OPTIMAL ECONOMIC OPERATION OF ELECTRIC POWER SYSTEMS USING GENETIC BASED ALGORITHMS

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ABSTRACT

The thesis explores the potential of Genetic Algorithms (GAs) for optimising the operation of electric power systems. It discusses methods which have resulted in significant direct cost saving in operating an electric power system. In particular, the thesis demonstrates the simple search procedure and the powerful search ability of GAs in multi-modal, multi-objective problems, which are resisted by the most well known conventional techniques. Special emphasis has been given to the effectiveness of the enhanced genetic based algorithms and the importance of sophisticated problem structures. Finally, the feasibility and suitability of genetic based algorithms for power system optimisations are verified on a real power supply system.

The basic requirement in operating a power system is to ensure that the whole system is run at the minimum possible cost, and the lowest possible pollution level, while reliability and security are maintained. These requirements have resulted in a wide range of power system optimisation problems. In this work, a selection of problems concerning operation economy, security and environmental impact have been dealt with by Genetic Algorithms. These problems are in order of increasing complexity as the project progresses: they range from static problems to dynamic problems, single objective to multi-objectives, softly constrained problems to harshly constrained problems, simple problem structure to more rigorous problem structure. Despite the diversity, GAs consistently produce solutions comparable to conventional techniques over the wide range of problem spectrum. It has been clearly demonstrated that a sophisticated problem structure can bring significant financial benefits in system operation, it has however added further complexity to the problem, where the best result may only be sought from the genetic based algorithms. The enhancements of Genetic Algorithms have been investigated with the aim of further improving the quality and speed of the solution. They have been enhanced in two levels: the first is to develop advanced genetic strategies, and this is subsequently refined by choosing optimal parameter values to further improve the strategies. The outcome of the study clearly indicates that genetic based algorithms are very attractive techniques for solving the ever more complicated optimisations of electric power systems.

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CONTENTS

List of Acronyms

GA:	genetic algorithm
CT:	conventional techniques
CGA:	conventional genetic algorithm
HGA:	hybrid genetic algorithm
EGA:	a genetic algorithm with elitist scheme
SSGA:	steady-state genetic algorithm
RGA:	ranking genetic algorithm
TGA:	two-point crossover genetic algorithm
VGA:	genetic algorithm with a variable mutation rate
DGA:	deterministic genetic algorithm
ED:	economic dispatch
SED:	static economic dispatch
DED:	dynamic economic dispatch
VED:	economic dispatch with valve-point loading
UC:	unit commitment
VAR:	reactive power
OPF:	optimal power flow
DP:	dynamic programming
MIP:	mix-integer programming
MED:	minimum emission dispatch
EED:	economic-environmental dispatch
FS:	fuel switching
GR:	generation ramping rate constraint
NIE:	Northern Ireland Electricity

List of Symbols

F_i:	fuel cost of ith generator (\$/h or £/h)
F_t:	total cost over a period of specified time (\$ or £)
P_i:	power output of ith generator (MW)
P_{imin}:	minimum power capacity for unit i (MW)
P_{imax}:	maximum power capacity for unit i (MW)
P_D:	customer load demands (MW)
P_L:	transmission losses (MW)
B_{ij}:	transmission loss coefficients
L_i:	penalty factor for transmission losses
λ:	Lagrange multiplier
$U_d(t)$:	maximum allowable power decreas over one time interval for unit i (MW)
$U_u(t)$:	maximum allowable power increase over one time interval for unit i (MW)
R(t):	spinning reserve for a power system at time t (MW)
E_{ij}:	type j emission produced by ith generator (Tons/h)
S_i:	fuel ratio between the high polluting and low polluting fuels
Q_{max}:	maximum allowable pollution level for a power system (Tons or Tons/h)
F:	fitness value
Fs:	scaling fitness value

CHAPTER

1

INTRODUCTION

1.1 THE ROLE OF OPTIMISATION TECHNIQUES IN OPTIMAL OPERATION OF ELECTRIC POWER SYSTEMS

The electricity industry suffers from the fact that electricity cannot be stored (apart from the limited storage available in pumped - storage plants), but must be generated when required. In addition, requirements of frequency and voltage stability makes necessary a rather precise matching between load (the demand on the system from the consumer) and generation (the supply from the power station). Moreover, recent public outcry for environmental protection makes it essential for a power system to provide adequate and reliable electricity not only at the cheapest possible cost, but also at the least level of pollution of the atmosphere. Therefore, electric power system operation is among the most important and complex tasks in today's civilisation. It has to involve many considerations. The basic requirement is to generate adequate electricity to meet continuously changing customer load demand at the lowest possible cost. Of equal importance is the need to reduce the pollution impact on the environment which is mainly from thermal plant fuel emission. System security and reliability constraints also have to be taken into account to provide high standards of voltage stability and continuous supplies of electricity. Though interconnection of power systems has improved the continuity of service and reliability, it has added further constraints and complication related to stability and security. These considerations form various optimisation problems for a power system engineer to deal with [El-Hawary, 1979]. The typical problems include economic dispatch, reactive power scheduling and allocation, maximum interchange, hydrothermal unit commitment and dispatch, generation, transmission and distribution expansion planning, and maintenance scheduling, and many others. These problems become progressively more complicated due to ever growing system size, stricter governmental and environmental regulations, and increased requirement of system integration. Power industries face great pressure to better utilise the existing network so as to defer power system reinforcement. As a result, improved operation strategies are in great demand.

There emerge two directions for research which are important in achieving the goal of optimal operation in power systems: one is towards the development and formulation of a rigorous body of knowledge concerning problems of increased complexity; the other is towards the development of powerful optimisation and computational techniques. The optimal operation of power systems is strongly influenced by the availability of advanced algorithms. The efficiency of an algorithm directly decides the acceptability of optimal operational strategies once the problem formulation is certain. Although there is extensive literature on how to effect algorithmic efficiencies [Sasson, 1974], it must be realised that conventional techniques (CTs), such as non-linear, linear; quadratic, and dynamic programming, are not good enough to solve the problem in all respects. Early experience showed that the CTs face difficulties in dealing with the increased complexity of multi-modal, multi-objective, highly constrained power optimisation problems, and limited either by convergence problems, solution accuracy and/or computational efficiency. Furthermore, these techniques are susceptible to unforseeable constraints and contingencies which occur in the field, and the solution thus obtained is not robust and is case sensitive. Although the popular dynamic programming technique is attractive in its ability in dealing with a variety of problems, its applications remain successful only on moderate sized systems. It is difficult to scale up due to the exponentially increased requirements of computing memory and time with an increasing number of generators. Consequently, the disadvantages of the CTs have provoked a strong requirement for a more accurate and efficient algorithm to enable better utilisation of existing power systems. The research work documented in this thesis is stimulated by such a growth demand, and offers alternative Genetic Algorithm based approaches to the optimisation problems of optimal economic operation in power systems.

Genetic Algorithms (GAs) which are inspired from Charles Darwin's natural evolutionary theory, 'survival of the fittest', have gained increasing recognition in many engineering fields. This is largely due to its potential in handling complex problems, where conventional techniques have not achieved the desired speed, accuracy and efficiency. The major attraction of GAs lies in that the algorithms are computationally simple yet powerful in their search for the global optimum. What is more, the algorithms are not fundamentally limited by restrictive assumptions concerning continuity, and/or the existence of gradient information, but allow non-linearities and discontinuities to appear in the search space. GAs are thus potentially attractive techniques for solving many practical difficult problems which are either impossible to solve or are not easily solved by conventional means. Furthermore, the more complex the problem is, the more benefit that one can get from GAs. Since the GA was first introduced to solve reactive power scheduling in [Ajjarapu, 1991], many papers ([Walters, 1993], [Mori, 1993] etc.) have appeared to study the feasibility and capability of GAs over a broad range of power system optimisation problems. Researchers in this field are active in two directions: one is further improving computational efficiencies of the conventional Genetic Algorithms, another is seeking more application areas in the system planning and operations. This thesis puts efforts into both of the research directions with the aim of providing guidance in formulating robust, efficient and flexible system operating strategies, where the search space is large, complex, and/or poorly understood. Ultimately, costly redesigns can be reduced or eliminated.

1.2 MAJOR CONTRIBUTIONS OF THE THESIS

There are five major contributions documented in this thesis. The work has:

(1) Investigated the accuracy, efficiency and robustness of GAs over a selection of power optimisation problems under various system and operational constraints.

(2) Investigated the possible performance enhancements with a number of advanced Genetic based algorithms applied to Economic Dispatch problems. The research

clearly demonstrated the improved search ability of the proposed Hybrid Genetic Algorithms over the commonly defined Genetic Algorithms.

(3) Proposed a novel two-phased problem structure by employing both the Economic - Environmental technique and Fuel Switching to maximum emission reduction capacity and reduce the need for costly plant level action.

(4) Proposed a novel constraint handling method for GAs to easily handle various constraints in a ever more complex problem landscape resulting from the environmental and security issues.

(5) Further tested the capability and the suitability of GAs and HGAs on a number of economic dispatch problems in a practical moderately sized system.

1.3 OVERVIEW OF THE THESIS

This research work has attempted to investigate the potential of a class of GAs compared with conventional techniques on a variety of power system optimisation problems, and has demonstrated the ease of GA implementation. The ultimate goal of the thesis is to provid practitioners with information and guidance in choosing a suitable genetic strategy for their own applications. The research work presented in this thesis is organised into the following 9 chapters:

Chapter 2 describes and defines electric power system optimisation problems. In depth descriptions have been given to the problems of economic dispatch, unit commitment, reactive power planning and dispatching, and emission dispatch. Current popular methods to solve these four problems are reviewed, and their strength and weakness are discussed.

Chapter 3 states the general framework of optimisation problems. GAs are then defined and their mathematical foundation is outlined. This is followed by a summary of the unique characteristics of GAs and a review of their application in power system optimisations. Finally, a detailed genetic implementation procedure is presented.

Chapter 4 makes a performance comparison on the classic static economic dispatch problem between a commonly defined GA and a few conventional techniques, such as Priority List and Lambda Iterative method. The strength and weakness of GA techniques over conventional techniques are discussed.

Chapter 5 firstly investigates the possible performance improvements with the advanced genetic strategies and optimal genetic parameter tuning on a classic static Economic Dispatch problem. Several conclusions have been drawn upon performance enhancements. However, improvements thus made can only balance the two conflicting search efforts: exploration and exploitation, which implies that the increased solution quality comes at the cost of a longer computing time and vice versa. They can not be improved at the same time. Yet, by crossing a GA with other well-known local search techniques, a Hybrid Genetic Algorithm (HGA) makes it possible to both improve the solution quality and the solution speed. The second part of chapter puts emphasis on the potential search ability that a HGA exhibits over a pure GA.

In chapter 6, GAs are applied to the dynamic economic dispatch problem. The difficulties with this problem are that the solution should be able to track the time varying load demand, and that the solution has to be attained under the additional dynamic constraints which limit the search space severely.

In chapter 7, the problem of optimal operation of power systems has advanced from the single cost consideration to the combined cost and emission considerations. The emission issue enters the conventional economic dispatch problem as an additional constraint, which complicates the search space much more. In order to maximise the emission reduction capacity without major plant level actions, such as pre- or post-combustion processing, a two-phased problem structure is proposed by incorporating the economic-environmental dispatch together with the fuel switching. The proposed structure is proven to be effective in both cost reduction and emission alleviation.

Chapter 8 deals with multi-objective economic-environmental problems, where the environmental issue adds a second object to the original cost objective function as well as an additional constraint. A trade-off relation between cost and emission is set up to assist the decision maker to find the best operating point. To further enhance the genetic search ability, a novel constraint handling method is proposed to incorporate the concept of how far a solution is away from the feasible region so as to give better guidance to the search in the highly constrained problem space, consequently attain a better overall solution ultimately.

In Chapter 9, a commonly defined GA and the proposed HGAs are challenged by a practical moderate sized power system - Northern Ireland Electricity (NIE). Satisfactory results are obtained with the CGA technique. Yet, HGAs are more favourable over the CGA for their ability to provide more accurate solutions with less computing time.

Finally, Chapter 10 summaries the thesis and offers suggestions for future work of GAs in power system optimisations..

CHAPTER

2

OPTIMAL ECONOMIC OPERATION IN POWER SYSTEMS: PROBLEMS, MODELS AND TECHNIQUES

This chapter gives definitions and descriptions of some optimisation problems in electric power systems. The mathematical formulations for those problems are outlined, and reviews of various technical approaches to the problems are summarised.

2.1 OPTIMISATION PROBLEMS IN POWER SYSTEMS

In recent years, because of strict environmental and governmental regulations, the development of electrical power facilities has been restricted. As a result, optimal economic operation and planing of power systems becomes increasingly difficult. Problems such as: economic dispatch, emission dispatch, reactive power scheduling and allocation, maximum interchange, unit commitment and dispatch, generation, transmission and distribution expansion planning, and maintenance scheduling, as well as many other matters, are so diverse that economic operation of power systems becomes a sophisticated and very difficult task. It is made even more formidable with multi-objective optimisation problems which consist of several objectives and are subjected to a number of constraints in one problem formulation. Yet, multi-objective formulation expresses complex and highly interactive power problems in a more realistic way. The followings are brief descriptions of some power system optimisation problems [Sasson, 1974].

Economic Dispatch (ED) is among the most important issue in power system operation. The goal of the ED is that of scheduling the level of power output on the preselected units to match the customer load demand in order to achieve minimum operating cost. When excess generation is available in a system such that an economic choice of units can be made, unit commitment (UC) should be employed to determine the on or off schedule of generating units within a system to provide dispatchable units. Unit commitment and power dispatch are so much coupled that they tend to be solved simultaneously in recent research. With the increasing concern about environmental protection, alternative operational strategies are required. Emission Dispatch (EMD) which aims to reduce pollution from power plants while meeting the system's energy demand, has gained ever growing attention. The goal of reactive power scheduling and allocation is to provide a system with enough reactive power (VAR) sources for the system to operate in an economic manner, while load constraints and operational constraints, with respect to credible contingencies, are met. Maximum interchange is a means for utilities to decide the maximum interchange with the neighbouring interconnected systems ahead of time in case transmission contingencies occur. Optimal switching can be set up to minimise the number of switching operations for intermediate and low-voltage substations which link the high-voltage transmission system and the distribution networks of local loads, in order to alter the configuration of the substation for system reliability and protection purposes. This is the case when devices need to undergo maintenance or when emergency situations occur, which results in the need for configuration changes. Among these power optimisation problems, this thesis mainly deals with economic dispatch, emission dispatch and their extensions and combinations. Unit Commitment will be an extension of the current research work.

2.2 ELECTRIC POWER SYSTEM MODEL

A power system is basically composed of generation plants, transmission lines and loads.

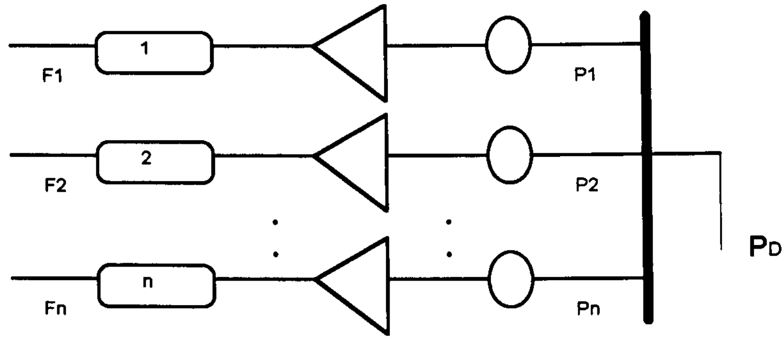


Figure 2.1 Power system model.

A simplified system is illustrated in Figure 2.1, which consists of n generator units connected to a single bus-bar, serving a received customer load. Basically, power enters a transmission system from energy (or power) source to supply load demand. The energy source can be thermal power plants, hydro-power plants, or a neighbouring system through interconnection. In this study it is assumed that all generator units are thermal. From an economic operation point of view, the energy source is the major concern. The fundamental requirement for the economic operation is a set of input-output characteristics of a thermal generator unit [Kirchmayer, 1958]. The input is the fuel cost, F_i, the output is the electrical power output, P_i, from generator i to supply the load demand P_D. An idealised input-output (F_i-P_i) form is a smooth, convex curve, as depicted in Figure 2.2. It can be fitted as a quadratic or linear function of the active power generation according to the utilities' preference, which can be expressed as:

$$F_i(P_i) = a_i P_i^2 + b_i P_i + c_i \qquad \text{(Quadratic Function)} \quad (2.1)$$

$$F_i(P_i) = a_i P_i + b_i \qquad \text{(Linear Function)} \quad (2.2)$$

For large steam turbine generators, the input-output characteristics are not as smooth as illustrated in Figure 2.2. Large generators have a number of steam admission valves that are opened in sequence to obtain ever-increasing output of the units. When a valve is newly opened due to the increasing load, the throttling losses increase rapidly and the incremental heat rate rises suddenly, which leads to the discontinuity in incremental heat rate characteristic. This type of input-output characteristic, shown in Figure 2.3, is non-convex. Therefore the normal optimisation techniques which require convex characteristics face great difficulties and can not give accurate results.

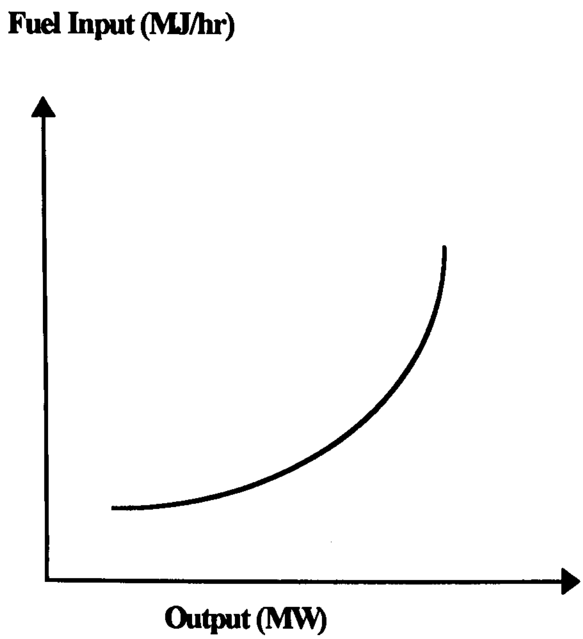


Figure 2.2 Convex fuel input-output curve.

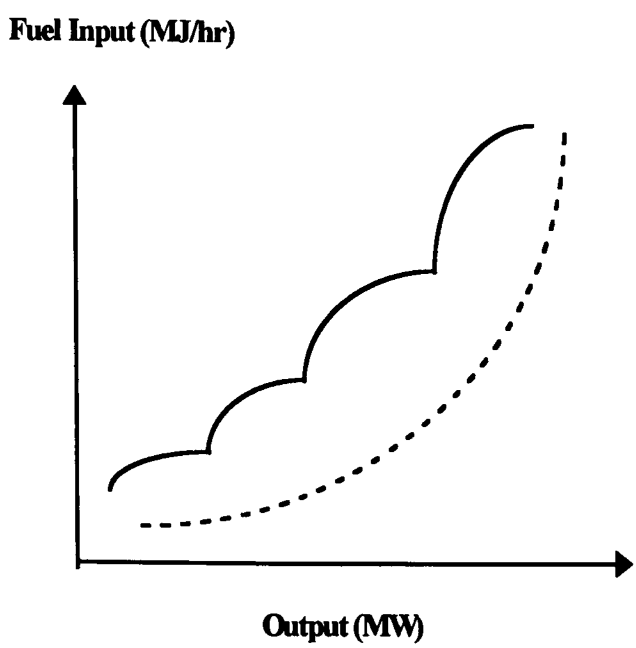


Figure 2.3 Multi-valve point input-output curve.

2.3 ECONOMIC DISPATCH

The Economic Dispatch (ED) problem is a constrained, non-linear optimisation problem. It has been actively studied since its inception in the 1920's, as reviewed by Happ [1977], an IEEE Working Group Report [1981] and Chowdhury [1990]. The starting point was the static economic dispatch, which aims to minimise total fuel cost by scheduling the level of power outputs for each committed unit at certain time so that the load demand at that time is met and each generator operates within its capacity. Soon after, it was realised that when applied to a practical power system, a perfect solution of the classic ED problem may not be optimal for real systems, which have been further constrained by: (i) security and reliability constraints, such as generator ramping limit, transmission limits and spinning reserve constraints; (ii) approximate fuel cost characteristic (without considering valve point loading); (iii) not considering future load trend. In the light of the above problems, security assessment and enhanced modelling have been introduced to broaden the classic ED formulation. With respect to the desired accuracy and relevance to the problem considered, the ED problem is further classified into following four categories:

(1) Static Economic Dispatch with or without transmission losses (SED).

(2) Dynamic Economic Dispatch (DED).

(3) Economic Dispatch with valve-point considerations (VED).

(4) Optimal power flow.

A detailed description, for each problem, is given in the next four sections, while the technical review is only given to those problems which will be investigated in this research.

2.3.1 STATIC ECONOMIC DISPATCH (SED)

Suppose a power system consists of n generators that are in on-line operation as shown in Figure 2.1. The generation level of each unit is denoted by P_i and the load demand to be supplied is denoted by P_D. The fuel cost C_i incurred by each unit can be expressed as a function of the power output P_i:

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

Where a_i, b_i, c_i are constant parameters for unit i. The total operational cost associated with this system is:

$$F_t = \sum_{i=1}^{N} C_i$$

The objective of the ED problem is to minimise the total operation cost, F_t, by scheduling individual generator output, P_i, for each unit. The essential operation constraints are the power balance constraint, where the total generated power must be equal to the load demand, and the power limits constraint, where each individual generator unit must be operated within its specified range. Let P_{imin} represent the minimum power capacity for unit i, and let P_{imax} denote the maximum power capacity. The power limits constraint is then given by:

$$P_{imin} \le P_i \le P_{imax}$$

The power balance constraint is stated differently according to the consideration of transmission network loss.

A Transmission loss is neglected:

When transmission loss is neglected, the power balance constraint is:

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

B Transmission loss is considered:

When transmission loss is included in the network, the power balance equation becomes:

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

Transmission loss inclusion will result in potential saving in fuel cost. It is also very important in future power system planning regarding the location of plants and the building of transmission lines. Transmission loss was discussed in detail by [Kirchmayer, 1958], who proposed to express the transmission loss as a function of the power output of each unit, namely B matrix:

$$P_L = B_{00} + \sum_{i=0}^{n} B_{i0}P_i + \sum_{i=0}^{n}\sum_{j=0}^{n} P_i B_{ij} P_j$$

where B_{ij} are constant coefficients determined by the network.

2.3.1.1 SED Objective Formulation

Finally, the mathematical formulation of SED problem can be stated as the constrained optimisation problem as given by the following equations:

$$\min \quad F_t = \sum_{i=1}^{N} C_i = \sum_{i=1}^{N} (a_i P_i^2 + b_i P_i + c_i) \tag{2.3}$$

$$\text{subject to:} \quad P_{imin} \le P_i \le P_{imax} \tag{2.4}$$

$$\sum_{i=1}^{n} P_i - P_D = 0 \quad \text{(Transmission neglected)} \tag{2.5}$$

$$\text{or} \quad \sum_{i=1}^{n} P_i - P_L - P_D = 0 \quad \text{(Transmission included)} \tag{2.6}$$

$$\text{where:} \quad P_L = B_{00} + \sum_{i=0}^{n} B_{i0}P_i + \sum_{i=0}^{n}\sum_{j=0}^{n} P_i B_{ij} P_j \tag{2.7}$$

The problem of the SED is to find the optimal generation output for each unit P_i, so that the cost F_t in equation (2.3) is minimised, while either equations (2.4) and (2.5) are satisfied (when transmission loss is neglected), or equations (2.4) and (2.6) are satisfied (when transmission loss is considered).

