, the population size was chosen as 100 individuals; crossover and mutation probabilities were 0.9 and 0.34, respectively. The distribution index for crossover and mutation were set at 10 and 20, respectively. The simulations were run for 10000 generations.

Case 4a: Without Wind

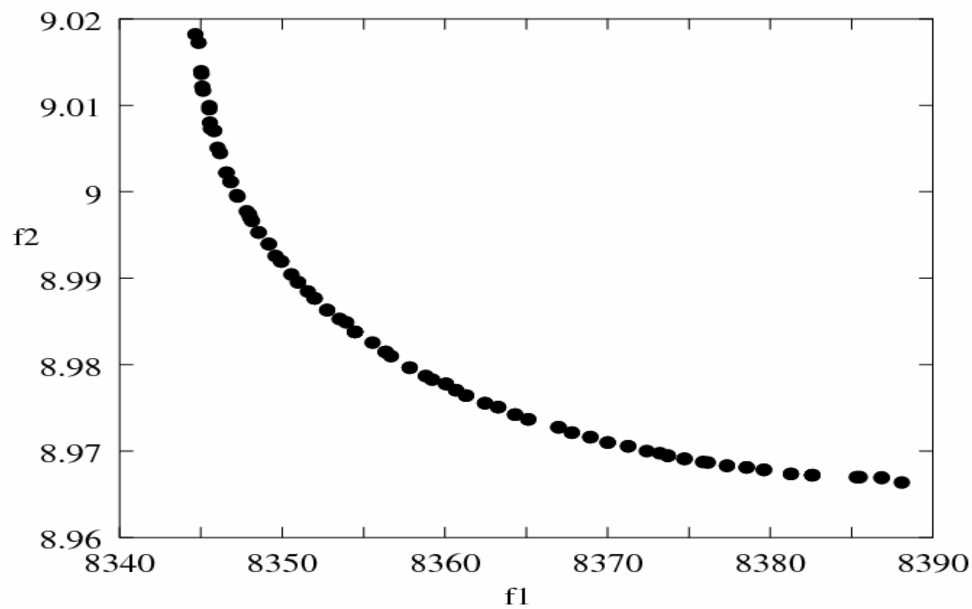

Fig.4.9 Pareto-optimal front for fuel cost (f1) and SO_2 emission (f2) without wind unit

Table 4.19 Best Compromise Solution

P1 (MW)	490.551
P2 (MW)	262.923
P3 (MW)	111.463
Cost ($/hr)	8356.358
Emission SO2 (ton/hr)	8.981

Case 4b: With Wind

In this case, wind penetration is assumed to be 12% (100 MW). The program was run with three thermal and one wind unit.