2.3.1.2 Review of Techniques

(1) Merit Order Techniques

Prior to 1930, the most popular methods used for the SED problem included: (1) the base load method, where the next most efficient unit is loaded to its maximum capacity, then the second most efficient unit is loaded; and so on; (2) best point loading, where units are successively loaded to their lowest heat rate point beginning with the most efficient unit, and working down to the least efficient units. Both methods are very easily implemented, since mathematically they involve a simple sorting function to rank individual units into order according to their efficiency. However, such dispatch policies are not the most economic way to allocate load demands.

(2) Lambda Iterative Method

It was as early as 1930 that the idea of equal incremental method was recognised to yield the most economic results. The idea of equal incremental cost is: when the next incremental cost of all generating units are equal, the system is operated in the most economic manner. The initial approach to the equal incremental method is to transfer the constrained minimisation problem into unconstrained optimisation with the Lagrange multiplier, which is expressed as:

$$F = Ft - \lambda\psi \tag{2.8}$$

where ψ is equation (2.5) for the case of neglected transmission loss. The optimal operating strategy is achieved when:

$$\frac{\partial F_1}{\partial P_1} = \frac{\partial F_2}{\partial P_2} = \frac{\partial F_i}{\partial P_i} = \lambda \tag{2.9}$$

For the case of transmission losses included, ψ represents equation (2.6) and the optimal operation is achieved when:

$$L_1 \frac{\partial F_1}{\partial P_1} = L_2 \frac{\partial F_2}{\partial P_2} = L_i \frac{\partial F_i}{\partial P_i} = \lambda \qquad (2.10)$$

Where L_i is a penalty factor for transmission losses, and is defined as:

$$L_i = [1 - (\partial P_L / \partial P_i)]^{-1} \qquad (2.11)$$

When the generator outputs are at their operational limits, the necessary conditions need slightly changing to:

$$\frac{\partial F_i}{\partial P_i} \le \lambda \qquad \text{for} \qquad P_i = P_{i,,max} \qquad (2.12)$$

$$\frac{\partial F_i}{\partial P_i} \ge \lambda \qquad \text{for} \qquad P_i = P_{i,,min} \qquad (2.13)$$

The Lambda iteration method [Wood, 1984] is a quite efficient way to find the equal incremental cost among the committed units. This popular method tends to find the optimal λ through iterative procedure for equation (2.9) or (2.10), and subsequently find the optimal power output P_i for each generating unit. The method is very simple, has very quick convergent speed and gives satisfactory results. Yet, it has difficulties in including the additional objectives and constraints when more rigorous problem formulation is encountered which is desired in practical applications.

(3) Gradient Techniques

Another set of popular methods are the search techniques, such as the first and second order gradient methods [Wood, 1984]. These methods tend to find search direction from where the maximum improvements are sought. The Gradient technique has a desirable characteristic in that it always starts off with a feasible solution (though it is not necessary), and searches for the optimum solution along a trajectory that maintain a feasible solution at all times. This characteristic ensures that the gradient information can provide a feasible solution even if the computational procedure is interrupted midway through the calculation. The disadvantages associated with these methods are: they require a great deal of understanding of the problems; they are susceptible to the initial starting point, subsequently can be easily trapped in a local minimum; they can be sensitive to the determination of the gradient step size. However, once the initial point is located in the potential area, and the gradient information does exist, gradient techniques guarantee finding the global optimum.

2.3.2 DYNAMIC ECONOMIC DISPATCH

The aim of Dynamic Economic Dispatch (DED) is to allocate load among the available generating units using knowledge of both the present and the predicted load to minimise the fuel cost over a short period of time, while meeting some instantaneous constraints. The DED considers temporal costs and uses forecasts of system load to develop optimal generator output trajectories for the generators to follow. The DED incorporates the costs which correspond to the change of generator output over some period of time to provide more accurate results, enabling the cost saving. The Static Economic Dispatch is a special case of the DED, which contains merely one time interval.

Considering the n generators network from Figure 2.1, the DED problem tends to minimise the operating cost Ft over a time period T:

$$Ft = \sum_{t=1}^{T} \sum_{i=1}^{n} C_{i,t} = \sum_{t=1}^{T} \sum_{i=1}^{n} (a_i P_{i,t}^2 + b_i P_{i,t} + c_i)$$

where the load demand is given as $P_{D,i}$ and transmission loss is $P_{L,i}$, both at the time interval i.

The essential operational constraints, power balance constraint and power limitation constraint at any time t are given by:

$$\sum_{i=1}^{n} P_{i,t} - P_{L,t} - P_{D,t} = 0$$

$$P_{imin} \leq P_i \leq P_{imax}$$

Additional Constraints

The additional instantaneous constraints typically include power ramp rate limit and spinning reserve constraint.

(1) Ramping Rate Constraint

In practice it is extremely important to account for the ramp rate constraint. When a change of a generator unit output is required due to the load variation, the maximum permissible output change should be limited to a certain level in order to avoid wide variation of process variables (i.e. temperature, pressure, and boiler water level). This ensures the safety of the equipment and smoother control of power output. The ramp rate constraint of a generator is a dynamic operational constraint. The mathematical formulation is given as:

$$P_i(t) - U_d(t) \leq P_i(t+1) \leq P_i(t) + U_u(t)$$

where $U_u(t)$ is the maximum increase in output of generator i over one time interval, and $U_d(t)$ is the maximum decrease in power output over one time interval.

(2) Spinning Reserve Constraint

Spinning reserve R(t) is defined as the amount of unused power which can be delivered within short time by the committed generators. This power is reserved to improve the reliability of the system to cover cases such as: unexpected changes in the demand, load prediction error, sudden loss of equipment. The spinning reserve for each committed generator at time t is P_{imax} - $P_i(t)$. The spinning reserve constraint for the N generator system is expressed as:

$$\sum_{i=1}^{N} [P_{imax} - P_i(t)] \geq R(t)$$

As the power balance equation at time t is: $\sum_{i=1}^{N} P_i(t) = P_D$, the spinning reserve can be transformed as:

$$\sum_{i=1}^{N} P_{imax} \geq P_D + R(t)$$

2.3.2.1 DED PROBLEM FORMULATION

In conclusion, the mathematical formulation for the DED problem over a time period t can be expressed by the following equations:

$$\min \quad Ft = \sum_{t=1}^{T} \sum_{i=1}^{N} C_{i,t} = \sum_{t=1}^{T} \sum_{i=1}^{N} (a_i P_{i,t}^2 + b_i P_{i,t} + c_i) \tag{2.14}$$

Subject to:

$$\sum_{i=1}^{n} P_{i,t} - P_{L,t} - P_{D,t} = 0 \tag{2.15}$$

$$P_{imin} \leq P_i(t) \leq P_{imax} \tag{2.16}$$

$$P_i(t) - U_d(t) \leq P_i(t+1) \leq P_i(t) + U_u(t) \tag{2.17}$$

$$\sum_{i=1}^{N} P_{imax} \geq P_D(t) + R(t) \tag{2.18}$$

2.3.2.2 TECHNICAL REVIEW

The DED problem is a highly constrained non-linear optimisation problem. The difficulties of the problem lie in its high dimensionality and multi-modal search space. Therefore, it needs sophisticated techniques to search for solutions in the difficult search space. Ross and Kim [Ross, 1980] have proposed dynamic programming for the DED problem taking into account the power rate limits, which yielded quite good results on a system comprising 15 generators. However, as the number of generator increases, the proposed technique is limited by an exponential increase in computer memory and calculation time. Bosch [1985] used a gradient projection method with conjugate search direction to solve the DED problem owing to both spinning reserve and power rate limits. The proposed method has quite comparable computing speed, but it is easy to be trapped in the local optimum if the starting point is near the local optimum. Recently, Fukuyama [1991] has discussed the application of Neural Networks to the DED problem. The new method has the advantage of easily taking more constraints and contingencies into consideration. However, Neural Network methods can not guarantee a global minimum.

2.3.3 ED WITH VALVE POINT LOADING

Large generators normally have 4 to 12 inlet control valves to control power output as shown in Figure 2.3. The rippling effect in the cost curve is the result of the procedure of sequential valve opening, where there are sharp increases in throttle loss due to the disturbance of steam flow. As a result, the efficiency is lowest when the valve is just opened, and it is highest when the valve is fully open. Most utility companies have found that it is quite acceptable to approximate this discontinuous unit input-output characteristic with a smooth quadratic function, as shown by the dotted line; consequently, the valve point effects are ignored. However, if a method avoids this approximation, overcoming the inaccuracy introduced by the approximation, one could have great financial benefit compared with the classic piece-wise linear fuel cost curves [Fink, 1969]. Valve point loading considers more detailed knowledge of the input-output characteristic of the generator units and hence requires techniques that easily model these characteristics. For such a non-monotonically increasing input-output economic dispatch problem formulation, the most general solution is based on Dynamic Programming (DP) [El-Hawary, 1979]. Unlike other traditional techniques, DP imposes no restrictions on the generating unit characteristic. However, DP suffers from the curse of dimensionality by the dramatically increased computing time and computing storage with the increase in number of generators.

2.3.4 OPTIMAL POWER FLOWS (OPF)

The OPF represents an exact system formulation to determine the voltages and phase angles at all buses of the network, from which active and reactive power outputs of generators can be found and cost can be minimised subject to security constraints [Burchett, 1982]. The advantage of the OPF does not lie in higher accuracy of results, but in its ability to include security constraints in the formulation, which is not easily handled by software using traditional ED models. The detailed study of the OPF is beyond the scope of this project.

2.4 EMISSION DISPATCH (EMD)

2.4.1 INTRODUCTION

With increasing concern about environmental protection, the conventional approach to electric power dispatch, with its emphasis on economic considerations, can no longer be sole consideration for the operation strategy. Society demands adequate and secure electricity not only at the cheapest possible price, but also at the least level to pollute the environment [Cadogan, 1975]. Therefore, when a dispatch procedure is formulated in a power plant, it is beneficial to consider both economic and environmental requirements while satisfying customer load demand.

2.4.2 EMISSION MODELLING

When power is generated from a generator unit several types of emissions are released, such as Sulphur Oxides (SO_2), Nitrogen Oxide (NO_X) and Carbon Dioxide (CO_2). They are formed in the boiler when unused oxygen combines with sulphur from coal and nitrogen from the air. The extent of the emission released from each unit can be modelled as a function of power output, which has the similar curve as the cost function. The extent of emissions produced by each unit is:

$$E_{ij} = a_{ij} + b_{ij}P_i + c_{ij}P_i^2 \tag{2.19}$$

where E_{ij} is emission of type j (i.e. SO_2, NO_X, CO_2) for unit i , P_i is i-th unit power output, a_{ij}, b_{ij}, c_{ij} are the constant coefficient for emission type j for unit i.

2.4.3 OPTIONS FOR EMISSION CONTROL

A reduction of emissions into the atmosphere can be achieved either by system redesign or by changing operational strategy. The following options are currently available to reduce emission:

(1) **Minimum Emission Dispatch (MED):** to allocate the load demand among the committed units so that the emission produced is minimised regardless of the operation cost.

Evaluation: it has been dismissed owing to the lack of cost consideration, which would result in unnecessary high cost.

(2) **Economic-Environmental Dispatch (EED):** to schedule the generators so that the one with lower emissions produces the more power output. The environmental object could either be a second objective or an additional constraint to the classic economic dispatch.

Evaluation: it shows the desirable characteristic to take account of both emission and cost, and requires minimal additional cost and least lead time. Further attraction lies in its ease of implementation. The disadvantage is its limited operational capacity.

(3) **Fuel Switching:** to replace a fuel with a high content of pollutant, such as high sulphur fuel, with one of lower polluting potential. This is a function of the ratio of fuel mix between high sulphur fuel and low sulphur fuel. Though the cost is increased, the emission produced from each generator unit is decreased.

Evaluation: this option is cost effective, needs only minor modification to the existing plant, but could be affected by the availability and the price of the fuel.

(4) **Use of scrubbers**: a post-combusting cleaning system, also known as flue gas desulphurisation.

Evaluation: it requires not only considerable time for design, testing and installation, but also considerable capital cost.

(5) Use of natural gas

Evaluation: natural gas is an attractively cheap fuel in the UK at present, especially in combined-cycle operation. However, it should be noted that not all the generator units can burn natural gas, also there is a possibility that the North Sea and the Irish Sea will be depleted in the next 20 years, and replacement will be more expensive.

Practically, most of the industrial effort has been made on plant level action, such as post-combustion modification and stack-gas scrubbing, that change of power dispatch only serves as a supplementary tool for pollution abatement. Though its operational capacity is limited, the EED strategy is attractive as it requires less lead time and less capital investment than most changes or additions to power generating equipment. In practice, it is more likely to combine several options to get the best compromise between cost and emission. In this study, EED strategy, Fuel Switching and their combination are investigated further, in order to get maximum emission reduction and minimum operational cost without major plant level action.

2.4.4 MINIMUM EMISSION DISPATCH

The issue of minimising emission was first discussed [Gent, 1971] to minimise NO_x emission rather than cost as the priority. The minimum emission strategy is defined by the functions similar to the classic economic dispatch:

$$\min \ E_t = \sum_{i=1}^{N} E_j = \sum_{i=1}^{N} (a_{ij}P_i^2 + b_{ij}P_i + c_{ij}) \tag{2.20}$$

subject to:

$$P_{imin} \le P_i \le P_{imax} \tag{2.21}$$

$$\sum_{i=1}^{n} P_i - P_L - P_D = 0 \tag{2.22}$$

where:

$$P_L = B_{00} + \sum_{i=0}^{n} B_{i0}P_i + \sum_{i=0}^{n}\sum_{j=0}^{n} P_iB_{ij}P_j \tag{2.23}$$

The obvious weakness with the MED dispatch procedure is its lacking consideration of cost, which led to the Economic-Environmental Dispatch (EED), where both economy and emission are taken into consideration.

2.4.5 ECONOMIC ENVIRONMENTAL DISPATCH

2.4.5.1 DEFINITION OF EED

The purpose of the EED power dispatch is to supply the load demand while minimising the environmental impact at the minimum possible operating cost. One complication, introduced by such a dispatch strategy, is the fact that the cost and the emission functions are two conflicting, incommensurable objectives. Favouring one objective may degrade another. There is no possibility of a third term which might minimise both of them simultaneously. The optimal solution is more likely to be the best compromise between those two.

2.4.5.2 EED PROBLEM FORMULATION

The EED problem formulation has been studied by many researchers, such as [Lamont, 1973], [Friedmann, 1974], [Zahavi, 1975], [Bernow, 1991], and [Petrovic, 1993]. A review of the mathematical formulation is given by [Talaq, 1994], which is summarised as follows:

(1) Minimise 'full cost':

$$\min \quad F = \sum_{i=1}^{N}[C_i + \alpha E_i] \tag{2.24}$$

The full cost is formed by assigning prices to emission and adding the result to the fuel cost.

(2) Minimise weighted sum of Cost and Emission:

$$\min \quad F = \sum_{i=1}^{N}[\alpha_i C_i + \beta_i E_i] \tag{2.25}$$

(3) **Minimising cost with controlled emission:**

$$\min \quad C_t = \sum_{i=1}^{N} C_i \tag{2.26}$$

$$\text{Subject to:} \quad E_t = \sum_{i=1}^{N} E_i \leq Q_{max} \tag{2.27}$$

where Q_{max} is maximum allowable emission produced.

(4) Minimising emission with constrained cost:

$$\min \quad E = \sum_{i=1}^{N} E_i \tag{2.28}$$

$$\text{Subject to:} \quad C_t = \sum_{i=1}^{N} C_i \leq C_{max} \tag{2.29}$$

where C_{max} is maximum allowable cost.

(5) Economic-environmental trade-off study:

The cost and emission trade off curve is mainly for off-line operational investigations [Heslin, 1989] and [Yokoyama, 1988]. Their studies had the goal to assist the decision maker how to approach the optimal dispatch policy. The dispatch objective is formed as a weighted sum of cost and emission:

$$\min \quad F = \sum_{i=1}^{N} [\alpha C_i + (1-\alpha) E_i] \tag{2.30}$$

The best EED policy can be found by increasing α from 0 to 1 to cover the entire search region. $\alpha = 1$ states the conventional economic dispatch, while $\alpha = 0$ accounts for minimising emission only. The best operating α is chosen by the decision maker as a compromise between the cost and the emission.

It should be noted that all minimisation strategies run the risk of emission overkill, which might lead to emissions reduced to a level below that required by environmental regulation, and result in unnecessarily high cost. Hence, practical dispatch strategies have the tendency to include the environmental objective as an additional constraint, where the dispatch policy can be either the operation cost, or the 'full cost'.

2.4.5.3 MORE RIGOROUS EED STRATEGY

Granelli et al [1992] formed a dynamic EED strategy to take into account the integral nature of the environmental constraints on the daily amount of emission. Hu and Wee [1994] presented a hierarchical dynamic EED system to combine the off-line system and on-line system to minimise both cost and emission. The treatment of multiple pollution strategy is suggested in papers [Gjengedal, 1992] and [Ramanathan, 1994], while papers [Yoloyama, 1987] and [Nakamura, 1987] include additional security constraints into the original EED policy to provide more secure and clean electric power with the least possible cost.

2.4.5.4 MATHEMATICAL APPROACH

It has been observed that most of the papers in the present literature still focus their attention on the formulation of the EED problem while only few papers have appeared to investigate the effectiveness of solutions by employing advanced techniques. Among the earliest, El-Keib and Ding [1994] presented a linear programming method to approach the EED problem. King and El-Hawary [1995] examined a Neural Network approach in finding optimal solutions for the EED problem. A more rigorous problem formulation, which has the form of heavily constrained multi-objectives, raises questions to the existing mathematical techniques. A great deal of research work still remains to be done.

2.5 FUEL SWITCHING (FS)

The EED strategy can only be used as a supplementary method to give abatement of emission, as its operational capacity is limited. Without major plant level action, another attractive method is fuel switching. FS tends to determine the optimum fuel mixture of high- and low-sulphur fuels in order to minimise total fuel cost under environmental constraint. As stated before, it is a cost effective means to reduce emission, yet requires only minor plant modification.

The operational cost in this case is more complex. It becomes the function of both power output and fuel ratio:

$$F_i = (\alpha_i - \beta_i S_i)(a_i + b_i P_i + c_i P_i^2)$$

where α_i, β_i are the cost per kcal coefficients, and a_i, b_i, c_i are fuel consumption coefficients.

The newly appeared variable S_i is the sulphur contents in fuel for unit i. The sulphur contents in fuel for each unit is determined by the mix ratio of high and low sulphur fuels. Assuming the percentage of high sulphur content SU_i(%) is W_i(W_i<1.0), the low sulphur fuel with SL_i(%) then becomes (1-W_i). The overall sulphur in fuels can thus be expressed as:

$$S_i = SU_i \times W_i + SL_i \times (1 - W_i)$$

The additional inequality constraint introduced by fuel switching is the upper and lower bounds upon sulphur in fuels, and is expressed as:

$$SL_i \le S_i \le SU_i$$

where SL_i, SU_i are the maximum and minimum sulphur contents in fuels respectively. The emission produced at each unit is:

$$E_i = e_i S_i (a_i + b_i P_i + c_i P_i^2)$$

2.5.1 FS PROBLEM FORMULATION

The complete FS problem formulation is given by following equations:

$$\min \quad Fs = \sum_{i=1}^{n} F_i(P_i, S_i) \tag{2.31}$$

subject to:

$$P_{imin} \le P_i \le P_{imax} \tag{2.32}$$

$$\sum_{i=1}^{n} P_i - P_L - P_D = 0 \tag{2.33}$$

$$SL_i \le S_i \le SU_i \tag{2.34}$$

$$E_t = \sum_{i=1}^{N} E_i \le Q_{max} \tag{2.35}$$

where:

$$F_i = (\alpha_i - \beta_i S_i)(a_i + b_i P_i + c_i P_i^2) \tag{2.36}$$

$$S_i = SU_i \times W_i + SL_i \times (1 - W_i) \tag{2.37}$$

$$E_i = e_i S_i (a_i + b_i P_i + c_i P_i^2) \tag{2.38}$$

$$P_L = B_{00} + \sum_{i=0}^{n} B_{i0} P_i + \sum_{i=0}^{n} \sum_{j=0}^{n} P_i B_{ij} P_j \tag{2.39}$$

2.5.2 TECHNICAL REVIEW

FS is a highly constrained bi-variable optimisation problem. FS always works closely with EED strategy, since the operation cost is the function of both fuel mixture and power output. Tsuji [1981] proposed the first model to determine the optimum fuel mixture as well as optimal load dispatch. He successfully solved the problem with the classic Lambda iterative method. Heslin and Hobbs [1989] presented a model which could evaluating the cost and employment impacts of effluent dispatch and fuel switching. Li et al [1995] proposed a two phase approach to the ramping rate constrained bi-optimization problem with a Genetic Algorithm. The method promised great financial benefits.

2.6 UNIT COMMITMENT

2.6.1 PROBLEM SPECIFICATION

Unit Commitment (UC) is a non-linear constrained optimisation problem. UC aims to minimise the cost of operation over a period of time by selecting which generator units should be turned on or off, the type of fuel, the power to be generated by each unit, the fuel mixture when applicable and the generation reserve margins over and above system demand, while paying due attention to major physical, operational and contractual constraints. The problem of UC involves hundreds or even thousands of 0, 1 variables and a large and complex set of constraints. The UC schedule could be performed with planning horizons ranging from one day to one week. The schedule objective is obtained by considering many cost factors which include unit fuel costs, maintenance costs and start-up costs. The constraints on thermal units are listed below:

(1) **Minimum-up time**: Once the unit is running, it should not be turned off immediately.

(2) **Minimum-down time**: Once the unit is decommitted, there is a minimum time before it can be recommitted.

(3) **Crew constraint**: If a plant consists of two or more units, they can not be turned on at the same time.

(4) **Power rate**: The maximum rate of change of real power output is not allowed to exceed its rated value.

The system constraints are mainly spinning reserve constraints, which guarantee that a sufficient amount of spinning reserve should be maintained at all times.

2.6.2 TECHNICAL REVIEW

The major difficulty in the unit commitment problem is the high dimensionality of the possible solution space. The exact solution to the above highly constrained problem can only be obtained by enumeration, which costs excessive computing time. The most widely used conventional techniques [Sheble, 1993] for the solution of UC problems are:

(1) **Priority-list schemes**: a simple, fast and highly heuristic solution method, but is apt to miss the optimal commitment.

(2) **Dynamic programming (DP):** effective but decreases in efficiency as the number of units increases, because of the high dimensionality of the problem. Although many papers have appeared to reduce the search space of DP, it cannot avoid making excessive demands on computing storage and computing time.

(3) **Integer and Mix-integer programming (MIP):** using the Branch and Bound technique can reduce the solution space enormously through discarding the infeasible subsets, which results in the possibility of finding the local minimum.

These approaches have two common defects: the first is that it is easy to be trapped in a local minimum solution, the second is the integer decisions which need to be modelled. Although MIP provides very good solution to UC, the process is rather complicated. Currently, all the solution methods are based on some assumptions, there is no technique that could solve the UC problem exactly.

Recent practice in UC is now to use artificial intelligence techniques. Its solution methods can treat the UC problem and the ED problem simultaneously, which promises to provide faster computing speed and the ability to accommodate more complicated constraints. Expert systems have been used to investigate UC problem by Mokhtari [1988], Wong [1991] and Salam [1991]. Experience from power system operators are combined with unit commitment expertise to create a rule based expert system, which is used to get more comprehensive information to reach a decision. Test results showed that this approach can provide a better and more operationally acceptable unit commitment solution. The application of Neural Network in this field was found by Sendaula and Biswas [1991] to treat several objectives simultaneously. Zhuang [1990] used Simulated Annealing to solve the UC problem. The method is based on the resemblance between the annealing of a metal and a minimisation process. It starts with a random feasible solution and moves along the feasible direction towards an unique global minimum with high probability.

2.7 RESEARCH TRENDS IN POWER SYSTEM OPERATION

2.7.1 TRENDS IN PROBLEM FORMULATION

Recent research has a tendency to devote the effort to multi-objective optimal economic operation problems. Beside economic dispatch, other objectives such as security, reliability, unit commitment, and emission consideration, are combined and attained simultaneously. However, these objectives may contradict each other so that preference of one objective may degrade the performance of another. This makes it difficult to handle this class of problems with conventional techniques, which are designed to solve one single objective. Yokoyama [1988] used probability security criteria to solve a multi-objective optimisation problem, with a satisfactory result being obtained among these trade-off objectives. Sendaula [1991] treated unit commitment and economic dispatch simultaneously with various constraints using Artificial Neural Networks. Fuzzy Logic techniques incorporated with a knowledge based system are used to solve multi-objective dynamic generation scheduling [Srinivasan, 1994], in which economy, security, emission and unit commitment are transferred to one objective and the problem is solved by maximising this function.

2.7.2 TRENDS IN MATHEMATICAL TECHNIQUES

Recent advances in the solution methods to various optimisation problems in power systems have been achieved by a group of techniques described by the general title of *artificial intelligence*. It includes techniques such as Neural Networks, Fuzzy Logic, Simulated Annealing and Genetic Algorithms. When they are applied to the simple optimisation problems for the applicability study, such as SED problem, they cannot achieve much improvement regarding the solution accuracy or speed over conventional techniques, for instance the Lambda Iteration Method. However, as the problem formulation becomes progressively more complicated, the conventional techniques are gradually limited by either convergence problems, solution inaccuracy or computational deficiency. Though the popular dynamic programming techniques offer a few attractive advantages, such as being able to solve problems of a variety of sizes and wide range of functions for moderate systems, however, they are restricted by their efficiency. As a consequence, the advanced artificial intelligence techniques have a increasing advantage over the conventional techniques, and are able to give more accurate solutions.

2.8 POTENTIAL OF GENETIC ALGORITHMS

Genetic Algorithms (GAs) have been introduced as alternative powerful tools to handle complex, multi-modal, multi-objective optimisation problems [Goldberg, 1989], where conventional techniques have not achieved the desired speed, accuracy or efficiency. GAs are unique in that they operate from a rich database of many points simultaneously. They exploit historical information by using 'bits and pieces' of the fittest of the old structures to create new sets in an attempt to improve future system performance. The major beauty of such algorithms lies in their computational simplicity and their powerful search ability to attain the global optimum. The further attraction of GAs is that they are extremely robust with respect to the complexity of the problem. Moreover, these robust solution methods do not need assumptions concerning continuity, existence of derivative information, or uni-modality, but allow non-linearities and discontinuities to appear in the solution space.

In conclusion, GAs are extremely useful for an ill-structured, complex system where other techniques can not solve the problem exactly, or the existing techniques are too complicated. The more complex the problem is, the more benefit one could get from GAs. They are thus the ideal techniques to offer robust and efficient strategies for a broad range of power system optimisation.

2.9 THE OPTIMISATION PROBLEM SCOPE FOR GA APPLICATIONS

GAs are employed in this project to tackle the following optimisation problems in optimal economic operation of power systems:

(1) classic static economic dispatch (chapters 4, 5).

(2) dynamic economic dispatch (chapters 6, 9).

(3) dynamic economic -environmental dispatch (chapters 7, 8, 9).

(a): environmental issue as additional constraint (chapters 7, 9).

(b): environmental issue as the second objective (chapter 8).

(4) dynamic economic -environmental dispatch + fuel switching (chapter 7).

CHAPTER

3

BACKGROUND INTRODUCTION OF GENETIC ALGORITHMS

This chapter states the general framework of optimisation problems, introduces the concept of GAs, and a formal mathematical framework is laid out afterwards. A review of application of GAs in electric power systems is presented, followed by the detailed genetic implementation procedure.

3.1 THE GENERALISED OPTIMISATION PROBLEMS

1.1.1 THE GOAL OF OPTIMISATION

Optimisation is the act of obtaining the best possible results under given circumstances [Rao, 1979]. The ultimate goal is to either minimise the cost or maximise the benefit. The cost or the benefit can be expressed as a function of certain decision variables, optimisation therefore tries to find the best (or a set of good) possible strategies which give the maximum or minimum value of the function.

The most desirable strategy should be able to give accurate, efficient and robust solutions. The strategy should not only attain the optimum, but should do it within reasonable time and when subjected to severe disturbances.

3.1.2 STATEMENT OF GENERAL OPTIMISATION PROBLEMS

An optimisation problem can be stated as follows:

Given an objective function, f, find a set of points $X^* = \{x_1^*, x_2^*, \ldots\ldots x_n^*\}$, which

$$\text{minimise } f(X)$$

$$\text{subject to:} \quad g_i(X) \leq 0 \qquad i = 1, 2, \ldots\ldots\ldots\ldots, m$$

$$\text{and} \quad h_i(X) = 0 \qquad i=m+1, m+2, \ldots\ldots, p$$

Where X is an n-dimensional vector, $g_i(X)$ are inequality constraints and $h_i(X)$ are equality constraints. The number of constraints need not be related to the number of variables. In the case of p being zero, the problem is referred to as an unconstrained optimisation problem. Otherwise, problems are known as constrained optimisation problems.

3.1.3 CONVENTIONAL MATHEMATICAL APPROACH

The above problem statement is very general and can be applied to any kind of linear or non-linear optimisation problems. However, there is no single generic method available for solving all problems efficiently. Hence, a number of optimisation methods have been developed for solving different types of optimisation problems in the past with a certain degree of success, such as gradient, linear, non-linear, quadratic, and dynamic programming. These methods fall into the following three categories: Calculus-based methods, enumerative methods and random search techniques [Goldberg, 1989].

Calculus-based methods are useful in finding the optimum of continuous and differentiable functions. They make use of the techniques of differential calculus in locating the optimum points. In doing so, they either perform steepest ascent hill climbing, or find the points with slopes of zero in all directions. Since some of practical problems involve objectives that are not continuous and/or differentiable, the applications of this set of search techniques are limited in scope.

Enumerative methods are a human kind of search. They check objective values for every point in the search space, one at a time. If it is for a small search space, the method can guarantee to find the best possible solution. However, many practical spaces are too large for this kind of method to complete even within a lifetime. This kind of method is therefore not attractive for the reason of efficiency.

Random Search methods seek and save the best solution during random walks. Though they are intended to overcome the shortcoming that the previous two methods exhibit, they do no better than the enumerative method in a long run.

To better illustrate the problem solving ability of the conventional methods, Figure 3.1 [Goldberg, 1989] depicts the efficiency of technique versus complexity of the problem. The obvious preference is the robust scheme, where the powerful search ability is independent of the complexity of the problem.

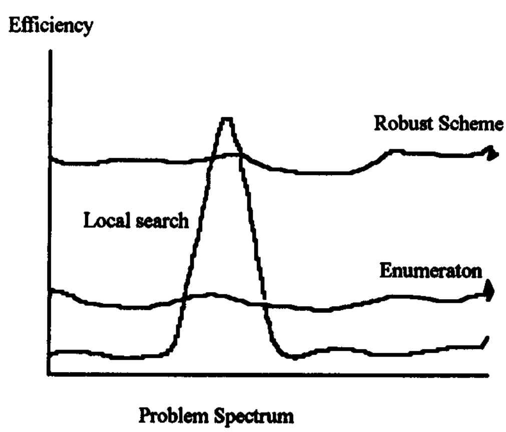


Figure 3.1 Efficiency of different optimisation techniques.

3.2 OUTLINE OF GAs

3.2.1 DEFINITION OF GAs

Genetic Algorithms are general purpose techniques for optimisation and learning. They were developed by Holland [1975], and advanced by many other researchers [Jong, 1975], [Lawence, 1987]. The mechanism of a GA is analogous to the evolutionary behaviour of biological systems. In the same way as nature evolves its living things, GAs evolve a group of initially poor solution guesses of a problem, to a set of acceptable solutions through successive generation (or iteration in computing terminology). The initial candidates or guesses are generated at random with little knowledge of correctness. Parameters of each solution guess are represented as bit strings instead of actual parameters, so that they can be improved repeatedly with a series of genetic operators, known as reproduction, crossover and mutation. This simple genetic procedure is applied with the aim to exchange valuable information between fitter solutions in an attempt to increase performance of future solution structure. The population of solution structures are maintained during a course of a GA run, so that the entire solution space has been investigated. Therefore GA searches are not susceptible to initial starting points, but are able to lead the search towards the global optimal point.

3.2.2 MATHEMATICAL FRAMEWORK OF GAs

The computing language of GAs is binary strings. A search for a good solution is merely a search for particular binary strings. The possibility of all strings for a practical difficult problem represents a very complex landscape, which involves many high points and valleys. The valley marks the location of strings that encode poor solutions, and the land's highest point corresponds to the best possible strings. When confronted with such a difficult search space, the conventional techniques can only move in one direction at one time. A method such as hill-climbing technique has difficulty in finding the right hill. Even in determining which way is up becomes increasingly difficult as the number of dimensions of the problem space increases. In addition, such search spaces are usually very large, and as a consequence, one step - one time conventional search strategy is simply not practically applicable, and would take enormous computing time and effort to even attain a feasible solution, rather than the optimum.

In contrast, the unique genetic search strategy provides itself with an assurance against prolonged searches. Instead of the conventional single path search, Genetic Algorithms cast a net over the entire search space, so that useful regions which contain partial solutions can be identified. The search can therefore focus its attention on the most promising space. These identified partial solutions serve as the basic building blocks, from which better and better solutions can be constructed. As one solution contains many of these partial solutions, an evaluation of a single string is equivalent to testing and computing a significant number of search regions. So called inherent parallelism provides the essential insurance for a GA to seek near optimal solutions.

The building blocks have a special terminology of schema in genetic algorithm, which are defined as subset of strings with 1's or 0's in specified places, and represent a certain region in the search space. For example, the string 1010010 belongs to a number of regions (or schemata): 10*****, 1****1, *0*0***, and so forth. The bit represented by * denotes *do not care*. The unspecified bit implies that it will not make any difference or have any effect whether they are represented by 1 or 0 on those bits. The largest region which contains many unspecified bits will be sampled by a large fraction of all the strings in a population. Therefore, a genetic algorithm that manipulates a population of a few hundred strings actually samples a vastly large number of regions, and can thus find comparable solutions with much less computing time and effort. Moreover, the short, low-order (small number of defining bits), and above average schemata receive exponentially increased trials in subsequent generations as concluded in Holland's Schema Theory [Holland, 1975]. These highly fit, low-order schemata serve as partial solutions to a problem, and a GA discovers new solutions by speculating on many combinations of the best partial solutions contained within the current population.

The role of the three simple genetic operators is therefore to identify the potential schemata among the population, and to construct better structures by combining schemata which associate with high performance. Consequently, the search can focus its attention on the most promising region. The reproduction operator samples building blocks at near optimal rates, and the identified potential building blocks are then recombined via crossover. Mutation which occasionally alters the value of a string position, has little effect on those building blocks, but provides background insurance to restore the beneficial genetic material. Hence, in working with these particular schemata, the complexity of a problem is reduced greatly. Instead of trying every conceivable combination, the best string should be sought from the best partial solutions (schemata) through past samplings. As a result, the string as a whole is no longer significant in seeking performance improvement. Instead, the growth of highly fit and short defining schemata plays a more important role in guiding the search towards the most promising region. This inherent parallelism gives GAs a central advantage over other problem-solving processes, and contributes their major attraction of simple implementation procedure, yet powerful search ability to identify the global optimum.

3.2.3 CHARACTERISTICS OF GAs

The uniqueness of the GA search strategy contributes a number of advantages of GAs over other traditional techniques:

(1) GAs are accurate: GA searches the optimum with a group of candidates, and climbs many hills in parallel. This ensures that the GA search is less susceptible to the initial starting points, and make it possible to escape the local minimum, and arrive at the global one.

(2) GAs are robust: GA search has the capacity to locate the global optimum in a multi-modal search space, where the GA needs no assumptions about continuity or gradient information of objectives, but only the raw objectives. GAs can therefore have wide practical application, and be able to guide the search towards the solution area even if the problem domain is substantially complex and uncertain.

(3) GAs are simple: Computational implementation of GAs is surprisingly simple. It involves nothing more complex than string generating, string copying and partial strings exchanging. Yet, such search procedure is powerful.

(4) GAs use probabilistic transition rules rather than deterministic rules: the transition rules of Genetic Algorithms are obtained by sampling the search at random, which makes GAs more suitable for more complex problems.

3.3 A REVIEW OF THE APPLICATIONS OF GAs IN POWER SYSTEM OPTIMISATIONS

These advantages (Section 3.2.3) contribute to the suitability of GAs for power system optimisations. They avoid many of the shortcomings exhibited by local search techniques, which need further improvements in respect to accuracy, efficiency and robustness for the following reasons:

(1) CTs are becoming very complicated formulations due to increased complexity and uncertainty arising from environmental issues, thus exposing deficiencies in problem solving techniques.

(2) CTs have to sometimes decompose a highly integrated problem into several more manageable sub-problems and solve them sequentially, which greatly increases the complexity of the problem and reduces the efficiency of computation.

(3) CTs are not robust to unforeseeable constraints and contingencies which occur in the field.

(4) CTs are susceptible to the initial starting point.

In contrast, GAs can provide an inherent global optimisation property, and offer fast, robust and efficient solutions. Its simple yet powerful strategies have attracted wide attention. A complete comparisons between GAs and CTs is summarised in Table 3.1.

Table 3.1 Comparisons Between GAs and CTs.

	CTs	GAs
Computational implementation procedure	complex	simple
Information requirement	objective functions plus auxiliary information such as: gradient information and continuity of the search space	objective functions only
Robustness over a spectrum of problems	case sensitive	robust
Constraint handling	inequality constraints impose extra burden to the problem objective	inequality constraints can be easily handle by the algorithm inherently
Transition rules	deterministic	probabilistic
Computing Time	short	long

Since the GA was first suggested to optimise capacitor placement for reactive power scheduling [Ajjarapu, 1991], many papers have appeared to study the feasibility and capability of GAs over a broad range of power system optimisations. Walters [1993] is among the earliest who successfully implemented GAs in power system operation. In the paper, he focused his attention on the highly non-linear economic dispatch problem with Valve-point Loading. However, the system considered is a simple three generator system. Iba [1993] gave the first report of using GAs on reactive power allocation. Richards [1993] used GAs to find optimal combinations of switched capacitors and load impedance in the distribution system. Nara [1993] minimised distribution system losses by GAs. Yoshimi [1993] demonstrated the algorithm's feasibility on the ED problem on a 15 generator system, while Mori [1993] presented papers to improve the accuracy over conventional GAs. The difficult Unit Commitment problem was first solved with GAs by Adapa [1994]. Economic Dispatch, as a popular subject in power system operation again, gained much attention with the new algorithm. Currently, researchers in the economic operation field concentrate their effort in two major directions: one is to further improve the computational efficiencies of existing Genetic Algorithms, another is to apply GAs to the more rigorous problem formulation. Some initial achievements of genetic approach to optimal economic operation of power systems have been obtained by Bakirtzis [1994], Li [1994], Sheble [1995], Wong [1995] and Chang [1995].

3.4 OUTLINE OF A CONVENTIONAL GA

3.4.1 GENETIC SEARCH PROCEDURE

A genetic search starts with generating a population of chromosomes (binary strings) randomly, each of which can be decoded into a solution to represent a point in the search space. For each iteration of the genetic algorithms - a generation, the process begins with evaluation of the fitness value for each string. Chromosomes are then stochastically chosen to become parents and reproduce according to their evaluated fitness. In order to explore the new search space, some variation is introduced into the new strings by genetic resembled crossover and mutation operators. Crossover causes a structured, yet randomised exchange of genetic material between good solutions with the aim of generating even better ones. The role of mutation is in restoring lost or unexplored genetic material into the population to ensure the whole space is searched. Each generation end with new strings (offspring) replacing the old ones (parents), and the next generation begins. The process is repeated until some termination conditions are satisfied. The termination conditions can be chosen either as system convergence or maximum generation number. An abstract view of GAs can be represented as the following structure:

```
Initial generated population G(0)
Evaluate structures in G(0);
t = 0;
Repeat:
  t = t+1
  reproduce G(t)' from G(t-1);
  recombine G(t) from G(t)'
    with crossover and mutation;
  replace G(t-1) with G(t);
  evaluate structures in G(t);
Until termination condition reached
```

3.4.2 CGA IMPLEMENTATION PROCEDURE

The following are the basic steps to implement GAs:

(1) Mapping objective functions to GA recognised fitness function;

(2) Generating initial population;

(3) Encoding system structure to binary string;

(4) Decoding individual binary strings to real variable;

(5) Evaluating individual strings' fitness values;

(6) Applying genetic operators: reproduction, crossover and mutation.

(a) Novel Fitness Function Formulation

Among the procedures, the mapping method which transfers the objective functions to the fitness function is one of the most important issues in GA implementation. As the fitness value directly guides the search for improvement, it is vitally important to have a formula which best expresses the objectives and constraints. Furthermore, it has to be flexible enough to consider additional objectives and constraints easily.

Under such requirements, a novel mapping method is proposed in this project. The idea behind the fitness formulation is that the objective function and the constraints can be treated equally. To achieve this goal, the best way to express each objective function and constraint is to use a percentage formula. That is, the best solution has the biggest value of 1 for each objective and constraint, and the worst has the smallest value of 0. The advantage of this formula is that the formulation can consider additional objectives and constraints very easily. The proposed formulation has been further developed by employing weight coefficients for the constraints so as to adjust their importance. With a weight coefficient exceeding 1, the constraint is rendered more important. A less important constraint is represented by a weight coefficient less than 1. While the inequality constraints are handled in decoding section, which effectively reduces the searching space, and improve the search efficiency. The overall fitness function for a minimisation problem under several constraints is stated as:

$$F=\left(\frac{cost_{max}-cost_{obj}}{cost_{max}-cost_{min}}\right)+\sum_{i=0}^{w}W_i\times\left(\frac{consi_{max}-consi_{obj}}{consi_{max}-consi_{min}}\right) \tag{3.2}$$

Where

w: number of constraints.

W_i: distance based weighting coefficient.

$cost_{sub}$: value of the objective function, where the maximum and the minimum values among the current population are self defined by the subscripts, any individual values between them are defined by the subscript obj.

$consi_{sub}$: value for ith constraint, the subscription has the same meaning as it has for the objective function.

(b) Scaling

Fitness scaling is suggested for maintaining a more careful control over the entire population. Simple scaling helps to prevent the early domination of extraordinary individuals which could cause premature failure, while later on it encourages an adequate competition among near equals. With the scaling factors, the fitness function becomes:

$$Fs = a\times(F-b) \tag{3.3}$$

Where 'a' is a problem dependent coefficient and 'b' is the average string fitness during each generation.

(c) Encoding

Encoding is the process of coding a problem as a number of finite strings. Normally, the smallest alphabet should be selected to permit a natural expression of the problem, which leads to the decision of using binary encoding. In the ED problem, assuming each generator represented by a 5 binary bit string. For a system with n committed generators, the overall string length will be $n\times 5$.

(d) Decoding

Decoding a binary string into an unsigned integer can play a very important role in GA implementation. The inequality power limit constraint is performed in such a way that the individual string is normalised to its specified range [Pimin, Pimax], which determines the individual generator output as:

$$P_i = P_{imin} + X \cdot (P_{imax} - P_{imin}) / C \tag{3.4}$$

X is the unsigned integer. C is chosen to normalise X, which is equal to $(2^L - 1)$.

(e) Genetic Operators

Genetic algorithms modify the bit strings with three operators: reproduction, crossover, and mutation to drive the individuals towards the optimal points or near to them.

Reproduction is a process to select highly fit strings as parents to make copies passing to the next generation according to their fitness. The easiest way which is widely used to carry out this survival competition is a simple roulette wheel method. This selection method is designed as follows: the strings with a higher fitness value will have a larger portion of the wheel, while those strings with low fitness are given a relatively small portion of the roulette wheel. When the weighted wheel is spun to yield the reproduction candidates, the more highly fit strings have a higher probability to make more copies, consequently, improving their chance to survive in the next generation. Once the string has been selected for reproduction, a replica of the string is made being a member of G'(t). This string is then entered into a temporary mating pool ready for recombination.

Crossover allows highly fit members in G'(t) to be mated at random. Each pair subsequently undergoes crossover with a high probability. When the pair are chosen to crossover, a point along the string is selected at random among {1, n-1}, the portions to the right of that point are swapped over to produce two offspring. This procedure is illustrated in Figure 3.2.

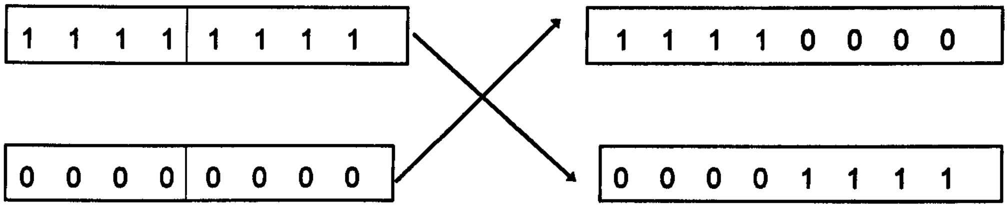


Figure 3.2 The procedure of a simple crossover operation.

Mutation appears to flip the value of a bit from 1 to 0, or vice versa with a very small probability. Mutation provides background variation and introduces beneficial material into strings. It serves as an insurance for the search to be explored further rather than stagnated at a premature stage.

3.4.3 GENETIC PARAMETERS

Running a genetic algorithm entails setting a number of parameter values. The choice of the parameter values can have significant impact on the system performance. The typical genetic parameters include:

(1) Population Size: affects search accuracy.
(2) Crossover Rate: controls primary search exploration speed.
(3) Mutation Rate: controls secondary search exploration speed.
(4) Scaling Window: controls search pressure.

Though a great deal of effort has been devoted to the optimal parameter setting, such as Grefenstette [1986], Schaffer [1989] and Srinivas [1994], there still does not exist a generic parameter setting to suit all problems. A perfect parameter set for one problem can be a disaster for another, and the setting is very much problem dependent. The issue will be discussed in detail in Chapter 5.