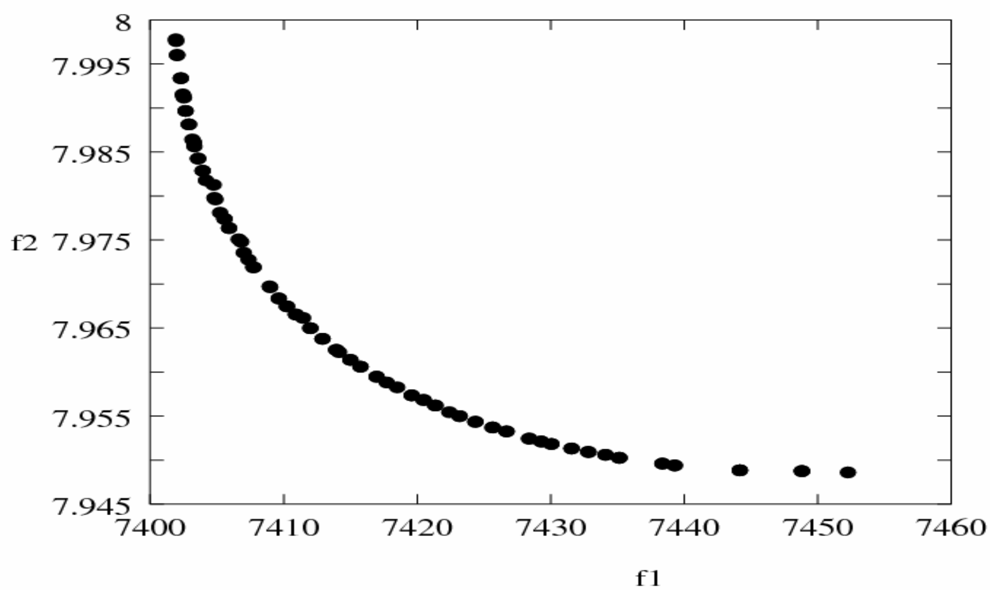

Fig.4.10 Pareto-optimal front for fuel cost (f1) and SO_2 emission (f2) with wind unit

Table 4.20 Best Compromise Solution

P1 (MW)	441.110
P2 (MW)	224.064
P3 (MW)	96.294
Cost ($/hr)	7414.994
Emission SO2 (ton/hr)	7.961

4.5.5 Sample Test Case 5

This sample test case presents the application of the algorithm to solve the multi-objective generation scheduling problem with hydro-thermal-nuclear-wind energy sources. Operating fuel cost and NO_x emissions are the two objectives undertaken to be minimized simultaneously. The fuzzy set theory is applied to extract the best compromise non dominated solution. Simulation results for two thermal, one nuclear, one hydro and one wind unit sample power system have been presented to illustrate the performance and applicability of the proposed method in solving the multi-objective scheduling problem with more than two types of energy sources together. The transmission losses of the standard IEEE 14-bus system [Appendix B] have been included while solving the problem. The load demand is assumed as 2500 MW for the entire period. The test case data for this problem is the same as the 3.1.1 sample test case with assuming 10% penetration of the wind energy for entire period. So, wind power available is assumed as 250 MW. The NO_x emission functions for the two thermal generating units are taken as follows [80]:

$$E(P_{S1}) = 1.4721848e\text{-}7 * P_{S1}\hat{}2 - 9.4868099e\text{-}5 * P_{S1} + 0.04373254 \tag{4.27}$$

$$E(P_{S2}) = 3.0207577e\text{-}7 * P_{S2}\hat{}2 - 9.7252878e\text{-}5 * P_{S2} + 0.055821713 \tag{4.28}$$

In all the simulations, the population size was chosen as 200 individuals; crossover and mutation probabilities were 0.9 and 0.143, respectively. The distribution index for crossover and mutation were set at 10 and 50, respectively. The simulations were run for 30000 generation. The algorithm is implemented to optimize the power dispatch for two objective problems: fuel cost (f_1) and NO_x emissions (f_2). The obtained result is shown in the Fig.4.11.