3.4.4 DEFINITION OF A CGA

GAs include a broad range of algorithms. The commonly defined conventional GAs (CGA) are: use binary encoding, blind initial population, generational reproduction, some fitness normalisation, one-point crossover and constant mutation rate to solve the optimisation problems:

$$\max F(X) \tag{3.5}$$

Where F is called the fitness function, with which individual candidates evaluate themselves. All minimisation problems should be transferred to non-negative fitness function to be maximised. The CGAs is the simplest yet quite efficient search strategy to attain the optimum, however it is imperfect. Further enhancements upon CGAs are made in Chapter 5.

CHAPTER
4
COMPARISON OF GAs WITH CONVENTIONAL TECHNIQUES ON CLASSIC ECONOMIC DISPATCH PROBLEMS

This chapter makes a comparison between CGAs and conventional optimisation techniques on the classic ED problems. Four test cases have been employed to verify the GA's accuracy and robustness on the different ED problems with varying degrees of complexity. The systems undertaken are small in scale, so that comparisons are easier to make, and implementations are simple to carry out.

4.1 ECONOMIC DISPATCH PROBLEM

The classic ED problem as discussed in Chapter 2 is a static optimisation problem. It has been assumed that it is known which generators are operational, that the customer load demand is known, and the cost functions for each unit are supplied. The task of the ED problem is thus to find the optimal generator outputs so that the total cost is minimised, customer load demand is met, and each unit is operated within its specified operating limits. The formal problem formulation is restated below:

$$\min \quad F_t = \sum_{i=1}^{N} C_i \tag{4.1}$$

$$\text{subject to:} \quad P_{imin} \leq P_i \leq P_{imax} \tag{4.2}$$

$$\text{Transmission neglected:} \quad \sum_{i=1}^{n} P_i - P_D = 0 \tag{4.3}$$

$$\text{Transmission included:} \quad \sum_{i=1}^{n} P_i - P_L - P_D = 0 \tag{4.4}$$

$$\text{where:} \quad P_L = B_{00} + \sum_{i=0}^{n} B_{i0} P_i + \sum_{i=0}^{n} \sum_{j=0}^{n} P_i B_{ij} P_j \tag{4.5}$$

4.2 TEST CASES

Four example cases have been studied to illustrate a GA's search ability in finding the optimal power outputs P_i, while the degree of problem complexity was increased in ascending order. They are listed as follows:

Test 1: Economic Dispatch Neglecting Transmission Losses. To schedule the power outputs among the committed generator units so that the total fuel cost is minimised and the customer load demand is satisfied. The cost function in equation (4.1) is represented by a smooth and convex quadratic curve. As the real power losses on the transmission network are neglected in this case, equation (4.3) was used as the power balance equation.

Test 2: Economic Dispatch Considering Transmission Losses. The test case is similar to that of test 1, except that the power losses on the transmission network are included. The test therefore takes additional transmission losses into account with equation (4.4), while the same smooth quadratic cost curve is applied.

Test 3: Valve-Point Loading Without Transmission Losses. To schedule the power outputs among the committed generator units based on the more precise unit characteristics. The Valve-point Loading accounts for the ripple effect for larger generators in order to obtain further financial benefit. In this case, a more accurate, highly non-linear, non-convex cost curve is used to represent the cost function in equation (4.1). The power losses on the transmission network are excluded, and equation (4.3) is used for the loss neglecting power balance.

Test 4: Valve-Point Loading With Transmission Losses. Again the more accurate cost function was put into use in this test and equation (4.4) was used for the loss considering power balance.

4.3 THE TEST SYSTEM

The example tests have been carried out on a three generator system which is obtained from Wood [1984]. The detailed data are given as follows.

The customer load demand needed to be supplied is 850 MW.

The quadratic cost functions are given for each generator as:

$$\begin{aligned} F_1\,(\$/h) &= 0.001562P_1^2 + 7.92P_1 + 561 \\ F_2\,(\$/h) &= 0.00194P_2^2 + 7.85P_2 + 310 \\ F_3\,(\$/h) &= 0.00482P_3^2 + 7.97P_3 + 78 \end{aligned} \tag{4.6}$$

The power limitations for each generator are given by:

$$\begin{aligned} &100 < P_1 < 600 \\ &100 < P_2 < 400 \\ &50 < P_3 < 200 \end{aligned} \tag{4.7}$$

The transmission loss coefficients (B-coefficients) for the system are:

$$\begin{aligned} B_{3\times 3} &= \begin{bmatrix} 0.00676 & 0.00953 & -0.00507 \\ 0.00953 & 0.0521 & 0.00901 \\ -0.00507 & 0.00901 & 0.02940 \end{bmatrix} \\ B_0 &= \begin{bmatrix} -0.0766 \\ -0.00342 \\ 0.0189 \end{bmatrix} \\ B_{00} &= 0.040357 \end{aligned} \tag{4.8}$$

In the case of valve-points loading, the cost functions are approximated by adding a sinusoid contribution to the original quadratic input-output cost curve, which has the following formula:

$$\begin{aligned} F_1\,(\$/h) &= 0.001562P_1^2 + 792P_1 + 561 + |300 \bullet \sin(0.0315(100 - P_1))| \\ F_2\,(\$/h) &= 0.00194P_2^2 + 785P_2 + 310 + |200 \bullet \sin(0.042(100 - P_2))| \\ F_3\,(\$/h) &= 0.00482P_3^2 + 797P_3 + 78 + |150 \bullet \sin(0.042(50 - P_3))| \end{aligned} \tag{4.9}$$

The data required for each case are listed in Table 4.1.

Table 4.1 Date Requirements for the Four Cases.

Cases	Description	Cost Function	Power Limit	Transmission Loss
Test One	ED neglecting transmission losses	Quadratic (4.6)	(4.7)	neglect
Test Two	ED considering transmission losses	Quadratic (4.6)	(4.7)	B-coefficients (4.8)
Test Three	VP neglecting transmission losses	Non-convex (4.9)	(4.7)	neglect
Test Four	VP considering transmission losses	Non-convex (4.9)	(4.7)	B-coefficients (4.8)

4.4 GENETIC ALGORITHM APPROACH

4.4.1 Implementation Procedure

The basic procedure of CGA implementation is summarised in the following flow chart:

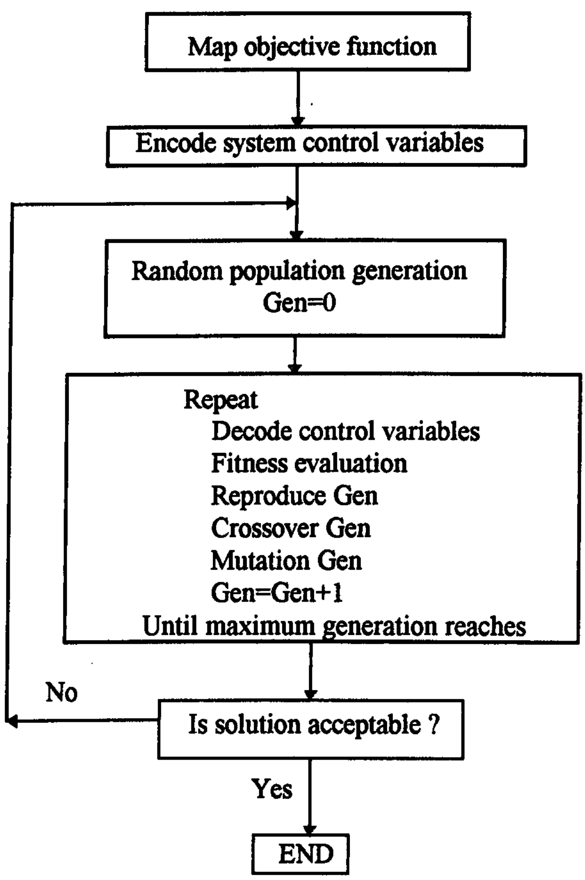


Figure 4.1 The GA implementation flow chart.

(1) The first step in the approach to the ED problem is to map the ED cost minimisation problem into a GA recognised fitness maximisation function. For the classic ED problem, the fitness function is composed of the cost function and the equality power balance constraint. The inequality power limit constraints are handled by the algorithm itself in the decoding section. This resulted in a fitness function derived from equation (3.2) as:

$$F = \left(\frac{cost_{max} - cost_{obj}}{cost_{max} - cost_{min}} \right) + w \times \left(\frac{cons_{max} - cons_{obj}}{cons_{max} - cons_{min}} \right) \tag{4.10}$$

(2) The initial population was generated at random, and the size was remained fixed during the course of a GA run.

(3) Each of the four tests contains three control variables, which are P_1, P_2, and P_3. The aim of genetic processing is to find the optimal values for these three variables in order to minimise the total cost while meeting load demand. The GA fulfils the task by working with coding of the variables rather than variables themselves in order to get an insight of the solution structure. In this application, each generator output, Pi, was encoded by L=10 binary bits. This resulted in each string in the population having a length of 3*10=30 binary bits.

4) The decoding procedure is to decode the binary string to an unsigned value X, and then use the following function to map X to the ith generator output within its specified operating range $[P_{imin}, P_{imax}]$:

$$P_i = P_{imin} + X \times (P_{imax} - P_{imin}) / C \tag{4.11}$$

Where $C = (2^L - 1)$, L=10.

(5) The parameter values for the fitness scaling function Fs = a $\times$ (F-b) are chosen as:

b is the average string fitness value over the whole population to insure that each average population member contributes at least one expected offspring to the next generation.

a = 1.8, which defines the number of expected copies desired for the best population member. It is normally chosen between the range of 1.2 to 2 [Goldberg, 1989].

(6) The optimal parameter setting varies with the selected GA structure. However, it is suggested by Grefenstette [1986] that if a small generation number is considered, then a high crossover rate and low mutation rate are necessary; on the other hand, if a relatively large population is used, there should be a moderate crossover rate and a low mutation rate. His suggested parameter setting for a general good behaviour with a relatively short search is as follows:

population size	30
crossover rate	0.9
mutation rate	0.01

These values will be used in this set of ED applications

4.4.2 RESULTS FOR FOUR TEST CASES

The GAs were programmed in C, and run on a 486 66MHz PC throughout this project.

4.4.2.1 A GRAPHIC ILLUSTRATION OF A GENETIC SEARCH

The genetic procedure, which evolves a set of poor solutions of an ED problem to a set of acceptable solutions, is illustrated in Figures (4.2-4.4) (A population of 100 was used here for better illustration). Figure 4.2 shows the initial randomly generated population (or solutions) which are widely distributed in the search space to keep the search diversity. These solutions have been improved significantly after 10 generations, as depicted in Figure 4.3. Figure 4.4 shows that after 30 generations, most of the points have been converged to the near optimal point. Figure 4.5 illustrates the best solution obtained at each generation.

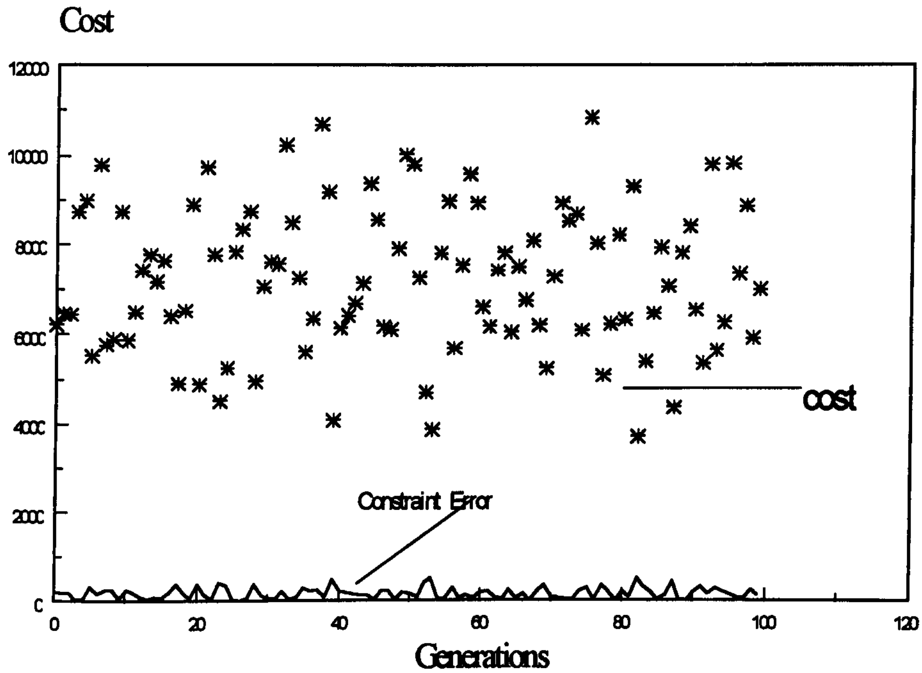


Figure 4.2 Initial randomly generated population.

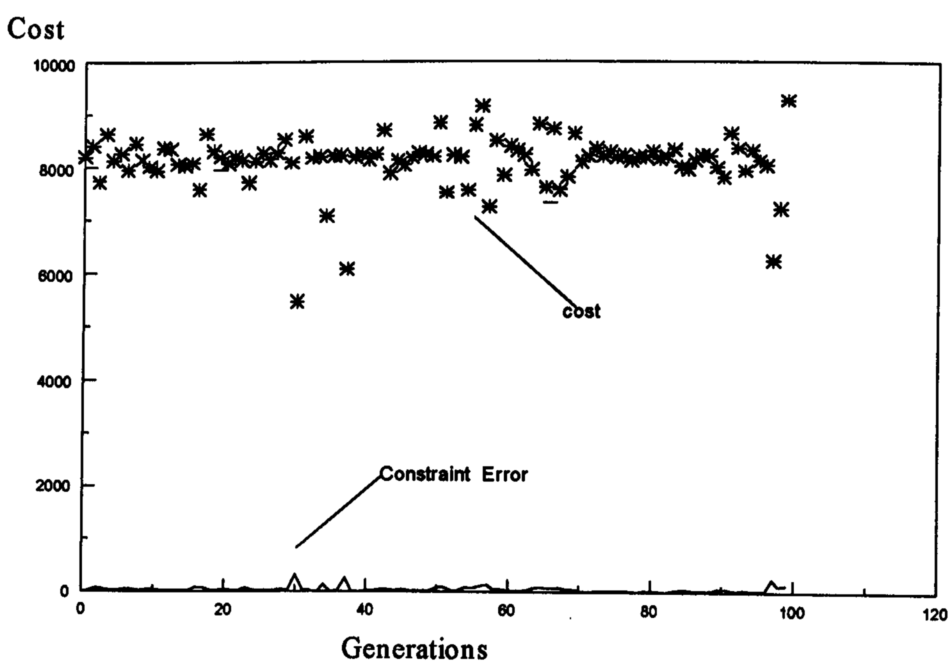


Figure 4.3 The evolving population after 10 Generations.

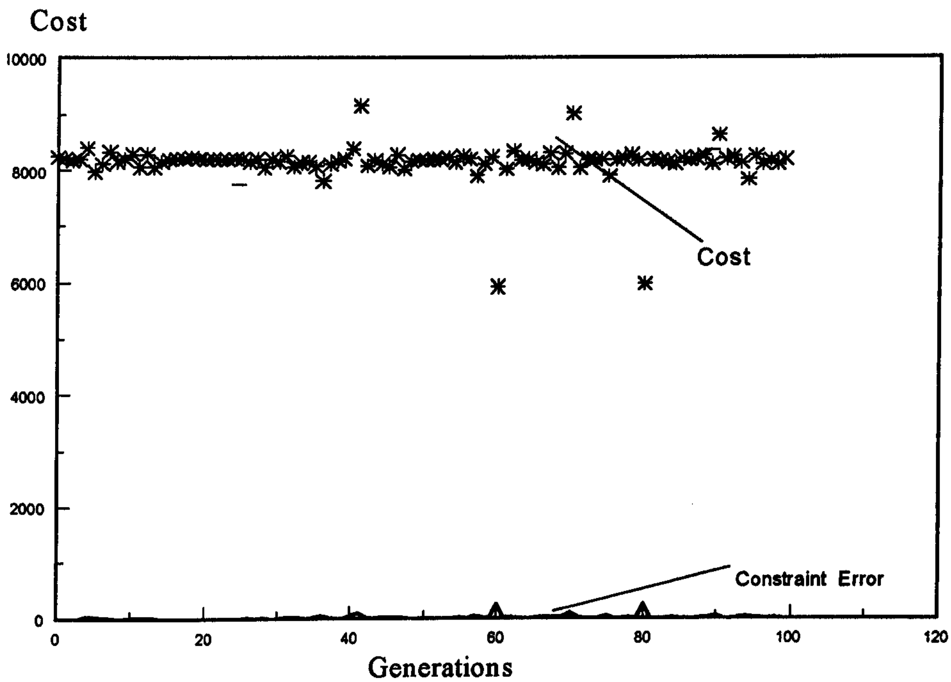


Figure 4.4 The evolving population after 30 Generations.

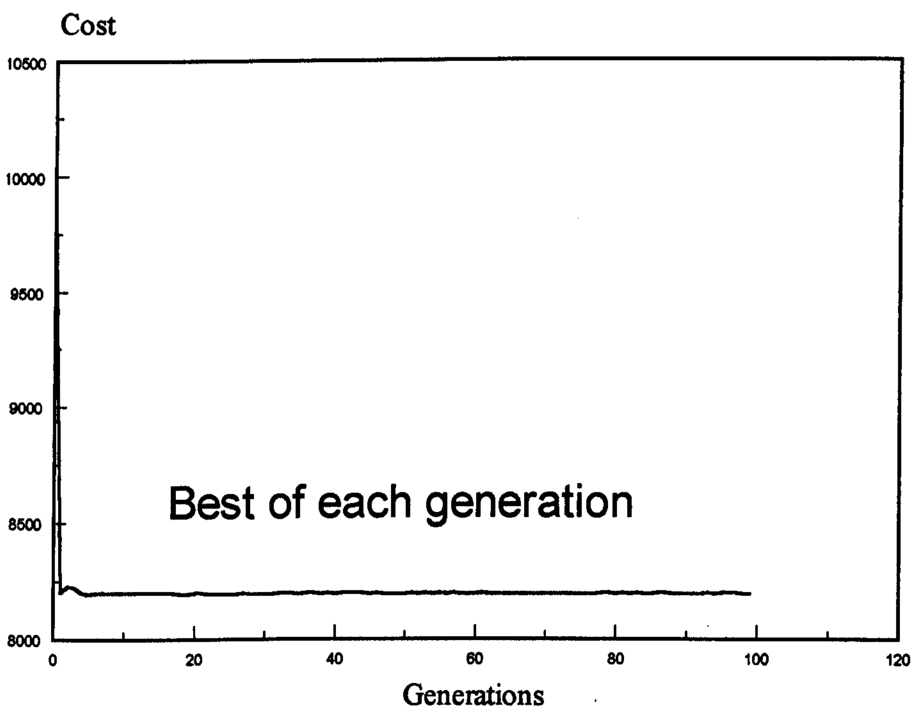


Figure 4.5 Best Solution of Each Generation.

As shown in Figures (4.2-4.4), a GA works with a group of populations, searches many areas in parallel. This ensures that the GA search is not easily trapped by the deceptive local minimum, and has improved probability to attain the global optimum.

4.4.2.2 SIMULATION RESULTS FOR THE CLASSIC ED PROBLEMS (TEST 1 & TEST 2)

Three identical CGA runs have been performed on both the Test 1 and the Test 2 problem. Each run started with a fresh initial population. The results are listed in Table 4.2 and 4.3 for the Test 1 and Test 2 problem respectively. The solutions obtained for both tests have assumed that the cost function for each unit is a smooth and convex quadratic cost curve, which is shown in Figures 4.6 (a, b, c) for unit 1, unit 2 and unit 3 respectively (the costs are per hour value). Though there are slight variations on the solution results among those GA searches (this is due to randomised search procedure of GAs), they showed acceptable consistency. The total fuel cost attained by GAs are listed under the title of Cost ($/h). However, such obtained optimal output might not be optimal in terms of more accurate cost curve with a ripple effect, which accounts for the valve-point characteristic. In order to show the effectiveness of Valve-point Loading, the optimal power outputs obtained from the test 1 and the test two were fed into the more accurate cost function (4.9). The costs thus obtained are listed under the title of V_Cost, and compared with that of valve-point loading in next section.

Table 4.2 Test 1 Results with A Simple Genetic Algorithm Load = 850.0 $P_L = 0$

Run	Unit 1	Unit 2	Unit 3	Total (MW)	Cost ($/h)	V_Cost ($/h)	Time (s)
1	449.46	293.55	106.16	849.17	8196.22	8744.22	1.59
2	404.99	355.72	88.42	849.12	8192.90	8538.90	1.59
3	438.22	321.41	89.44	849.07	8194.55	8592.55	1.59

Table 4.3 Test 2 Results with A Simple Genetic Algorithm Load = 850.0 $P_L \neq 0$

Run	Unit 1	Unit 2	Unit 3	Total (MW)	Cost ($/h)	V_CosT ($/h)	Time(s)	Loss(MW)
1	418.18	309.09	142.82	870.09	8387.19	8732.41	1.92	21.05
2	464.13	254.55	151.91	870.59	8407.14	8734.14	1.92	21.53
3	360.02	384.16	126.39	870.57	8389.16	8939.16	1.92	21.36

4.4.2.3 SIMULATION RESULTS FOR VALVE-POINT LOADING (TEST 3 & TEST 4)

The smooth and convex cost curves used in Test 1 & 2 are the approximation of the original cost curve for the ease of calculation. The more precise cost curves are the solid rippled lines in Figures 4.6 (a, b, c). When considering such a ripple effect in the cost function, Valve-point Loading is desirable to get further cost reduction. The power of the Valve-point strategy is that it can locate the power outputs close to the more efficient points, and avoid power allocations which would result in a higher cost. A unit is in its minimum efficiency when the valve is newly opened, and in its maximum efficiency when the valve is fully opened [Wood, 1984]. Therefore, the best operating points for those three generators are the points close to A, B, C, D and E in the given input-output figures.

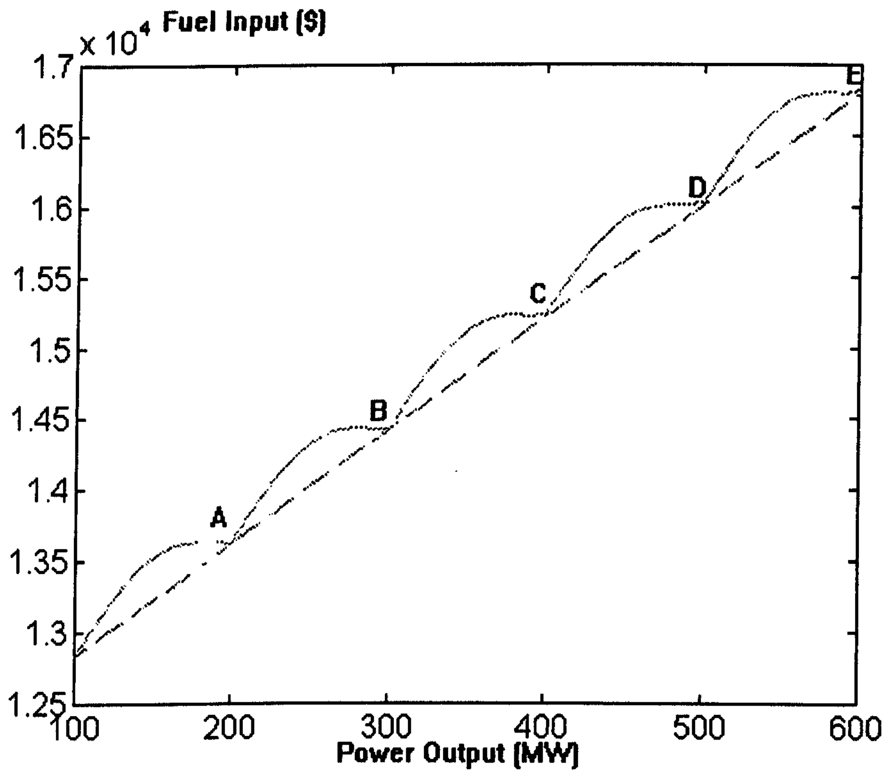


Figure 4.6a Unit 1 input-output curve.

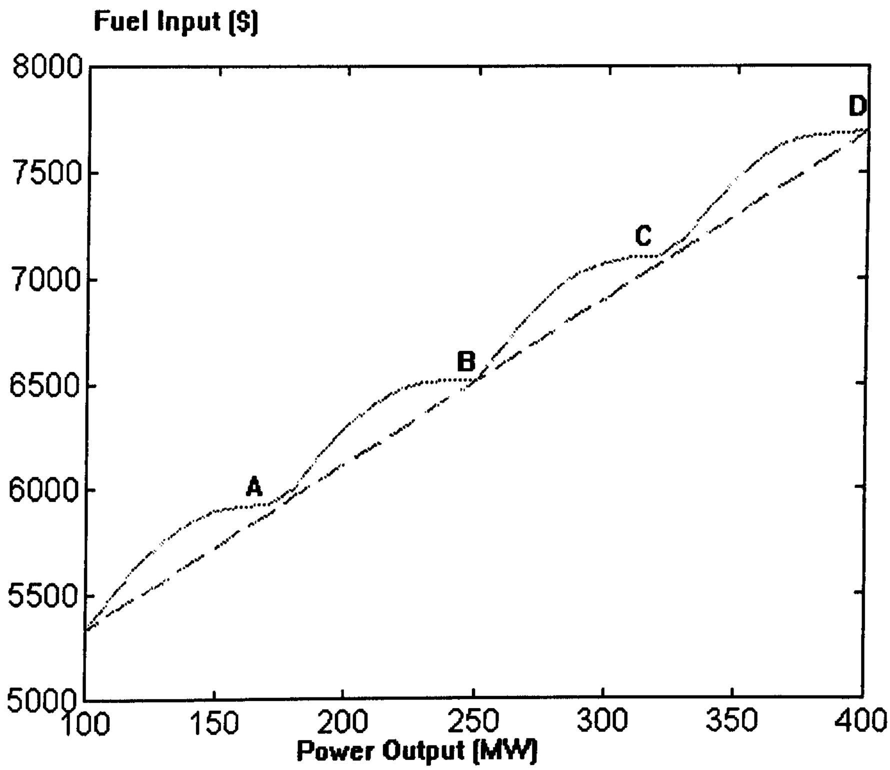


Figure 4.6b Unit 2 input-output curve.

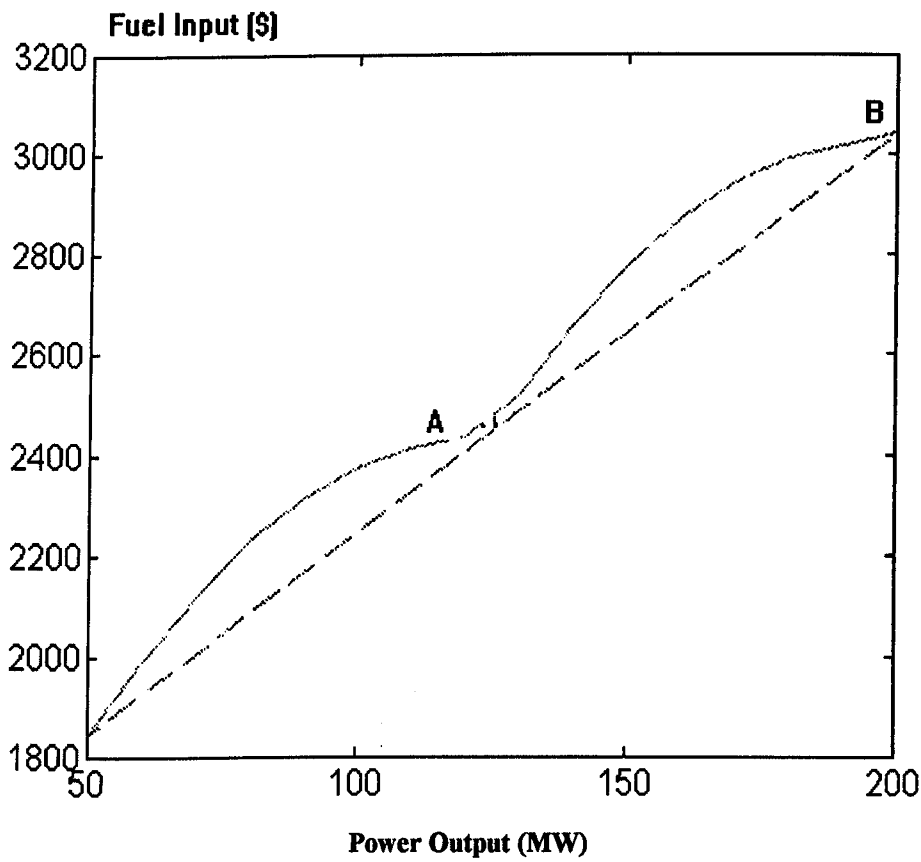


Figure 4.6c Unit 3 input-output curve.

The results of Test 3 and Test 4 based on the valve-point loading which were obtained by CGA are listed in Table 4.4 and Table 4.5 respectively. Again, three identical GA runs have been performed, each with fresh new starting points and each solution showed acceptable consistency with others in the same category.

Table 4.4 Test 3 Results with A Simple Genetic Algorithm Load = 850.0 $P_L = 0$

Run	Unit 1	Unit 2	Unit 3	Total (MW)	V_Cost ($/h)	Time (s)
1	357.58	333.43	158.21	849.22	8269.42	1.59
2	325.81	328.45	195. 01	849.27	8295.35	1.59
3	522.78	222.58	103.67	849.02	8313.66	1.59

Table 4.5 Test 4 Results with A Simple Genetic Algorithm Load = 850.0 $P_L \neq 0$

Run	Unit 1	Unit 2	Unit 3	Total (MW)	V_Cost ($/h)	Loss(MW)	Time (s)
1	359.53	321.41	187.39	849.05	8460.60	19.28	1.92
2	386.41	390.62	94.72	849.15	8479.13	22.60	1.92
3	487.59	202.93	180.06	849.18	8524.28	21.40	1.92

The average cost reduction achieved by the GA with valve-point loading over the classic economic dispatch are listed in Table 4.6. As indicated in the table, the advantage of valve-point loading is obvious. The cost saving is significant even on the three generator system. It should also be noticed that although the problem complexity has been increased over the four cases, their computational times are virtually the same. This is because the GA uses probabilistic rule rather than deterministic rules to obtain solutions. A GA works as a black box, which treats all problems alike, regardless of their simplicity or difficulty. Therefore, the more difficult the problem is, the more benefit that one can get from a GA. However, such probabilistic rule also imposes disadvantages, that the solution results are different from run to run, as it has been shown in Tables (4.2-4.5). Yet, the solution variation is only small (less than 0.5%), Table 4.7 gives the solution variation of each run compared with the average value for the four test cases.

Table 4.6 Cost Comparison Between CED and Valve-point Loading
Load = 850.0

	V_Cost ($/h) Classic ED	Cost ($/h) Valve_point	Saving ($/h)	Saving(%)
$P_L = 0$	8625.22 (Test 1)	8292.81 (Test 3)	332.41	4.01
$P_L \neq 0$	8801.90 (Test 2)	8488.00 (Test 4)	313.89	3.7

Table 4.7 Solution Variations for the Four Test Cases

	Run 1		**Run 2**		**Run 3**		**Average**
	Costs ($/h)	Variation(%)	Costs ($/h)	Variation(%)	Costs ($/h)	Variation(%)	**Cost ($/h)**
Test 1	8196.22	0.0203	8192.90	0.0201	8194.55	0.000	8194.56
Test 2	8387.19	0.0871	8407.14	0.1506	8389.16	0.0636	8394.50
Test 3	8269.42	0.2820	8295.35	0.0306	8313.66	0.2514	8292.81
Test 4	8460.60	0.3228	8479.13	0.1048	8524.28	0.4274	8488.00

4.5 CONVENTIONAL TECHNICAL APPROACHES

In this section, two conventional techniques - Merit Order and Lambda Iterative techniques, which use deterministic transit rules to determine the solution strategy, have been applied to the same four test cases. They are used as two opposite approaches to the probabilistic based GA search technique.

4.5.1 Merit Order Technique

Merit Order is the quickest technique to be implemented on the ED problem. It is generally used to work with Unit Commitment calculations, where speed is of particularly importance, and where the accuracy has to be sacrificed for speeding up the whole processing. The idea of Merit Order is quite straight forward in that the most efficient unit is running to its maximum capacity, the second most efficient unit is loaded next, and so on, until the required load demand is fully supplied. Computational implementation of the technique is very simple, only involving a sorting function to sort the committed generator in order according to their efficiency. The computational time required for all four test cases are so short that they are less than 1 second for this small system. However, the Merit Order technique is not the most economical dispatch strategy. Furthermore, it can not take transmission losses into merit consideration. Therefore, the optimal power output allocations are virtually the same for the ED problems with or without losses. This would undoubtedly result in unnecessary high fuel cost. Table 4.8 is the results attained by Merit Order method for Test 1 and Test 3. As the technique can not handle the transmission losses, the Test 2 and the Test 4 had the same results with Test 1 and Test 3 respectively.

Table 4.8 Merit Order Method Load = 850.0 $P_L = 0$

	Unit 1	Unit 2	Unit 3	Total (MW)	Cost ($/h)	V_Cost($/h)
Test 1	450.00	400.00	0.00	850.00	8279.71	8585.71
Test 3	250.00	400.00	200.00	850.00	N/A	8571.83

4.5.2 Lambda Iteration Method

The Lambda Iterative method is based on the principle of equal incremental cost. The idea is that the next incremental cost of all machines should be set equal to yield the most economic results. This method is still popular today, particular for the large power systems for its ease of implementation, short computational time, and ability to account for transmission losses. Mathematically, this optimal operation strategy can be stated as:

$$\frac{\partial F_1}{\partial P_1} = \frac{\partial F_2}{\partial P_2} = \frac{\partial F_i}{\partial P_i} = \lambda \tag{4.12}$$

where F_i is the fuel cost for the ith generator when the power output is P_i.
For the case of transmission losses included, the optimal operation is achieved when:

$$L_1 \frac{\partial F_1}{\partial P_1} = L_2 \frac{\partial F_2}{\partial P_2} = L_i \frac{\partial F_i}{\partial P_i} = \lambda \tag{4.13}$$

where L_i is the penalty factor for transmission losses, and expressed as:

$$L_i = [1 - (\partial P_L / \partial P_i)]^{-1} \tag{4.14}$$

and P_L are transmission losses contributed by unit i.
When the generator outputs are at their operational limits, the necessary conditions need amendment to:

$$\frac{\partial F_i}{\partial P_i} \le \lambda \qquad \text{for} \qquad P_i = P_{i,,max} \tag{4.15}$$

$$\frac{\partial F_i}{\partial P_i} \ge \lambda \qquad \text{for} \qquad P_i = P_{i,,min} \tag{4.16}$$

The simulation results on the first two cases attained by the Lambda Iterative method are listed at Table 4.9

Table 4.9 Lambda Iterative Method Load = 850.0 (Test 1 & 2)

	Losses	Unit 1	Unit 2	Unit 3	Total (MW)	Cost($/h)	V_Cost ($/h)
Case One	0	393.07	334.52	122.19	850.00	8192.4	8478.40
Case two	15.79	434.67	299.63	130.50	850.00	8335.17	8916.17

The Lambda Iterative method does not have the capability to resolve the Valve-point Loading problem. It is restricted by the need for the objective functions to be continuous, convex and the gradient information does exist. Once these conditions are satisfied, the method can guarantee to attain the most economic results. However, the practical system often includes objectives which are discontinuous. Additional constraints can be non-linear. The solution with the Lambda Iterative method has to be based on the approximated and simplified linear, continuous objectives and constraint, which will undoubtedly introduce inaccuracy in power dispatch.

4.6 COMPARISON BETWEEN GAs AND CTs

Finally, results obtained from three techniques are drawn together for the four test cases to analyse the effectiveness and robustness of CGA over the conventional search techniques.

Table 4.10 is the summary of solution results of the three techniques. For the results obtained with CGA, Cost_ave is the average cost over three GA runs, while Cost_best is the best result among those three runs. Table 4.11 is the comparison made regarding the solution accuracy among the three methods, the cost underneath CGA is taken as the average value of the three GA runs, together listed are the solution variation to show GA's relative consistency. The Lambda Iterative method is used as the benchmark. As the Lambda Iterative method can not resolve the problem of Valve-point Loading, optimal generator outputs are the same for Test 1 and 3, Test 2 and Test 4. The difference lies in that their operational costs are based on different cost functions.

Table 4.10 Summary of Solutions with Various Methods

	CGA			Lambda Iterative		Merit Order	
	Cost_ave ($/h)	Cost_best ($/h)	Time (s)	Cost ($/h)	Time (s)	Cost ($/h)	Time (s)
Test 1	8194.56	8192.90	1.92	8192.40	0.0005	8279.71	0.0001
Test 2	8394.49	8382.41	1.92	8335.17	0.0007	#	#
Test 3	8292.81	8269.35	1.92	8478.40	0.0006	8571.83	0.0001
Test 4	8488.00	8460.60	1.92	8916.17	0.0008	#	#

Table 4.11 Comparison of Solutions with Various Methods
Lambda Iterative Method is the benchmark

	CGA		Lambda Iterative	Merit Order
	Cost Improvement (%)	Solution Variations (%)	Cost Improvement (%)	Cost Improvement (%)
Test 1	- 0.024	0.02	0	- 1.055
Test 2	- 0.707	0.15	0	#
Test 3	2.528	0.18	0	- 1.090
Test 4	5.385	0.25	0	#

As indicated in Table 4.10, the two conventional techniques are attractive in their computational speed. Generally, as the size of system increases, the Lambda Iterative method requires more computing time over the Merit Order technique, while Merit Order technique needs more off-line time to design a suitable criterion. The attraction of GAs lies in its accuracy and robustness over the whole range of problems.

The Merit Order technique generally does not need assumptions about the search space, that the objectives can be non-linear and discontinuous. This enables the technique find a wide range of application. However, as for the solution of ED problem, the Merit Order must be dismissed by its lack of accuracy, and difficulty in forming a suitable criterion when multi-conflicting objectives and additional constraints are encountered. Even in the single criterion optimisation problem, the Merit Order technique can not take transmission losses into account and result in unnecessary high costs.

The attraction of the Lambda Iterative method lies in its accuracy when the auxiliary information is fully provided, such as the existence of gradient information, continuity of the search space, convex of the objective function. However, not all the practical system can be approximated by a function with such quality. Furthermore, this quality is inevitably obtained as the result of scarifying the dispatch accuracy. As for the case of Valve-point Loading, when the more accurate, non-convex functions were employed, the Lambda Iterative method failed to resolve the problem because of the discontinuity of the incremental cost curve.

CGA outperformed both conventional techniques when the problems became more complicated. For the case of Valve-point Loading, both Merit Order and Lambda Iterative methods failed to live up with that of the CGA. The effectiveness of three techniques versus problem complexity is depicted in Figure 4.7. As is shown in the diagram, the robustness of the CGA is unbeatable by the conventional techniques. The solutions attained by CGA remained near optimal even though the complexities of problems were increasing. Further, as a GA uses probabilistic rule rather than deterministic rule to determine a solution, the processing speed is independent of the complexity. Hence, a GA would result in same computational time over wide range of problem spectrum when the same power plant is applied. On the other hand, the Lambda Iterative method uses the transit rule for a solution result, and the computational time is therefore largely dependent on the complexity of the problem. It can then be concluded that the more complex the problem is, the more benefit that one can get with a CGA. However, due to its inherent parallelism, the CGA requires much longer computing time. The issue of speeding up GA processing by Hybrid Genetic Algorithm will be discussed in detail in Chapter 5. In addition, despite GA's comparable performance, the class of CGA has experienced difficulties in carrying out a genetic search both effectively and efficiently. Further performance enhancement can be done by optimising the CGA search strategy, which will be addressed in next chapter.

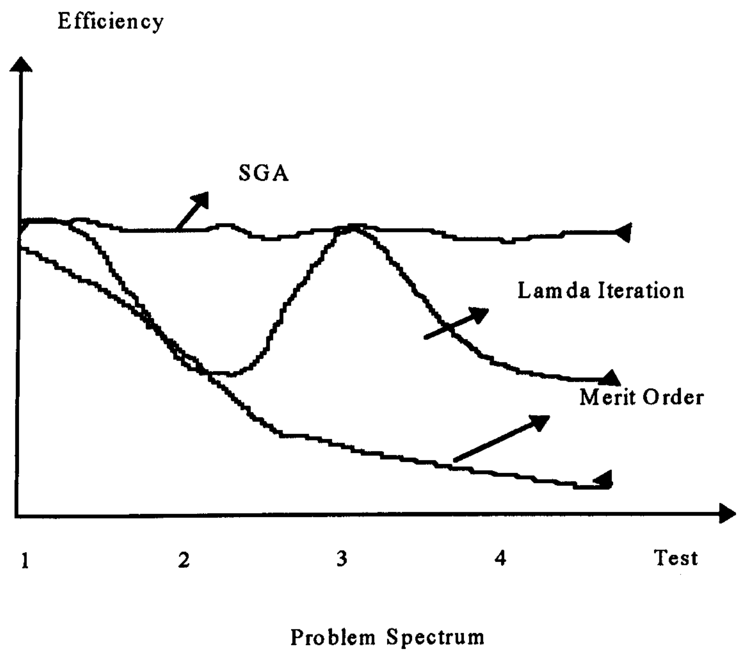


Figure 4.7 Comparison of efficiency with respect to problem complexity between the CGA and conventional techniques.

CHAPTER

5

PERFORMANCE ENHANCEMENT OF A CGA ON THE STATIC ECONOMIC DISPATCH PROBLEM

This chapter gives in-depth investigations on Conventional Genetic Algorithms(CGAs) and performs some modifications to improve the system performance. The outcome of the study is to try to find the best genetic operating strategy to work on the static economic dispatch problem (SED). Two levels of problem have been dealt with for performance improvement: firstly choosing a suitable genetic strategy, and secondly tuning various parameter values for the preselected genetic strategies. Both levels have been tested on a 6 generator system. The strength and weakness of individual strategies are analysed regarding both on-line and off-line system performances.

5.1 INTRODUCTION

Searching a complex space of problem solutions with any search technique often involves two conflicting objectives: exploitation and exploration. On one hand, a strategy must be able to gather broad information about the search space and use it to concentrate the search effort in the most promising regions (exploitation). On the other hand, if a region does not lead the search to the optimal point, the search must be able to move on to other regions of the space, so that the search can continue in more promising regions (exploration). A good genetic search strategy depends solely on its optimal balance between these two contradictory goals. A balanced strategy can not only identify the area where the optimum locates, but also concentrate its effort there and converge to the optimum with a reasonable time. Hill-climbing and Gradient techniques are two typical exploiting search strategies that fully make use of available knowledge to search for solutions where the improvements are most likely to be.

However, this kind of search is local in scope, and easily trapped in a local optimum which could be far removed from the global optimum. Random Search is a good example of exploring search strategy, which continuously explores the search space and keeps the current best solution. The Random Search ignores the available feedback information to reduce the uncertainty about the search space, and randomely samples every corner of the solution space. As a result, the search suffers intolerable inefficiency.

GAs are search techniques which are proposed to balance these two goals in a near optimal way. GAs possess both the properties of using accumulated historical information to locate the search to the potential region and the hill climbing ability to converge the search to the optimal point. With this powerful search ability, GAs are able to solve difficult problems in high-dimension, multi-modal, discontinuity or noisy problem environments. The success of GAs in the complex problem domain have been demonstrated in a number of applications, including function optimisation [DeJong, 1975], gas pipe control [Goldberg, 1985], pattern recognition [Cavicchio, 1970], as well as in the electric power industry.

5.2 LIMITATIONS OF A CGA

Despite their powerful search ability, the conventionally defined GAs (CGAs) fail to live up to the high expectations engendered by the theory [Davis, 1987]. CGAs experience difficulties in balancing the two conflicting search goals, and exhibit two undesirable behaviours: one is **premature convergence**, in which case the genetic search converges to a non-optimal plateau; another is **slow processing speed,** that the GA takes a considerable long time to complete a search. Both problems become extensively severe when the size and constraints of an operating system grow.

5.3 OVERCOMING PREMATURE CONVERGENCE

The cause of premature convergence behaviour can be intricate. It is partially due to the stochastic side-effect of random samples on a finite population. Baker [1985] observed that the premature convergence often occurs when a few highly fit individuals contribute a large number of offspring to the next generation. Since the overall population is fixed, a small number of offspring are available for the rest of the population. When too many individuals have no chance to reproduce totally, the search loses its diversity and prematurely converges to a local optimum.

Hence premature convergence is purely the result of the unbalance in the two contradictory search efforts: exploitation and exploration. Selection and crossover are two major factors which influence the balance between the two search efforts. The amount of exploration performed by crossover is limited by the amount of exploitation performed by selection. The exploration performed by mutation is small in scale, and only provides background variation and restoration. The degree of the two search efforts is controlled by the values assigned to each genetic operator. However, this adjustment can only be used as a secondary tool to keep the balance. By carefully implementing a genetic procedure, unbalance of the two search efforts can be avoided, and the premature convergence can be avoided also.

5.3.1 OPTIMISING GENETIC ALGORITHMS

Prevention of premature convergence should be sought from advanced genetic algorithms. This involves two levels of tasks. The bottom level is to select an advanced or problem oriented genetic strategy, while the top level is to finely tune the parameter value optimally in order to get maximum efficiency out of the preselected genetic strategies. [Lawrence, 1987] suggested five ways to improve a genetic search strategy, the bulk of which is actually seeking to balance the two search efforts of exploitation and exploration; they are:

(1) Advanced Genetic Operators: by employing the advanced genetic operators, the search may avoid the selection inaccuracy and recombination efficiency. Besides the commonly used proportional genetic selection, more advanced selection operators have been developed, which include ranking selection, and steady-state selection methods [Goldberg, 1991] to avoid a few super individuals dominating the whole population. An Elitist Genetic Algorithm [DeJong, 1975] has been proposed to maintain the current best one in the population for its beneficial genes to be passed to all generations even under severe sample error. Crossover is improved from simple one point crossover to two point crossover and multi-point crossover. A more disruptive crossover operator, known as uniform crossover, is suggested to provide even better results [Syswerds, 1989]. Fixed Mutation rate has been changed as functions of the string's fitness or maximum generations to enhance the system performances [Fogarty, 1989]. Moreover, an adaptive parameter setting is proposed by Srinivas [1994] to realise the twin goals of keeping search diversity and search pressure.

(2) Suitable Evaluation Function: a suitable evaluation function could enhance the system performance greatly with genetic approaches, normally by employing a normalization process and an appropriate way to implement complex constraints [Homailfar, 1994].