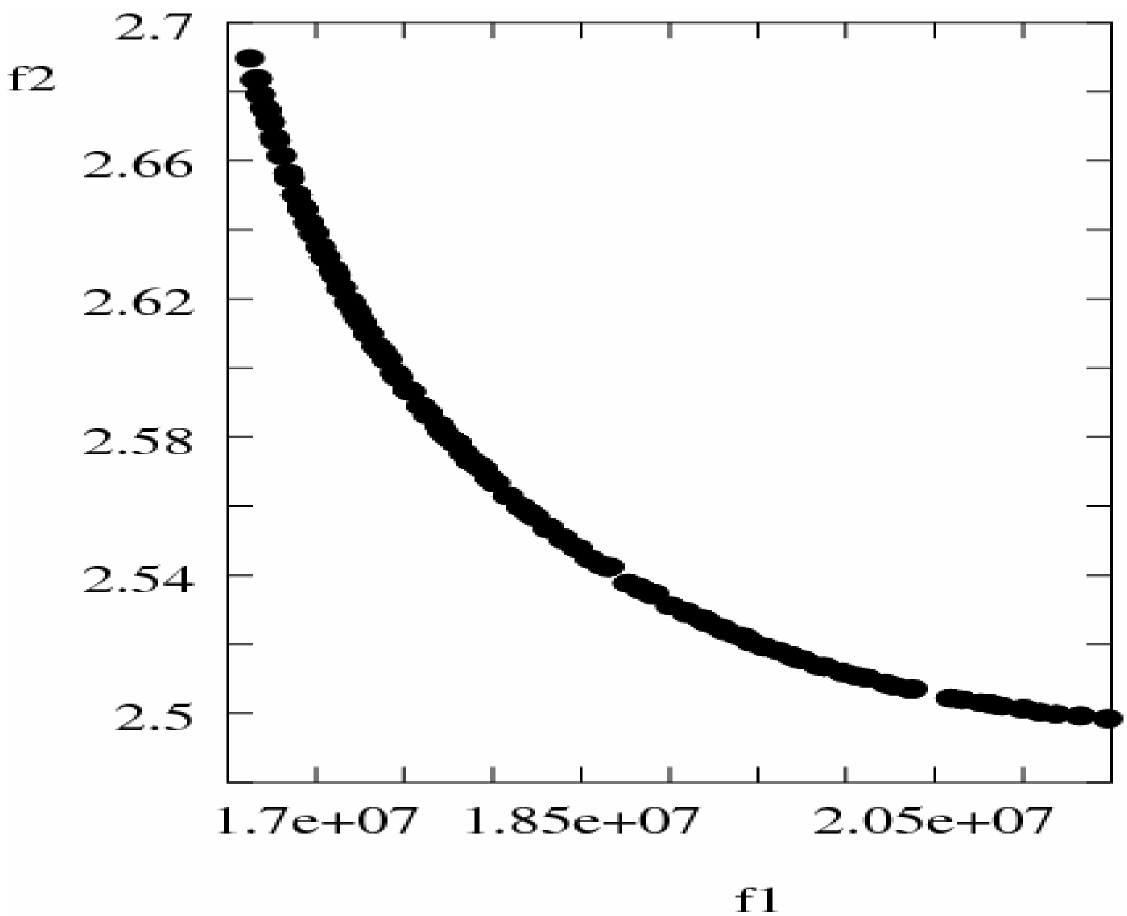

Fig.4.11 Pareto-optimal front for fuel cost and NO_x emission

Table 4.21 Minimum Fuel Cost Dispatch

P_{Th1} (MW)	370.4874
P_{Th2} (MW)	502.7408
P_{Nu} (MW)	500
P_H (MW)	771.9655
P_W (MW)	250
Cost ($)	1.6625E+07
Emission NO_x (ton)	2.6897

Table 4.22 Minimum NO_x Emission Dispatch

P_{Th1} (MW)	543.2757
P_{Th2} (MW)	421.2446
P_{Nu} (MW)	500
P_H (MW)	771.9657
P_W (MW)	250
Cost ($)	2.1479E+07
Emission NO_x (ton)	2.4984

The best compromise solution is selected by using fuzzy set theory and is shown in Table 4.23.

Table 4.23 Best Compromise Solution

P_{Th1} (MW)	455.0429
P_{Th2} (MW)	462.6953
P_{Nu} (MW)	500
P_H (MW)	771.9654
P_W (MW)	250
Cost ($)	1.8235E+07
Emission NO_x (ton)	2.5569