(3) Appropriate String Representation: string representation can be changed from bit string coding to grid coding or floating point representation [Janikow, 1991].

(4) Better Initial String Generation: the formation of the initial population is not limited to random generation, but can instead take into account the additional knowledge about the system [Davis, 1991].

(5) Optimal Choice of Genetic Parameters: system performance can be significantly influenced by the combined effects of population size, crossover rate, mutation rate, and the number of crossover points. The optimal setting of the genetic parameters can improve the realisation of the twin goals of maintaining diversity in the population and sustaining the convergence of the GA.

5.3.2 THE PROPOSED PERFORMANCE IMPROVEMENTS

For development and adaptation of advanced genetic strategies, this project mainly puts efforts in selection and crossover procedure, as they are the two principal and influential operators for the trade-off between exploitation and exploration. The following advanced genetic strategies have been employed in this project:

(1) **Steady-state Genetic Algorithm (SSGA).**
(2) **Elitist Genetic Algorithm (EGA).**
(3) **Ranking Genetic Algorithm (RGA).**
(4) **Two-points crossover Genetic Algorithm (TGA).**
(5) **Variable mutation Genetic Algorithm (VGA).**
(6) **Deterministic roulette wheel selection (DGA)**

Parameter values, such as population size, crossover rate and mutation rate, for each strategy are tuned till satisfactory results are obtained. Optimally combining two levels of improvement tasks can have significant impact on overall system performance. The search will be given enough selection pressure for better realisation of the "survival of the fittest". At the same time, the diversity of the search space is maintained.

5.3.2.1 STEADY-STATE GENETIC ALGORITHM (SSGA)

In a CGA, the new generation is created to replace the entire population of old individuals with the genetic modified new ones. This generational replacement technique has some potential drawbacks. Firstly, the diversity of solution is easily lost if there are few individuals with extraordinary high fitness. These individuals could dominate the whole population within a small number of generations, while the search is still in a local minimum. Secondly, the best individual among strings may be lost or destroyed by genetic operators. To overcome these problems, instead of replacing the whole population at every generation, SSGA only replaces a few of the old population at a time. It tends to slow down the convergence speed, and keeps the search space as diverse as possible.

5.3.2.2 ELITIST GENETIC ALGORITHM (EGA)

The SSGA is a quite effective method to prevent the best solution being disrupted by the genetic operator over generations. However, it is very inefficient due to the large iteration a SSGA requires, which in turn is owing to only a few new members introduced at each iteration. A simpler technique is to keep the current best individual unchanged, and always pass it to the next generation to allow the beneficial material to be maintained in the whole generation.

5.3.2.3 RANKING GENETIC ALGORITHM(RGA)

For the same reason as the SSGA, the RGA tends to keep the search diverse to prevent premature convergence. For the rank based GAs, an evaluation function becomes less important. Ranking assigns each string a new fitness value according to its performance related to other members in the population. The superiority of the RGA over other GAs lies in its ability not only to slow search speed to keep search diversity, but also to increase speed by exerting the selection pressure when necessary.

5.3.2.4 GENETIC ALGORITHMS WITH TWO-POINT CROSSOVER

The disadvantage that one-point crossover exhibits is that it can not reach every feature that strings can combine. This results in losing some beneficial parts among the strings. Two-point crossover overcomes this drawback and introduces more variations to offspring, which encourages the search to move towards the most promising area.

5.3.2.5 GENETIC ALGORITHMS WITH VARIABLE MUTATION RATE

The mutation rate is normally held constant throughout a run of the conventional genetic search. It is normally kept very low to provide only background variations. With such a low rate, the mutation operator might not be able to provide enough new material to test the search space thoroughly. Yet, a higher mutation rate will result in large disruptions of the highly fit solution. As a result, the variable mutation rate is introduced. It tends to give enough variation at the beginning of the search to keep the diversity, while offer less variation at the end of run to prevent too many good solutions from disruption. The variable mutation rate proposed in this study is exponentially decreased over the number of generations.

5.3.2.6 DETERMINISTIC ROULETTE WHEEL SELECTION

The reproduction procedure is easily performed by creating a roulette wheel. The idea is that strings with higher fitness values take a larger portion of the wheel, while strings with low fitness are given a smaller portion of the roulette wheel. A span of the weighted wheel yields the reproduction candidates, where the highly fit strings have a higher chance to contribute more copies into next generation. Hence, 'survival of the fittest' is realised with this simple procedure. However, sample errors might be introduced by the finite and randomised selection procedure. The reason is that the landing point is completely randomised at each spinning of the wheel. If only a finite population size is used, an imbalance can be introduced when some regions on the wheel receive more than two landings, while some others receive none. When the sample errors are accumulated over the generations, the overall effect can lose some beneficial material and lead the search away from those theoretically predicted. Although increasing population size can be the solution to this problem, it can only be done moderately, as this increased accuracy is at the cost of great computational expense.

A deterministic roulette wheel selection is proposed in this project to reduce the sample error. First, the roulette wheel is equally divided into different regions, and the number of regions is the same as the population size. Secondly, the wheel is forced to land only once at each region so that the entire search space is equally sampled. With the improved selection procedure, more accurate information is gathered to assist the algorithm to make the right decision and lead the search towards the right direction, consequently improving the reproduction accuracy.

5.3.2.7 OPTIMAL CHOICE OF GENETIC PARAMETERS

Optimal parameter tuning can have significant impact on overall system performance. However, there is no generic parameter setting available which will perform equally well in various problems. The best parameter setting for one problem might be quite different from that for another problem. The tuning for various parameter values is a time consuming task. Some general guidance has been drawn by several researches. DeJong concluded the effect of different parameters on the performance in his Ph.D. thesis [DeJong, 1975] as:

"Increasing the population size would improve long-term performance at the expense of slower initial response. Increasing mutation rate was seen to improve off-line (best performance at each generation) system performance at the expense of decreased on-line (average performance at each generation) system performance. Increasing the crossover rate results in overall performance improvements."

With this observation DeJong recommended a parameter setting which yields generally good behaviour for both on-line and off-line performances. They are:

population size	50-100
crossover rate	0.6
mutation rate	0.001

[Grefenstette, 1986] suggested a quite different way of choosing appropriate parameter values. His suggestion is: if a small generation number is considered, then a high crossover rate and low mutation rate are necessary; on the other hand, if a relatively large population is used, there should be a moderate crossover rate and a low mutation rate. Thus, the following parameter settings were chosen by him for the applications which favour in better on-line performance:

population size	30
crossover rate	0.9
mutation rate	0.01

Although these two conventional suggestions can generally attain reasonably good solutions, practical applications emphasise the need for robust settings which can adapt optimally to various search strategies and problem environments. [Srinivas, 1994] derived adaptive parameter settings for the crossover and mutation rates, where the recombination rates are determined by the GA itself. The user is therefore relieved of the burden of specifying the values of crossover and mutation rates.

5.3.3 EFFECTIVE IMPLEMENTATION OF GAs ON CLASSIC ECONOMIC DISPATCH PROBLEM

In this section, the impact of parameter tuning and the effectiveness of the proposed enhanced GAs are demonstrated on the classic ED problem. The solution quality will be measured with regard to both on-line performances (average performance at each generation) and off-line performance (best performance at each generation). The on-line system performance is simply the average performance of all structures tested during the search. This measure is appropriate in those situations in which an adaptive system is used to dynamically alter the performance of a system, where any tested structure which is shown to be poor will be penalised. To do well on the on-line performance, a search algorithm must be able to quickly decide where the best value lies and concentrates its search there. The off-line performance is computed by using only the current best solution, which does not give penalties for exploring the poor regions of the search space on the way to better solutions. It is applicable in situations where the test can be done independently of the system being controlled. The search might be done off-line while the current best structure is used until a better one is found. To do well off-line, an algorithm must give enough time for the search to explore the entire search space, which enhances the possibility to find the global optimum.

5.3.3.1 THE SYSTEM DESCRIPTION

The test system employed consists of six generator units supplying one constant load demand, which is obtained from Wood [1984]. The fuel cost function of each unit is a quadratic function of the generator's real power output. The cost functions and the output limits are given as follows:

$$F_1\ (\$/h) = 0.001562 P_1^{2} + 7.92 P_1 + 561.0 \qquad 100 < P_1 < 600$$

$$F_2\ (\$/h) = 0.00194 P_2^{2} + 7.85 P_2 + 310.0 \qquad 100 < P_2 < 400$$

$$F_3\ (\$/h) = 0.00482 P_3^{2} + 7.97 P_3 + 78.0 \qquad 50 < P_3 < 200$$

$$F_4\ (\$/h) = 0.00139 P_4^{2} + 7.06 P_4 + 500 \qquad 140 < P_4 < 590$$

$$F_5\ (\$/h) = 0.00184 P_5^{2} + 7.46 P_5 + 295 \qquad 110 < P_5 < 440$$

$$F_6\ (\$/h) = 0.00184 P_6^{2} + 7.46 P_6 + 295 \qquad 110 < P_6 < 440$$

The load demand is 1800 MW and transmission losses are ignored in the test.

5.3.3.2 EXPERIMENTAL DESIGN

Initially, a benchmark was established to assess the performance of each improved GA. The effect of parameter setting on the on-line and off-line system performances was investigated, followed by the tests of various improved GAs on the SED problems. The tests carried out are in the order as:

(1) Optimal parameter tuning.
(2) Elitist GA (EGA).
(3) Steady-state GA (SSGA).
(4) Ranking GA (RGA).
(5) Two-point crossover GA (TGA).
(6) Variable mutation rate (VGA).
(7) Deterministic GA (DGA).

5.3.3.3 EXPERIMENTAL RESULTS

Benchmark

The bench mark is established from the on-line and off-line results of a CGA on the SED problem using the six generator system. The ultimate goal for the SED problem is to determine the optimal generator output level for each unit in order to minimise the total operating cost. Two parameter sets for population size, crossover rate and mutation rate have been employed for the problem. One is DeJong's steady setting [50, 0.6, 0.001], and the other is Grefenstett's adaptive setting [30, 0.9, 0.01]. Each generator output is represented with a 10 bit string, which resulted in a fixed string length of 60 for each solution. A total of 50 generations were used throughout the parameter tuning test in the aim of providing adequate evolution to the initial Guessed solutions.

The on-line and off-line system responses with DeJong's and Grefenstette's settings are illustrated in Figure 5.1 and Figure 5.2 respectively. DeJong's settings have steadily improved the solution fitness on on-line system performance over generations. However, the improvement made is in small steps due to the slow exploring speed defined by the lower crossover rate and mutation rate. The results with Grefenstett's settings are quite disruptive because of the higher crossover and mutation rate, which are intended to emphasise the effort of exploration. Though the performance with Grefenstett's setting is not steady, it is quicker to obtain a good solution. Moreover, the search has better chances to attain a good solution strategy within a shorter time. Also, because of the larger population size with DeJong's settings, it takes a much longer computing time to complete a genetic process. For the SED problem on the 6 generator system, it took 9.83 seconds for the DeJong's setting to complete the 50 generation processing compared with that of 2.69 seconds for Grefenstett's setting. From the computational expenses and short-term performance point of view, Grefenstette's setting of [30, 0.9, 0.01] is more attractive. For long term system performance, DeJong's setting is safer because of its consistent improvement on the solution quality.

(1) Effect of Parameter Tuning

The effects of parameter tuning are addressed to the three most important parameters: population size, crossover rate and mutation rate. However, the effect of such parameter tuning is influenced greatly by the random search nature of genetic processing. Figure 5.3 shows performance variations with 10 trials on the SED problem with the typical parameter settings:

Total generations:	50
Population size:	30
Crossover rate:	0.9
Mutation rate:	0.01

It is notable that both on-line and off-line performances have large variation for the 10 identical runs, and only the preserved best solution showed some consistency. The reason is that each genetic processing always starts with a fresh initial starting point, which is quite different from one trial to another. Also, the whole processing is completely randomised, which can cause performance variation. However, over a long term, these variations should be reduced. Figure 5.4, 5.6 and 5.7 are the effect of parameter tuning in population size, crossover rate and mutation rate on on-line and off-line performances. Figure 5.5 is the relation between the computing time and population size.

It is clearly shown in Figure 5.4 that larger population size does not always imply a better solution quality. A large population can guarantee a better long-term off-line performance, but the on-line performance is adversely affected. For example, a GA with a population size of 30 gave the best on-line performance, while one with a size of 40 had the best off-line performance. For the population sized 60, the GA had relatively good results for both on-line and off-line performances. However, under the same number of generations, the GA with the larger population responded more slowly. It is clearly shown in Figure 5.5 that computing time is proportional to population size while the number of generation was kept as 50. For the population size of 30, the completion of 50 generations required 2.4 seconds, while for the size of 60, it needed 4.6 seconds to finish, and the cost saving thus made is only 0.38%. However, a too small population size, such as below 20, can not provide good results for either on-line or off-line performances.

The effect of an increased crossover rate and mutation rate mainly lies in their more disruptive on-line and off-line performances. The benefit is that a search can result better preserved best solution, which can be made use of in the case of the SED problem. This effect is more obvious in the case of changing crossover rate. A lower crossover rate and mutation rate tend to reduce the number of new individuals per generation, and are therefore not sufficient to attain better overall solutions.

In the application of the CGA on the SED problem, the best parameter settings for the 6 generator system were verified as:

Population size:	30
Crossover rate:	0.6
Mutation rate:	0.008

The resulting performance is illustrated in Figure 5.8. The advantages, which the optimal parameter setting achieved, lie in its steady improvement of on-line performance, yet keeps off-line advances over the generation. However, the improvement made is not significant. Therefore, parameter tuning can only be used as a supplementary tool for performance enhancements.

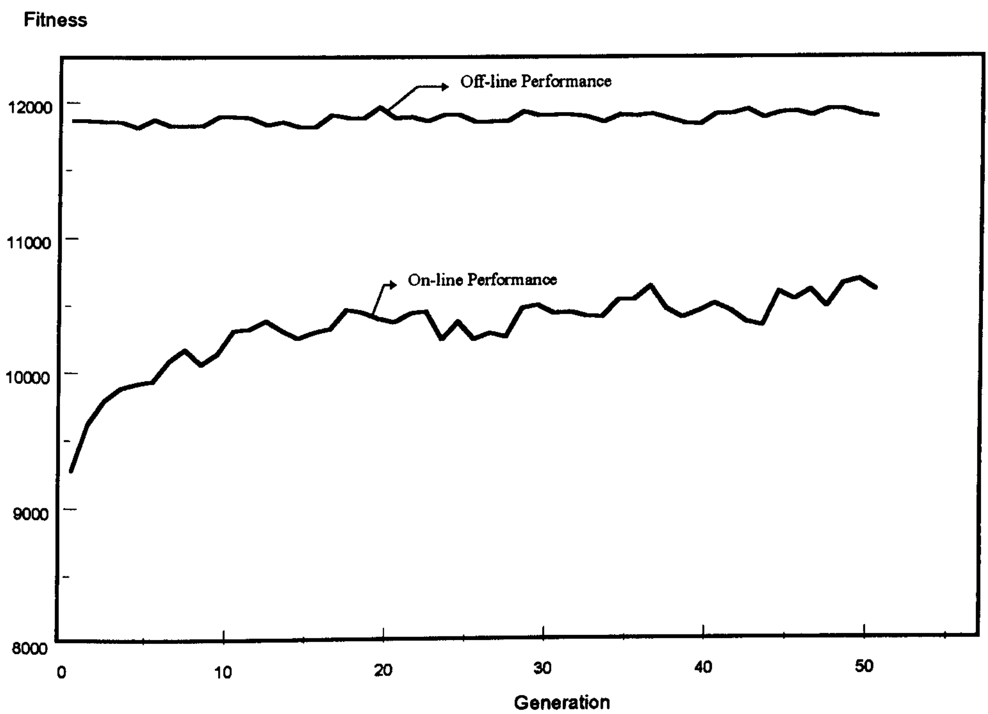


Figure 5.1 The CGA performance based on DeJong's setting [100, 0.6, 0.001].

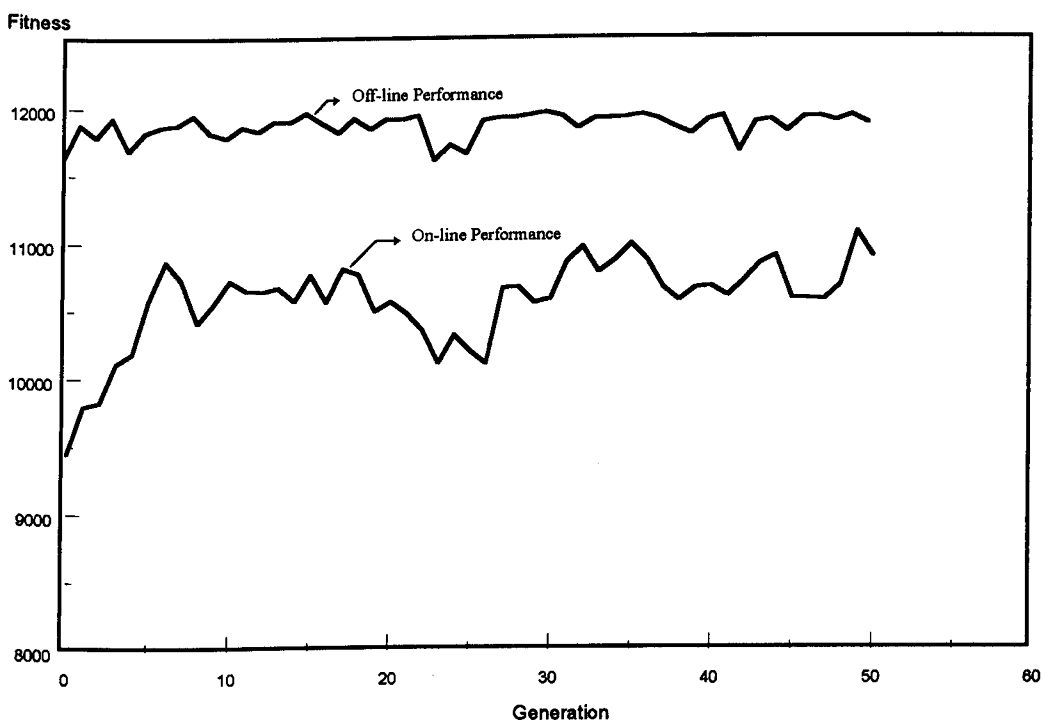


Figure 5.2 The CGA performance results based on Grefenstette's set [30, 0.9, 0.01]

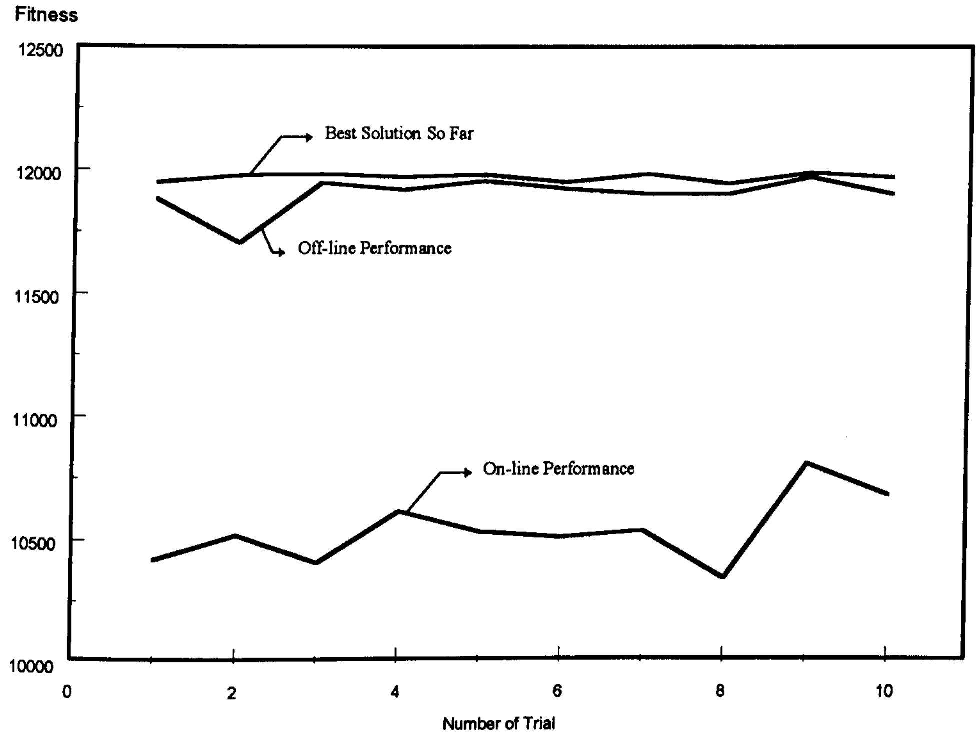


Figure 5.3 The effect of the randomised genetic procedure on system performances.

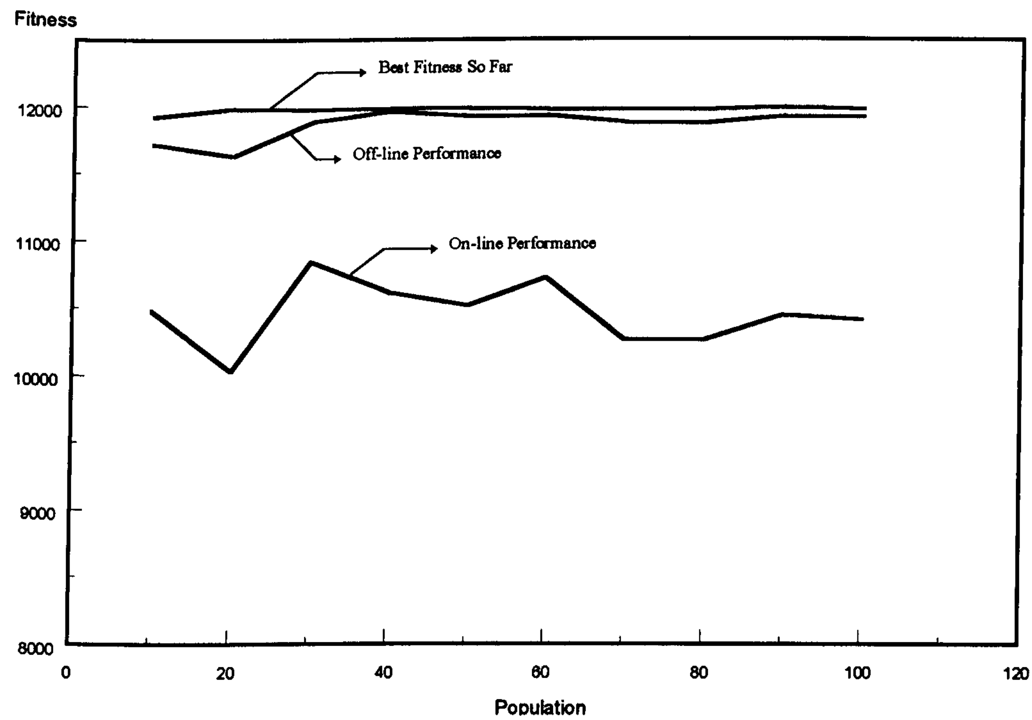


Figure 5.4 The effect of population size on system performances.