4.5.6 Analysis of Results

In the first sample test system, the multi-objective genetic algorithm has been implemented successfully on a 3 thermal unit test system considering fuel cost, SO_2 emission and NO_x emission objectives simultaneously. It has been illustrated by the results that the algorithm is capable of solving the multi-objective problem with more than two conflicting objectives. The results have been found in fewer generations, which show the fast convergence of the algorithm. In the second sample test case, the algorithm was applied to the standard IEEE 30 bus system, which has 6 thermal generating units. Two objectives in the form of fuel cost and total emissions have been considered in the problem. The fuel emission functions considered are highly non-linear with exponential components. The algorithm allocates the minimum load to unit one and maximum load to unit four for the minimum fuel cost dispatch. In the minimum emission dispatch minimum load has been allocated to unit four and unit one bears a large amount of the load. So, it can be concluded from the obtained results that unit one is the most expensive but least emission emitting unit and unit four is the least expensive but highest emission emitting unit among the six thermal units. In the third sample test system, the proposed method has been implemented successfully on a three thermal and one hydro unit test system considering fuel cost and SO_2 emission objectives simultaneously. Good coordination of the hydro and thermal units is achieved through the algorithm. The schedules of the hydro unit depend on the maximum total volume of water that may be discharged throughout the period. It can be deduced from the figures that the algorithm has converged to the Pareto-optimal fronts in both the cases and solves the problem effectively in a single simulation run. As a result, the cheaper and less emissions generating thermal unit bears a greater part of load demand. On the other hand, the scheduling algorithm allocates fewer generations for the more expensive and more emissions generating thermal units. It can also be seen that in the case 3b, the efficient use of hydro unit reduces the fuel cost and SO_2 emissions significantly. In the fourth sample test case, the algorithm has been applied to the three thermal and one wind unit hybrid energy system. The wind penetration available is assumed as 12% of the total load. It can be seen from the results that the efficient use of the wind energy in the case 4b reduces the fuel cost and SO2 emissions significantly. In the final sample test case, the algorithm was applied on the standard 14-bus system. This system has two thermal, one nuclear, one hydro and one wind unit. The third order fuel cost functions of the thermal units have been considered and the fuel emission functions have been considered as a quadratic function. Simulation results show that the desired trade-off curve has been obtained in a single simulation run. The best compromise solution was extracted by using fuzzy set theory.

4.6 Conclusions

In this chapter, a genetic algorithm based approach has been presented to solve the environmental/economic power dispatch optimization problem with different test cases of a hydro-thermal-nuclear-wind system. The environmental/economic dispatch problem has been formulated as a multi-objective optimization problem with fuel cost and emission as conflicting objectives. An efficient algorithm has been developed to solve the multi-objective optimization problem with hybrid energy resources where multiple Pareto-optimal solutions can be found in one simulation run. Highly non-linear fuel cost functions, emission functions and the equality and inequality constraints have been considered in this complex problem, when extremely low fuel cost as well as low emissions is required simultaneously. The results show that the proposed genetic algorithm approach can be applied to the environmentally economic dispatch problem. Simulation results show that the algorithm is able to find a diverse Pareto-optimal front for the environmental/economic dispatch problem. The best compromise solution can be extracted over the trade-off curve. It can be seen from the results that the proposed approach is efficient for solving the multi-objective optimization where multiple Pareto-optimal solutions are found in one simulation run. The obtained non-dominated solutions in the obtained Pareto-optimal set are well distributed and have diversity characteristics. All the optimal solutions are along a clearly identifiable curve as well. The results from all different test systems show the general use of the algorithm for any combination of energy sources. Since the algorithm provides multiple optimal solutions as a trade-off curve between two conflicting objectives, it is easy for the operators to make fast and accurate decisions. It can be seen from the results that the good coordination of the energy sources have been achieved through the algorithm. The general algorithm also provides the choice to study the effects of different renewable sources on the fuel emissions and the fuel cost of the system.

CHAPTER FIVE

SUMMARY AND FUTURE RESEARCH

5.1 Summary

This dissertation presents different techniques to study the generation scheduling problem with hybrid energy sources. In the process, indepth knowledge of various operational characteristics of the hybrid energy resources, especially hydro, thermal, nuclear and wind have been acquired. The most significant difference between the traditional and renewable energy sources are their operating fuel cost and the emissions generated by the generating units. But, since the continuous availability of the renewable sources is not guaranteed, there is a need of hybrid operations of different energy sources to achieve the maximum benefits. Different approaches have been implemented to solve the problem while considering important physical and technical constraints. The techniques developed in this dissertation focused on solving the problem efficiently while maintaining reasonable accuracy.

5.1.1 Single Objective Function

The initial focus of the work in this dissertation was on the single objective generation scheduling problem with different combinations of the energy sources. Minimization of fuel cost of the system was the only objective to achieve. The Lagrangian relaxation (LR) approach was applied to solve the hydro-thermal generation scheduling problem with aim to minimize the operating fuel cost. A $\lambda - \gamma$ iteration algorithm for the generation scheduling with transmission losses was used to solve the problem. The same technique was used to solve the scheduling problem with hydro-thermal-nuclear energy sources. The computer program was written in Matlab. Since this dispatch process demands vast computer resources (CPU time and memory space) due to coupling constraints of different units, it is not efficient in solving the problem of a system with a large number of different energy sources. It is also not efficient in solving the scheduling problems with higher order fuel cost functions. Later on, to improve the drawbacks of the LR method, the sequential quadratic programming (SQP) technique was used to solve the scheduling problem with higher order fuel cost functions. A function called fmincon was used in this method. It is an optimization program written in Matlab. It attempts to find a constrained minimum of a scalar function of several variables, starting at an initial estimate. It solves the higher order fuel cost function problem efficiently. It also shows its competency in solving the problems with a large number of different energy sources. But this method shows its inefficiency in the following cases: It does not solve the multi-objective problem in a single simulation run. So, it does not provide the trade-off information between the conflicting objectives. Since it follows the deterministic approach, it is unable to include the stochastic nature of the objectives and the constraints. This technique also does not work for discontinuous functions.

5.1.2 Multi-Objective Function

In the last part of the dissertation, the main focus of the research was to develop a technique using a genetic algorithm to solve a multi-objective environmental/economic dispatch optimization problem with hybrid energy resources. A new idea of multi-objective generation scheduling with hybrid energy resources was applied with the genetic algorithm. The genetic algorithm also solves the problems faced in earlier methods while solving the complex scheduling problems. This technique gives more information in solving the conflicting objective problems. A general algorithm was then developed for multi-objective generation scheduling in power systems with hybrid energy resources such as: hydro, thermal, nuclear and wind. Operating fuel cost, SO_2 emission and NO_x emission are the objectives undertaken to be minimized simultaneously by this method. Simulation results for a sample power system with a different combination of hybrid energy resources were presented to illustrate the performance and applicability of the proposed method. The trade-off curve, which is also known as the Pareto-optimal front was obtained for all the sample test cases in a single simulation run. The fuzzy set theory was applied to extract the best compromise non-dominated solution. Effects of renewable energy sources were studied to solve the scheduling problem more effectively. The computer program was written in C. In the absence of such techniques, the power system operators are limited to take their decisions with the single objective optimal solutions. These solutions may not be accurate and fast enough to achieve in the real time operations. However, the work in this dissertation may prove to reduce the operational fuel cost and the fuel emissions together which may reduce the dependence on the fossil fuels and solve some of the environmental issues and global warming.

5.2 Future Research

5.2.1 Actual Data

Since some of the sample test case data used to test the algorithm has been assumed or estimated, we may not get the realistic results. Therefore, this algorithm should be tested on more realistic and practical data. Based on the actual data, accurate modeling of the fuel cost functions, emission functions and different constraints can be done. Load forecast data is also required at different times such as daily, monthly and yearly.

5.2.2 Mathematical Models for Different Energy Resources

Accurate mathematical models can be formulated if more real-time constraints of different energy sources are included in the problem. For example, the constraints related to water flow in a reservoir should be taken into account. Integration of wind energy into the electric grid may cause problems related to the security of the system, so a security constraint or transmission line limit constraint should be included in solving the problem. This may improve the security of power system operations. More practical economic dispatch should consider multiple fuels with the prohibited operating zones.

5.2.3 Hybrid Technique and General Objectives

As a future work, a hybrid optimization technique can be created by coupling a broad, robust and efficient genetic algorithm with already existing deterministic optimization methods, which are considered best for the local search. This technique may prove to be a high performing method in solving complex generation scheduling problems. In this technique, after few generations, the results of the GA are given as the starting point to the deterministic approach. By this way, more accurate and faster results can be obtained by a more efficient local search approach. Parallel programming techniques can also be integrated with the GA to get faster results. Other renewable energy resources can be added in solving the generation scheduling problem. Since the proposed approach can be used for any number of objectives, future work can be extended with more objectives, such as transmission limitations, stability and security.