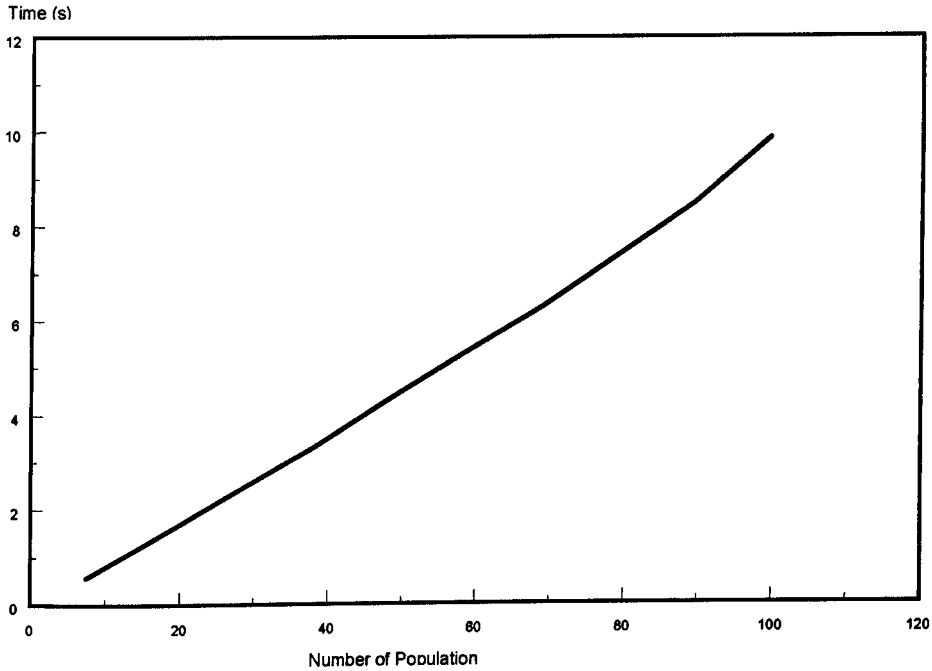


Figure 5.5 The effect of population size on computing time.

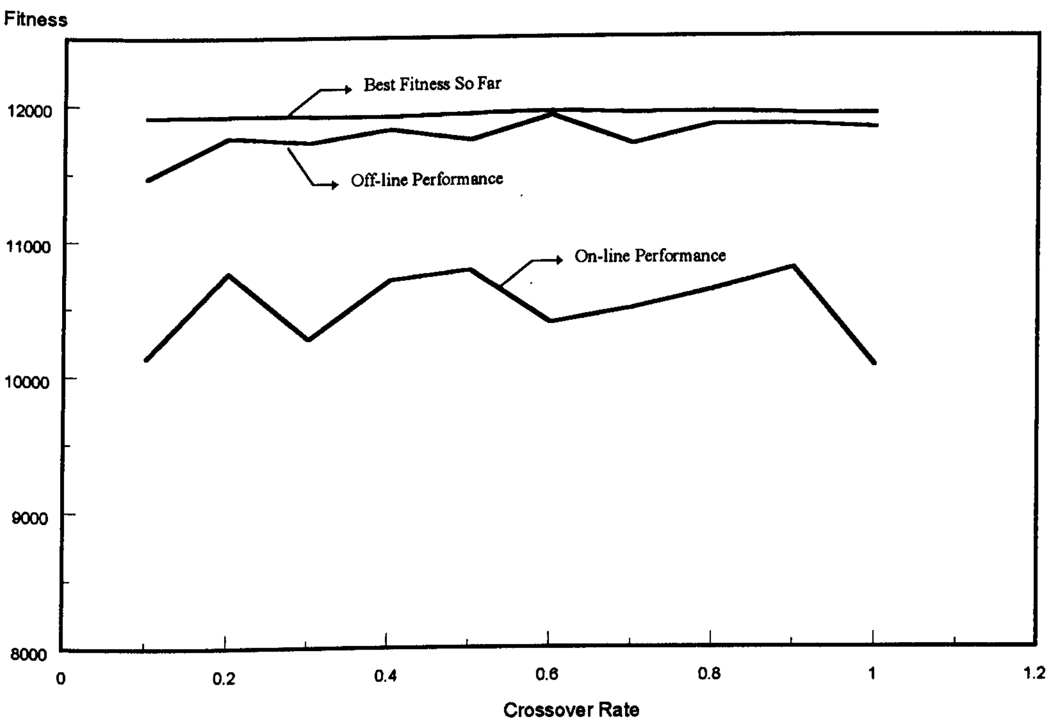


Figure 5.6 The effect of crossover rate on system performances.

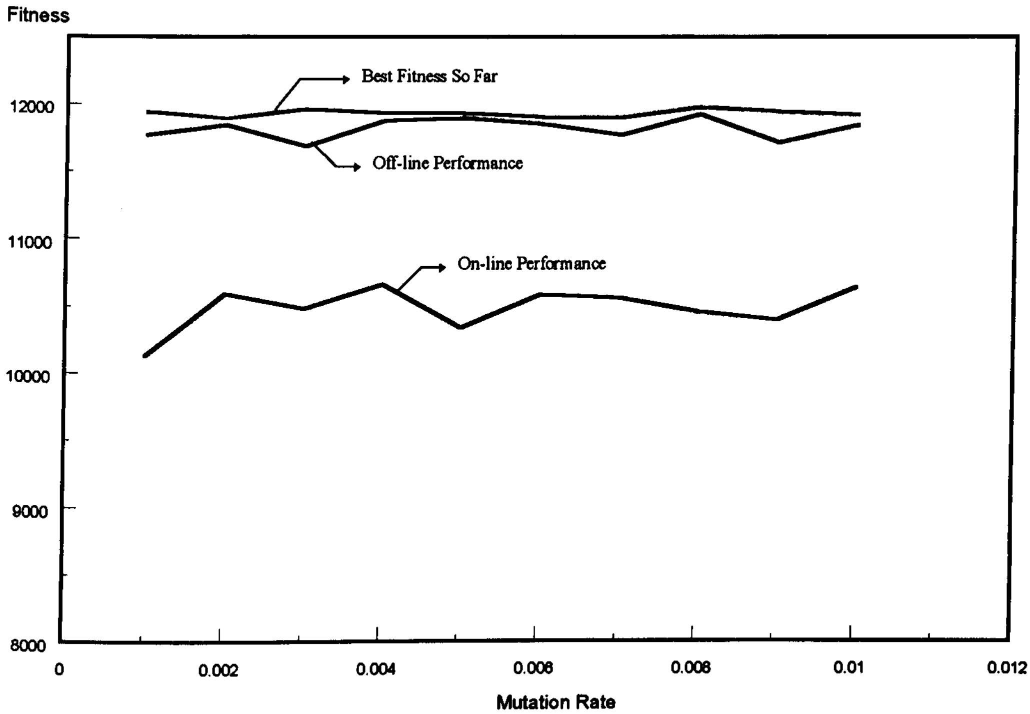


Figure 5.7 The effect of mutation rate on system performances.

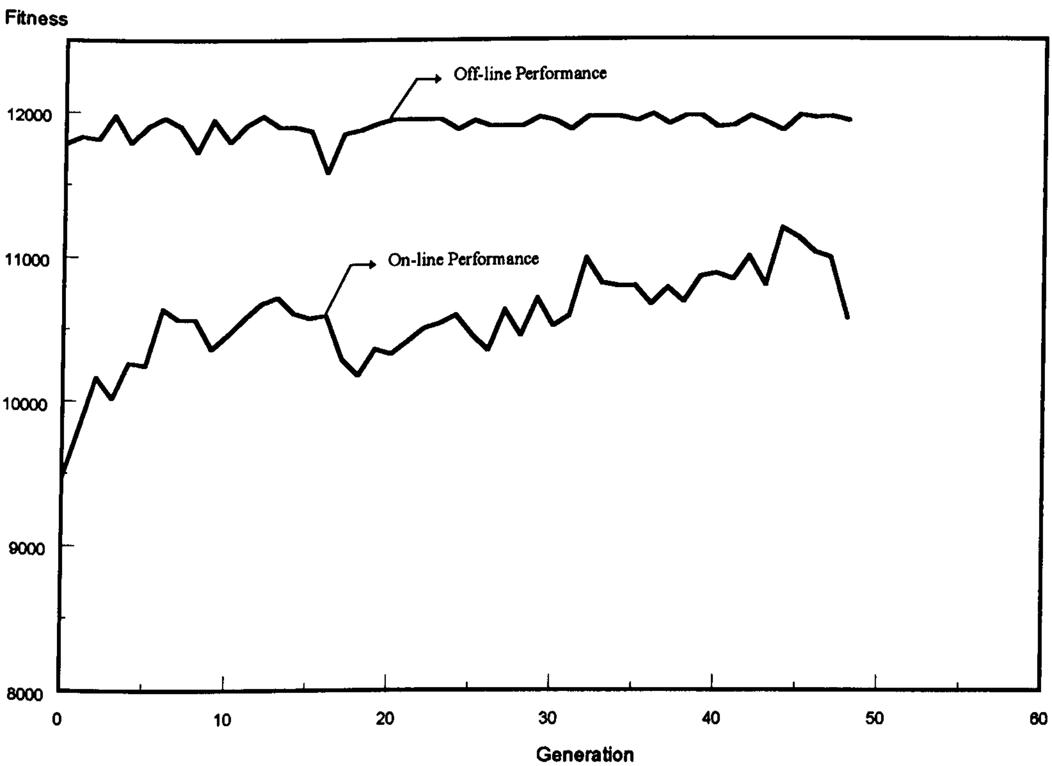


Figure 5.8 The CGA performances with the optimal parameter setting.

(2) Elitist Genetic Algorithms (EGA)

It is shown in Figure 5.2 that the performance of CGA with Grefenstette is superior for its ability to attain better results at very early stage, but limited by its unstable overall on-line performances. On the contrary, DeJong's settings consistently improve the performance over the time as seen in Figure 5.1. It is therefore attractive for its security and safety. However, the improvement over each generation is in much smaller steps. The EGA has therefore been developed [DeJong, 1975] to insert security in to the disruptive Grefenstette's setting by always passing on the current best solution among the population to sustain the beneficial material. The results of the EGA on the system for both parameter settings are shown in Figures (5.9-5.10), where it is clear that the performance improvement on Grefenstette's setting is significant from the very early stage.

(3) Steady-state Genetic Algorithms (SSGA)

The system performances on the ED problem with the SSGA are shown in Figures 5.11 and 5.12, where Figure 5.11 is the result with DeJong's setting while Figure 5.12 is that of Grefenstette's settings. The difference lies between the CGA and the SSGA is that the SSGA replaces only two worst parents at every generation, while CGA replaces the entire population each time. With a total of 200 generations, the on-line performance has been improved significantly on both parameter settings over the course of a GA run. The off-line performance has been improved substantially on Grefenstette's settings. This pictures clearly shows the benefit of the SSGA's ability in better preservation of beneficial genes, being able to keep its search diversity, and therefore have more chance to attain the global optimum. While other GAs tend to decide which way up at a much early stage, and can be trapped in a local optimum. For the GA with DeJong's settings, no significant off-line performance improvement has been made during the 200 generation. This is mainly due to its slow recombination speed, hence takes much longer time to complete the same search space compared with that of Grefenstette's setting. However, it is expected that given a longer time to DeJong's setting, same improved on the performance can be make. Because of the large generation it has to endure to provide enough manipulation to the initial population, the SSGA is a very time consuming search strategy. It takes about 5 times longer than

CGA to arrive at the same optimal point. Despite the time consuming problem, it still attracts wide attention because it guarantees the significant performance improvement in the long term.

(4) Ranking Genetic Algorithm (RGA)

The results of the RGA on the SED problem are illustrated in Figure 5.13 and Figure 5.14. The RGA exhibits significant improvement in on-line performance with Grefenstette's setting, which proves the RGA can reduce the sampling error and stochastic effect with the deterministic evaluation function. The on-line performance improvement has also been made with DeJong's setting, yet the improvement is rather small. The superiority of the RGA compared with the SSGA lies in its hugely improved on-line performance, and its reduced computing time compared with the SSGA. The argument against the RGA is that it ignores the large variation between the different solutions, but only assigns the fitness value according to the performance rank among the population. This is against the foundation of genetic search, where the fitness value is the only information to guide the search.

(5) Deterministic Genetic Algorithm (DGA)

A DGA can prevent a roulette wheel selection procedure from unbalanced landing, and therefore give each area an equal opportunity to be sampled. The DGA provides background insurance against the possibility of sampling error, consequently reducing chances of getting premature convergence. The comparison upon system performance has been carried out with the optimal parameter setting [50, 0.6, 0.008] as population size, crossover rate and mutation rate for the 6 generator system. From Figure 5.15, such insurance did improve both on-line and off-line performance, though the improvement is small in scale.

(6) Two-points Crossover Genetic Algorithm

The performances of TGA are depicted in Figures 5.16 and Figures 5.17. It is notable that significant on-line improvement has been made at a very early stage, however, the off-line performances were only improved slightly.

(7) Variable Mutation Genetic Algorithm

The performance of VGA is illustrated in Figures 5.18 and 5.19. The performance improvement on on-line performance is significant, especially with Grefenstette's parameter setting. This is due to its ability to preserve better individuals at later stage by decreasing the mutation rate. However this improved on-line performance is at the cost of the off-line performance.

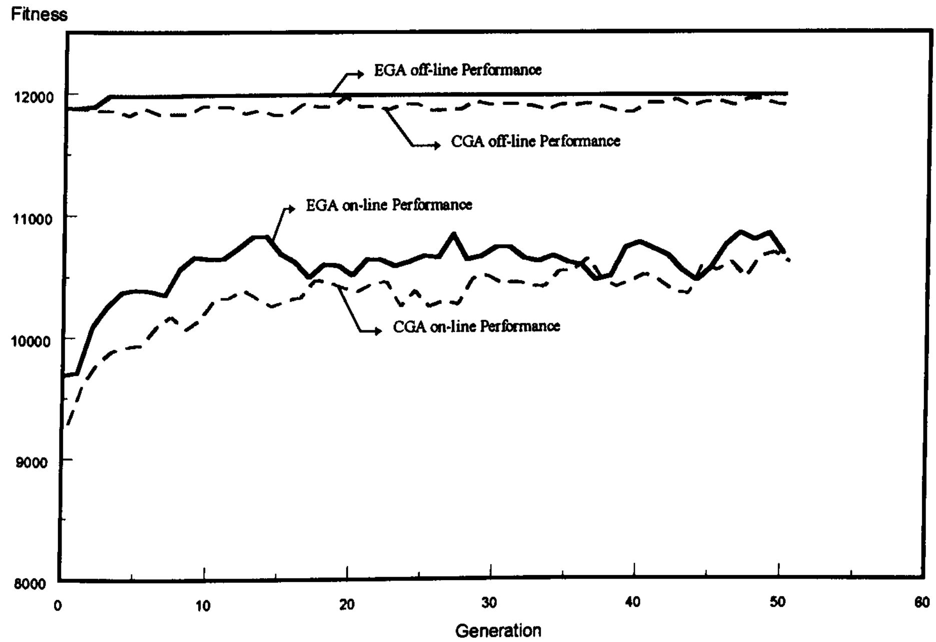


Figure 5.9 The EGA performances with DeJong's setting [100, 0.6,0.001].

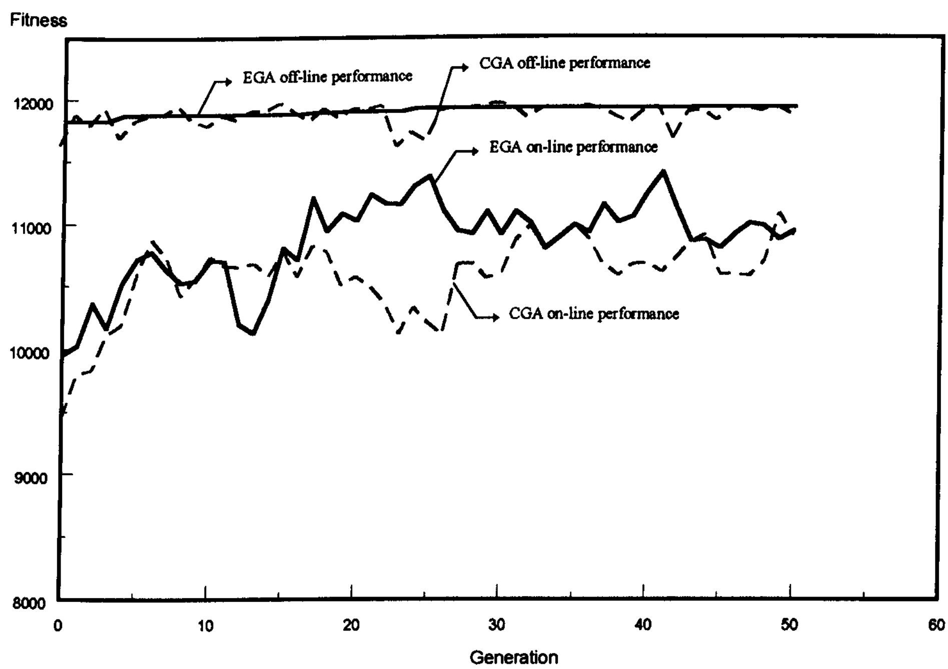


Figure 5.10 The EGA performances with Grefenstette's setting [30, 0.9,0.01].

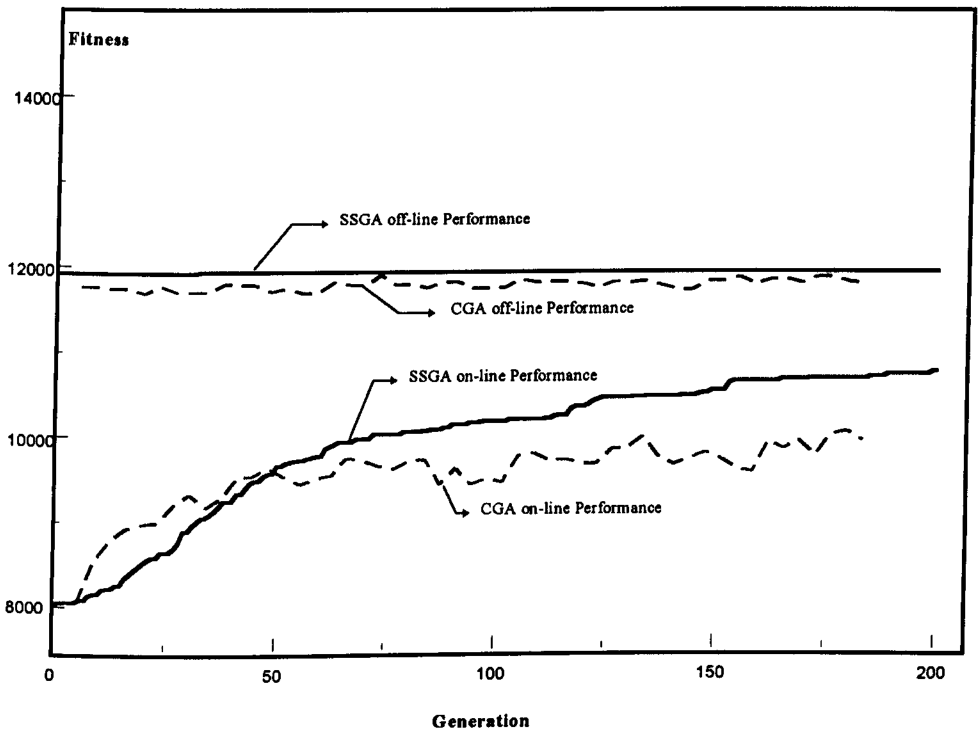


Figure 5.11 The SSGA performances with DeJong's setting [100, 0.6,0.001].

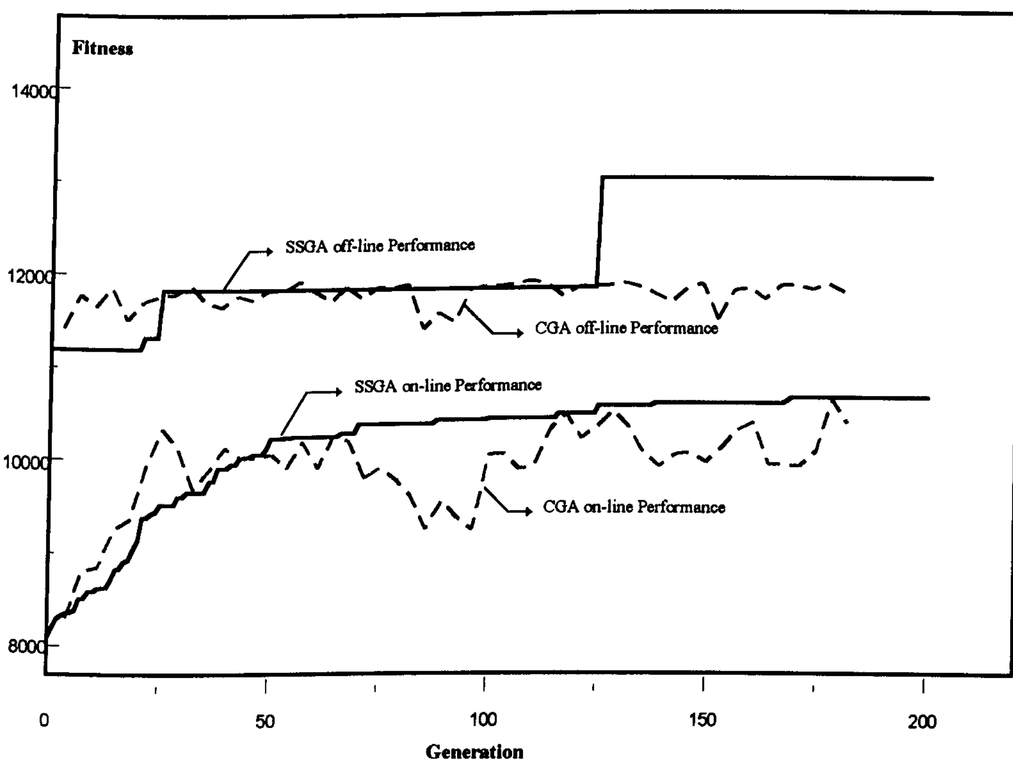


Figure 5.12 The SSGA performances with Grefenstette's setting [30, 0.9,0.01].

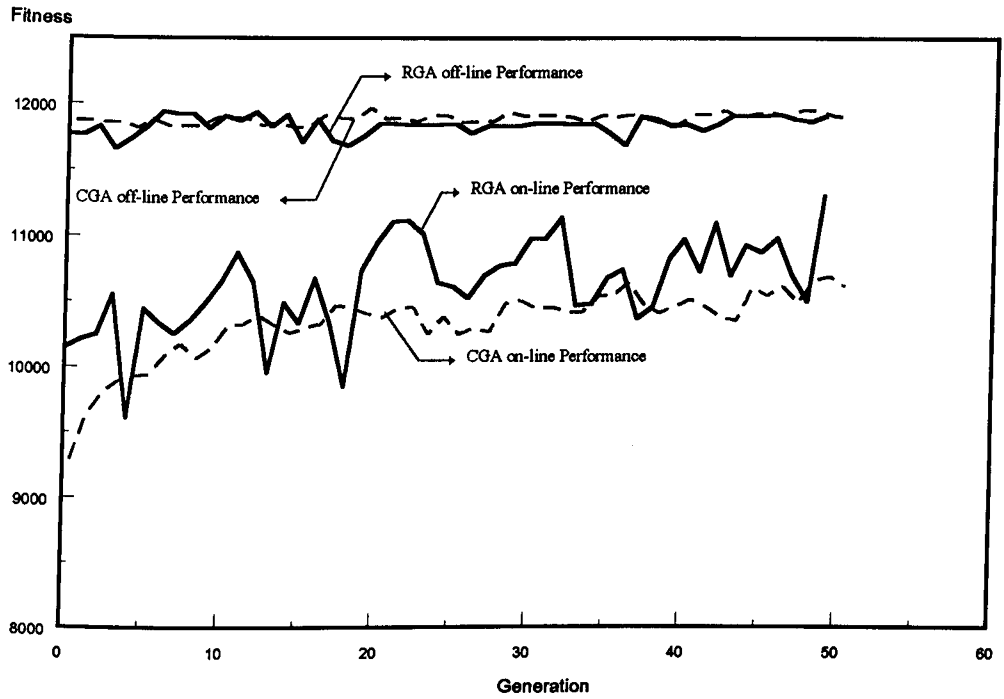


Figure 5.13 The RGA performances with DeJong's setting [100, 0.6,0.001].