APPENDICES

Appendix A

Loss Equation Derivation [2]

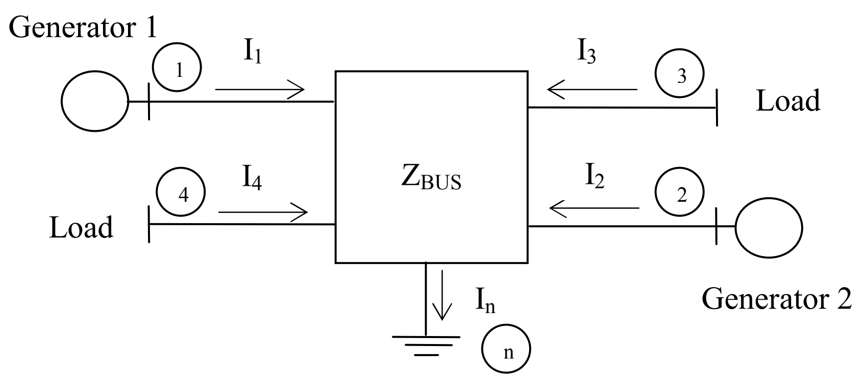

Fig.A.1 A Four Bus System Example

The current injections I_3 and I_4 at the load buses of Fig.A.1 are combined together to form the composite system load I_D given by

$$I_3 + I_4 = I_D \tag{A.1}$$

Assuming that each load is constant fraction of the total load, we set

$$I_3 = d_3 I_D \quad \text{and} \quad I_4 = d_4 I_D \tag{A.2}$$

From which it follows that

$$d_3 + d_4 = 1 \tag{A.3}$$

We now choose node (n) as reference for the nodal equations

$$\begin{bmatrix} V_{1n} \\ V_{2n} \\ V_{3n} \\ V_{4n} \end{bmatrix} = \begin{bmatrix} Z_{11} & Z_{12} & Z_{13} & Z_{14} \\ Z_{21} & Z_{22} & Z_{23} & Z_{24} \\ Z_{31} & Z_{32} & Z_{33} & Z_{34} \\ Z_{41} & Z_{42} & Z_{43} & Z_{44} \end{bmatrix} \begin{bmatrix} I_1 \\ I_2 \\ I_3 \\ I_4 \end{bmatrix} \tag{A.4}$$

We can write

$$V_{1n} = Z_{11}I_1 + Z_{12}I_2 + Z_{13}I_3 + Z_{14}I_4 \tag{A.5}$$

Substituting in this equation for $I_3 = d_3 I_D$ and $I_4 = d_4 I_D$, then solving the resultant equation for I_D yield

$$I_D = \frac{-Z_{11}}{d_3 Z_{13} + d_4 Z_{14}} I_1 + \frac{-Z_{12}}{d_3 Z_{13} + d_4 Z_{14}} I_2 + \frac{-Z_{11}}{d_3 Z_{13} + d_4 Z_{14}} I_n^{\circ} \tag{A.6}$$

In which the current I_n°, called the no-load current, is simply

$$I_n^{\circ} = -\frac{V_{1n}}{Z_{11}} \tag{A.7}$$

We can write

$$t_1 = \frac{Z_{11}}{d_3 Z_{13} + d_4 Z_{14}} \quad \text{and} \quad t_2 = \frac{Z_{12}}{d_3 Z_{13} + d_4 Z_{14}} \tag{A.8}$$

We can simplify the coefficients of Eq. (A.6), which then becomes

$$I_D = -t_1 I_1 - t_2 I_2 - t_1 I_n^{\circ} \tag{A.9}$$

Substituting in Eq. (A.2) for I_D from Eq. (A.9), we get

$$I_3 = -d_3 t_1 I_1 - d_3 t_2 I_2 - d_3 t_1 I_n^{\circ} \tag{A.10}$$

$$I_4 = -d_4 t_1 I_1 - d_4 t_2 I_2 - d_4 t_1 I_n^{\circ} \tag{A.11}$$

Eq. (A.10) and Eq. (A.11) can be used to define the transformation C of “old” currents I_1, I_2, I_3, and I_4 to the set of “new” currents I_1, I_2 and I_n°

$$\begin{bmatrix} I_1 \\ I_2 \\ I_3 \\ I_4 \end{bmatrix} = \begin{bmatrix} 1 & . & . \\ . & 1 & . \\ -d_3t_1 & -d_3t_2 & -d_3t_1 \\ -d_4t_1 & -d_4t_2 & -d_4t_1 \end{bmatrix} \begin{bmatrix} I_1 \\ I_2 \\ I_n^{\circ} \end{bmatrix} = C \begin{bmatrix} I_1 \\ I_2 \\ I_n^{\circ} \end{bmatrix} \tag{A.12}$$

The expression for the real power loss of the network can be written as

$$P_L = \begin{bmatrix} I_1 & I_2 & I_n^{\circ} \end{bmatrix} \begin{bmatrix} C^T R_{bus} C^* \end{bmatrix} \begin{bmatrix} I_1 \\ I_2 \\ I_n^{\circ} \end{bmatrix}^* \tag{A.13}$$

Where R_{bus} is the symmetrical real part of Z_{bus} of Eq (A.4). At each generator bus we can assume that the reactive power Q_{g_i} is a constant fraction s_i of the real power P_{g_i} or in other words we can say that each generator operates at a constant power factor, so we can write as

$$P_{g1} + jQ_{g1} = (1 + js_1)P_{g1}; \quad P_{g2} + jQ_{g2} = (1 + js_2)P_{g2} \tag{A.14}$$

Where $s_1 = \frac{Q_{g1}}{P_{g1}}$ and $s_2 = \frac{Q_{g2}}{P_{g2}}$ are real numbers. The output currents from the generators are then given by

$$I_1 = \frac{(1-js_1)}{V_1^*}P_{g1} = \alpha_1 P_{g1}; \quad I_2 = \frac{(1-js_2)}{V_2^*}P_{g2} = \alpha_2 P_{g2} \tag{A.15}$$

We can write as

$$\begin{bmatrix} I_1 \\ I_2 \\ I_n^{\circ} \end{bmatrix} = \begin{bmatrix} \alpha_1 & . & . \\ . & \alpha_2 & . \\ . & . & I_n^{\circ} \end{bmatrix} \begin{bmatrix} P_{g1} \\ P_{g2} \\ 1 \end{bmatrix} \tag{A.16}$$

Now substituting in Eq. (A.13), we obtain

$$P_L = \begin{bmatrix} P_{g1} \\ P_{g2} \\ 1 \end{bmatrix}^T \begin{bmatrix} \alpha_1 & . & . \\ . & \alpha_2 & . \\ . & . & I_n^{\circ} \end{bmatrix} C^T R_{bus} C^* \begin{bmatrix} \alpha_1 & . & . \\ . & \alpha_2 & . \\ . & . & I_n \end{bmatrix}^* \begin{bmatrix} P_{g1} \\ P_{g2} \\ 1 \end{bmatrix}^* \tag{A.17}$$

We can write as

$$T_\alpha = \begin{bmatrix} \alpha_1 & . & . \\ . & \alpha_2 & . \\ . & . & I_n^{\circ} \end{bmatrix} C^T R_{bus} C^* \begin{bmatrix} \alpha_1 & . & . \\ . & \alpha_2 & . \\ . & . & I_n \end{bmatrix}^*$$

If A, B, C are three matrices then we can write as $(ABC)^{T} = C^{T}B^{T}A^{T}$ and $(ABC)^{T*} = C^{T*}B^{T*}A^{T*}$ (from matrix multiplication properties). So by adding T_{α} and T_{α}^{*} cancels out the imaginary parts of the off-diagonal elements and we obtain twice the symmetrical real part of T_{α}, which we denote by

$$\begin{bmatrix} B_{11} & B_{12} & B_{10}/2 \\ B_{21} & B_{22} & B_{20}/2 \\ B_{10}/2 & B_{20/2} & B_{00} \end{bmatrix} = \frac{T_{\alpha} + T_{\alpha}^{*}}{2} \tag{A.18}$$

Using Eq. (A.17) and Eq. (A.18), we get

$$P_{L} = \begin{bmatrix} P_{g1} & P_{g2} & 1 \end{bmatrix} \begin{bmatrix} B_{11} & B_{12} & B_{10}/2 \\ B_{21} & B_{22} & B_{20}/2 \\ B_{10}/2 & B_{20/2} & B_{00} \end{bmatrix} \begin{bmatrix} P_{g1} \\ P_{g2} \\ 1 \end{bmatrix} \tag{A.19}$$

In which B_{12} equals B_{21}. We can write the Eq. (A.19) as follows:

$$P_{L} = B_{11}P_{g1}^{2} + 2B_{12}P_{g1}P_{g2} + B_{22}P_{g2}^{2} + B_{10}P_{g1} + B_{20}P_{g2} + B_{00}$$

The more general vector matrix formulation

$$P_L = P_G{}^T B P_G + P_G{}^T B_0 + B_{00}$$

If a system has K sources, then the general form of the transmission loss equation can be written as follows

$$P_L = \sum_{i=1}^{K}\sum_{j=1}^{K} P_{gi} B_{ij} P_{gj} + \sum_{i=1}^{K} B_{io} P_{gi} + B_{00}$$

The B terms are called loss coefficients or B-coefficients and the $K \times K$ square matrix B, which is always symmetrical, is known simply as the B matrix.

Appendix B

Table B.1 Bus Data

Bus Number	Bus Type (1-Slack) (2- P-V) (0-Load)	V (p.u)	θ (degree)	Load		Generation	
				PL (MW)	QL (MVAR)	PG (MW)	QG (MVAR)
1	1	1.060	0.0	0.0	0.0	232.4	-16.9
2	2	1.045	- 4.98	21.7	12.7	40.0	42.4
3	2	1.010	-12.72	94.2	19.0	0.0	23.4
4	0	1.019	- 10.33	47.8	- 3.9	0.0	0.0
5	0	1.020	- 8.78	7.6	1.6	0.0	0.0
6	2	1.070	- 14.22	11.2	7.5	0.0	12.2
7	0	1.062	- 13.37	0.0	0.0	0.0	0.0
8	2	1.090	- 13.36	0.0	0.0	0.0	17.4
9	0	1.056	- 14.94	29.5	16.6	0.0	0.0
10	0	1.051	- 15.10	9.0	5.8	0.0	0.0
11	0	1.057	- 14.79	3.5	1.8	0.0	0.0
12	0	1.055	- 15.07	6.1	1.6	0.0	0.0
13	0	1.050	- 15.16	13.5	5.8	0.0	0.0
14	0	1.036	- 16.04	14.9	5.0	0.0	0.0

$MVA_{base} = 100$

Table B.2 Branch Data

Bus		Series Impedance		Shunt Impedance (B/2) (p.u)	Branch Type (0 - T.L) (1-Transf.)	Transformer Tap	
From	To	R (p.u)	X (p.u)			Mag. (p.u)	Angle (Deg.)
1	2	0.01938	0.05917	0.0264	0	0	0
1	5	0.05403	0.22304	0.0246	0	0	0
2	3	0.04699	0.19797	0.0219	0	0	0
2	4	0.05811	0.17632	0.0170	0	0	0
2	5	0.05695	0.17388	0.0173	0	0	0
3	4	0.06701	0.17103	0.0640	0	0	0
4	5	0.01335	0.04211	0	0	0	0
4	7	0.0	0.20912	0	1	0.978	0
4	9	0.0	0.55618	0	1	0.969	0
5	6	0.0	0.25202	0	1	0.932	0
6	11	0.09498	0.19890	0	0	0	0
6	12	0.12291	0.25581	0	0	0	0
6	13	0.06615	0.13027	0	0	0	0
7	8	0.0	0.17615	0	0	0	0
7	9	0.0	0.11001	0	0	0	0
9	10	0.03181	0.08450	0	0	0	0
9	14	0.12711	0.27038	0	0	0	0
10	11	0.08205	0.19207	0	0	0	0
12	13	0.22092	0.19988	0	0	0	0
13	14	0.17093	0.34802	0	0	0	0

$MVA_{base} = 100$

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