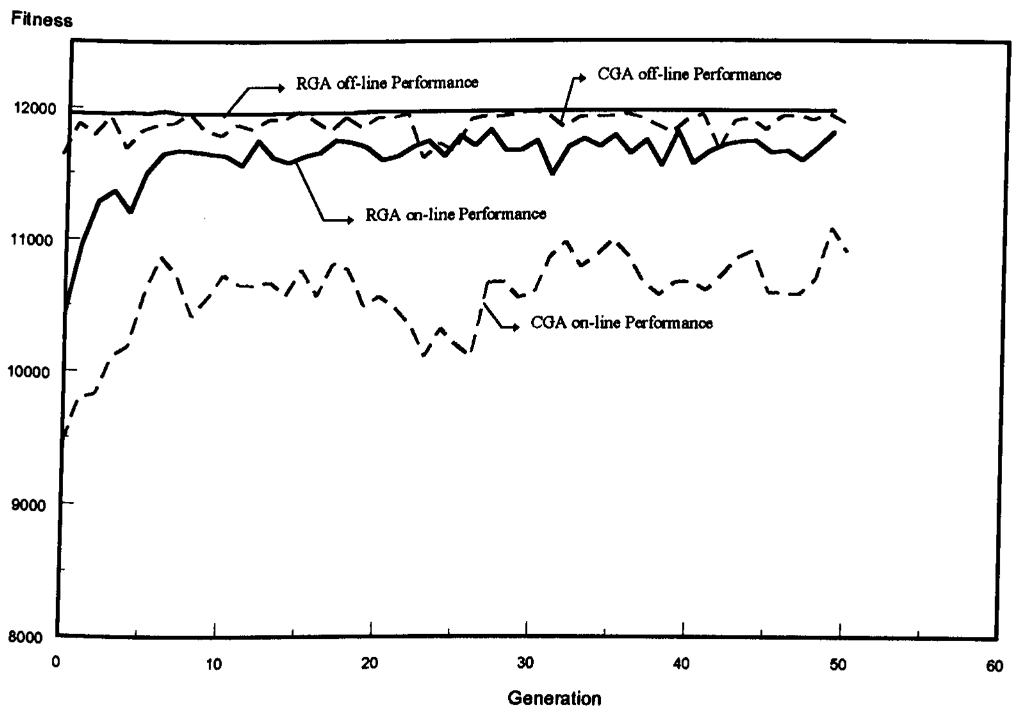


Figure 5.14 The RGA performances with Grefenstette's setting [30, 0.9,0.01].

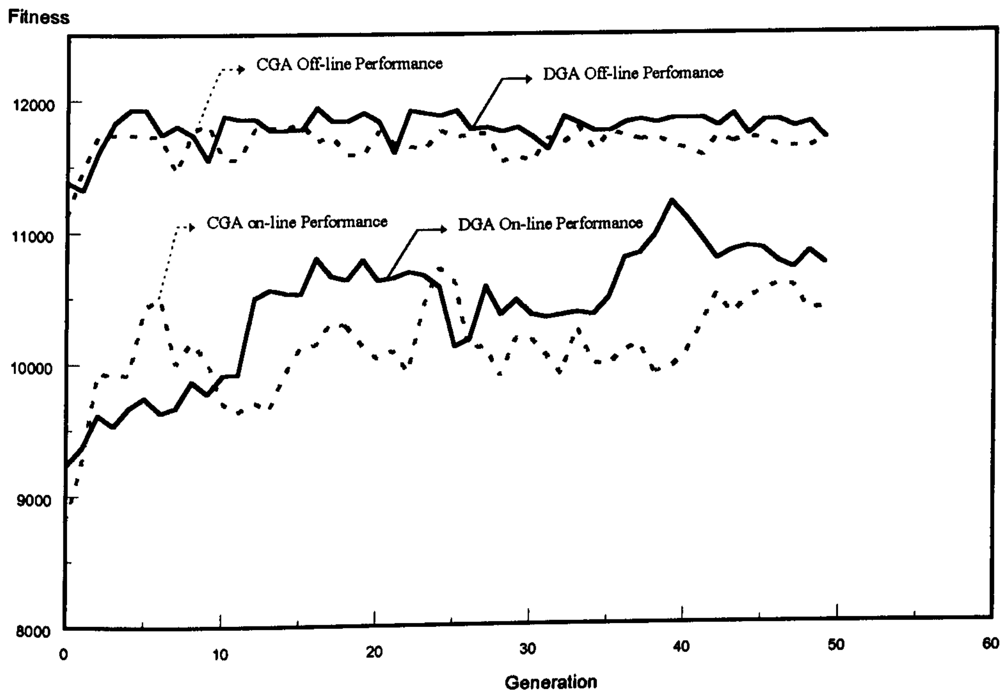


Figure 5.15 The performance comparison between the DGA and the optimal CGA.

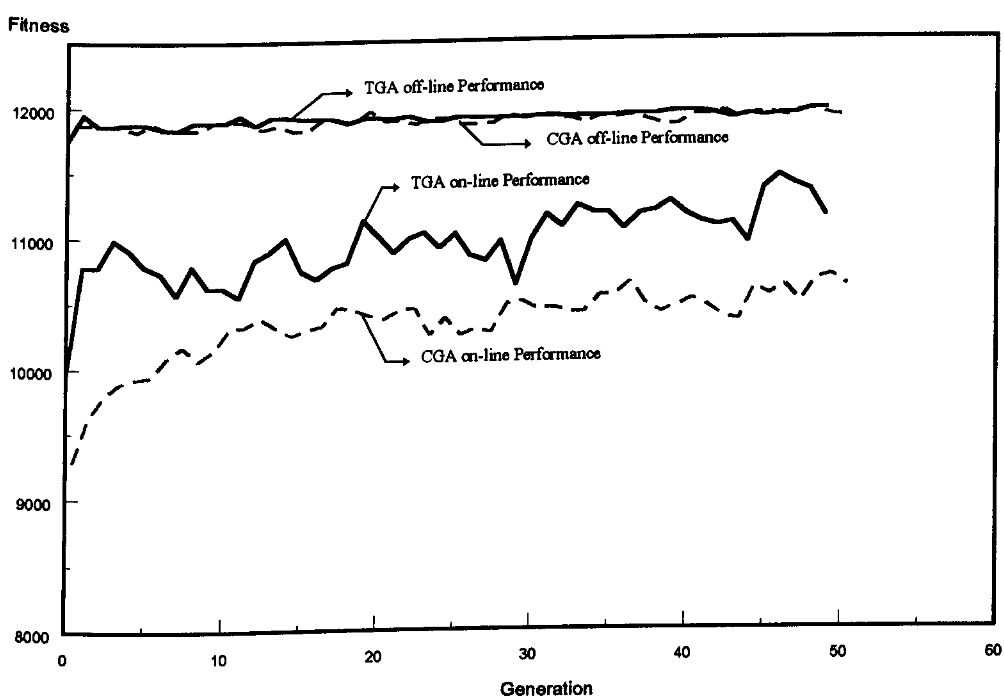


Figure 5.16 The TGA performances with DeJong's setting [100, 0.6,0.001].

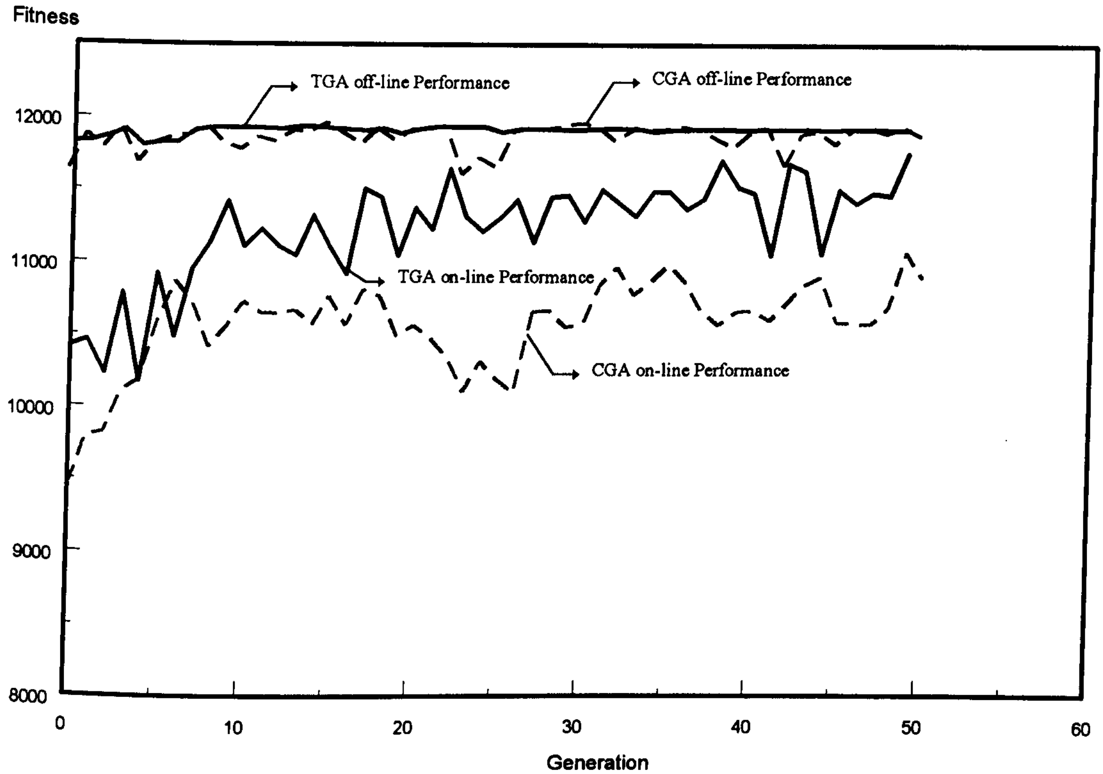


Figure 5.17 The TGA performances with Grefenstette's setting [30, 0.9,0.01].

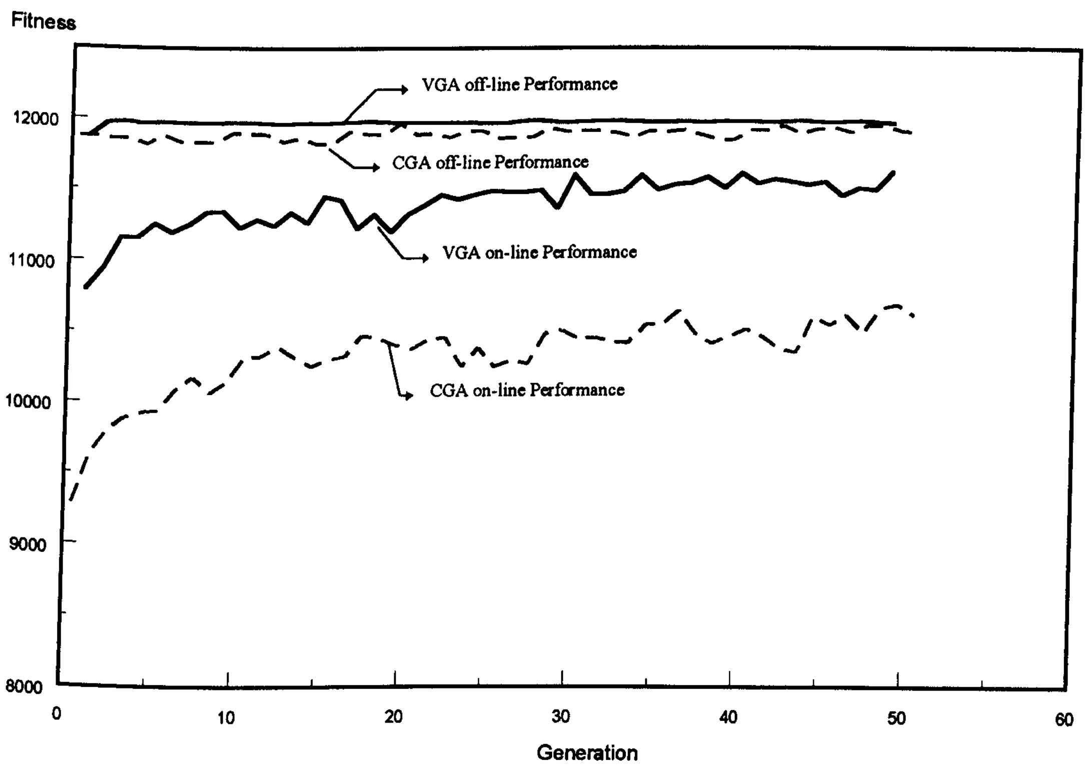


Figure 5.18 The VGA performances with DeJong's setting [100, 0.6,0.001].

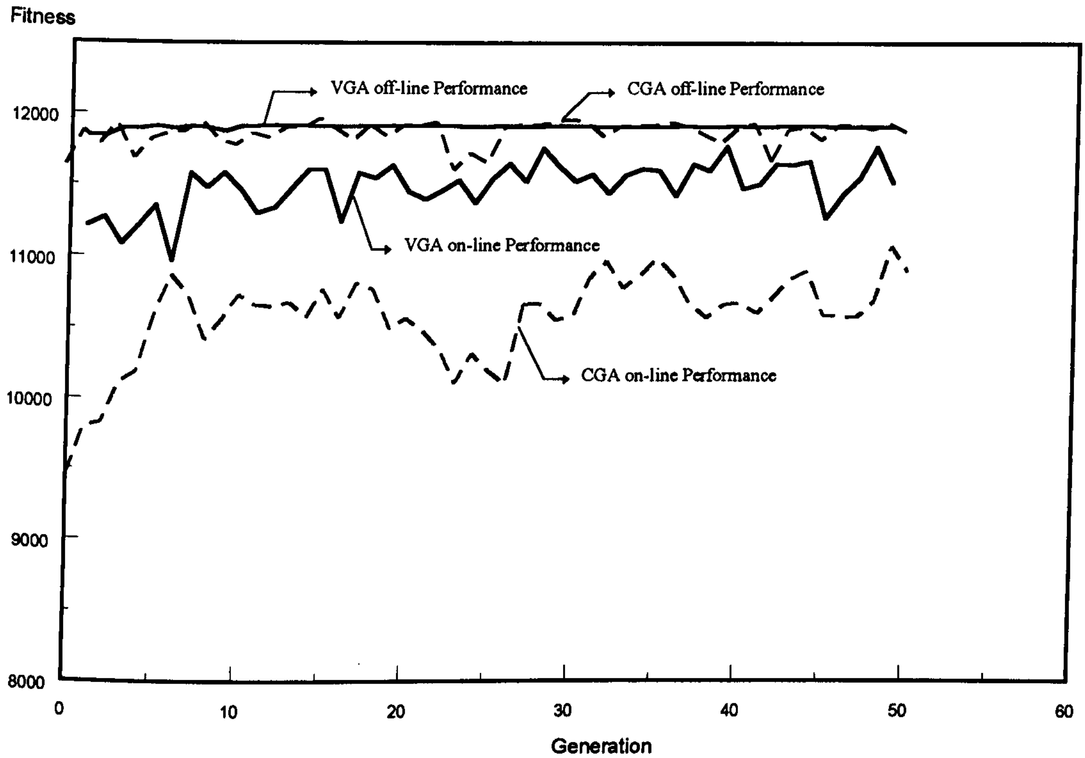


Figure 5.19 The VGA performances with Grefenstette's setting [30, 0.9,0.01].

5.3.4 DISCUSSION

A good genetic strategy lies in two levels of choice. The primary level is the selection of a suitable genetic strategy, the secondary level is the choice of the appropriate parameter setting. Optimal combination of these two levels can help a genetic strategy in seeking a balance between the two conflicting search efforts: exploration and exploitation. The experiments carried out in the previous section clearly indicate that the choice of a genetic strategy and an optimal parameter setting can influence system performance significantly.

Performance enhancement ought to be sought firstly from advanced genetic strategy, where the improvement made is fundamental, and therefore can be huge. From the experiments, it can be concluded that SSGA has the advantage of attaining better off-line solutions in the long term, while RGA, TGA, and VGA have the ability to obtain better on-line solutions. EGA and DGA have the capacity to improve both on-line and off-line performances, they can be coupled with any genetic strategy, though the improvements thus made were small in scale. Further advances in genetic strategy can be sought from the combination and extension of the above listed strategies.

Parameter tuning serves as a secondary tool to enhance system performance, yet it can play a very important role in performance improvement. An increase in population size will improve long-term off-line performance, but at the cost of on-line performance and slow system response time. An increase in crossover rate and mutation rate will adversely affect on-line performance, but improves off-line performance. Despite the significant impact that the parameter setting can have on a system performance, tuning parameter values is a time consuming job, and in many real-time cases, such time is not affordable. Under such circumstances, two conventional suggestions for parameter setting have been proved to be valuable and can be made use of. One is Grefenstette's setting, which has the advantage of quick processing speed and better off-line performance, and another is DeJong's setting, which is slower in speed, but provides generally good performance for both on-line and off-line performances.

Apart from the advanced genetic strategy and optimal parameter tuning, other factors such as a suitable fitness functions to better handle objectives and constraints, better initial population generation, etc., also play very important role in performance improvement. In conclusion, a good GA strategy is dependent on effective string representation, better initial population generation, a suitable evaluation function, advanced genetic operators, as well as optimal choice of GA parameters. By carefully implementing a genetic search algorithm, the imbalance of those two search efforts can be reduced, and the premature convergence can be alleviated.

5.4 OVERCOMING SLOW PROCESSING SPEED WITH HYBRID GENETIC ALGORITHMS

The improvement made by carefully implementing a genetic algorithm as discussed in section 5.3, can only balance the two conflicting search efforts: exploration and exploitation. This implies that an increase in the accuracy of a solution must be at the cost of sacrifice to the speed of the convergence, and vice versa. It is unlikely that both of them can be improved simultaneously. In contrast, by crossing a genetic algorithm with other well known conventional techniques, the hybrid operational strategy makes it possible to speed up the genetic search processing as well as to improve the solution quality.

5.4.1 INTRODUCTION

Slow processing speed is another vital weakness associated with GAs. A GA casts a net through the entire search space so that the potential hill can be identified no matter how complex the search space is. However, this increased robustness comes at the cost of considerable computational time because of a GA working with a group of solutions in parallel. This has prevented their use in many practical applications, where speed is of particular importance. Speeding up genetic processing is therefore a very important issue in GA applications. Although many researchers suggested using parallel processors to make the multiple genetic search serial, which can indeed improve the genetic processing speed significantly, it needs considerable capital cost and lead time for design and implementation.

HGAs are the cheap and simple solutions to the slow processing speed of genetic search. The attraction of a GA search is its ability to identify the potential hill. However, as a GA spends most of the time in competing between different hills, rather than improving the solution along the potential hill, a GA takes a considerably long time for the fine tuning local search. In contrast, local search techniques have the advantage of climbing hills very fast. However, they are blind to the neighbourhood search area, and therefore can become easily trapped in a local optimum. By crossing a

GA with other well known local search techniques, a HGA can take advantages of both the local and GA techniques, so that the global perspective of the GA is made use of and the convergent capability of the local search techniques is utilised . So called hybridisation of Genetic Algorithms (HGAs) can boost the system performance greatly by improving the search algorithm both effectively and efficiently.

5.4.2 DESIGN OF A HYBRID GENETIC ALGORITHM

In this study, HGAs are designed by crossing an Elitist Genetic Algorithm (EGA) with a first order gradient technique (GT). The EGA employed has the mechanism of generational reproduction, one-point crossover, random mutation and preservation of the best solution among the population. The EGA is used as the base search technique to quickly identify the optimal region and consequently reduce the search space. The feasible solution obtained with the EGA is subsequently passed over to a first-order GT [Wood, 1984] which is adopted as a local hill climber to rapidly climb the remaining hill. Consequently, the optimum can be attained very quickly. The GT has one characteristic which is desirable in hybridisation with a GA, that the GT always starts with a feasible solution, and searches for the optimal solution along a feasible trajectory. In the case of interruption of computation, the most recent operating point will still be a reasonable point to be utilised. Therefore, the GT might be one of the most suitable algorithms to work together with GAs. As for the search space shown in Figure 5.20, the proposed hybrid scheme uses the EGA to identify the potential hill - H2 within a reasonably short time, while the first-order gradient technique is next employed to quickly climb the remaining hill of H2. Thus constructed hybrid genetic algorithms boost the search performance greatly by resolving the premature convergent problem and slow processing speed simultaneously.

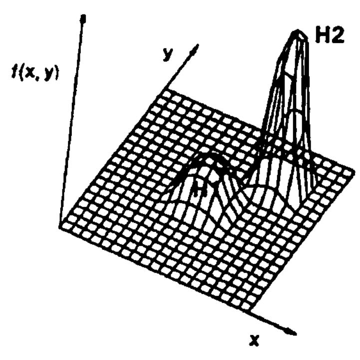


Figure 5.20 A multi-modal search space.

5.4.3 IMPLEMENTATION OF A HYBRID GENETIC ALGORITHM

The test of the proposed HGA on the SED problem is carried out on the six generator system as described in section 5.3.1.1. The number of generations for the EGA is restricted to a relatively small number so that only small computational expense is required. However, it has to be sufficient to be able to identify the hills which contain the potential solutions. The best generation number for the base search is case dependent, mostly obtained by experiments or experience. The best generation number for this case will be discussed in next section. The other parameter values chosen for the EGA in this application are based on DeJong's suggestion.

The results of the base EGA search are then passed over to a first-order GT. Based on the feasible solution provided by the base EGA search, the GT performs changes on the selected unit output to get further cost reduction subject to the following constraint equation:

$$\sum_{i=1}^{n} \Delta P_i(t) = 0 \qquad (5.1)$$

Equation (5.1) states that the sum of the changes in all the power outputs must be equal to zero. This implies that, when a change of power output for any random selected unit x is made, the remaining n-1 units should correspondingly change the total power output at the equal amount but in the opposite direction. Therefore, when the output of unit x is increased by a certain amount, the remaining n-1 units must be decreased by the same amount, and vice versa. This ensures that the newest operating point is still feasible. Mathematically stated, this move can be shown as:

$$\Delta P_x(t) = -\sum_{i \neq x} \Delta P_i(t) \qquad (5.2)$$

Repeatedly performing this move, the GT is able to climb to the top of the hill. By crossing the EGA with the GT, the proposed HGA can attain better solutions within a reasonably short time on the constrained ED problem. The flow chart for the proposed HGA is drawn in Figure 5.21.

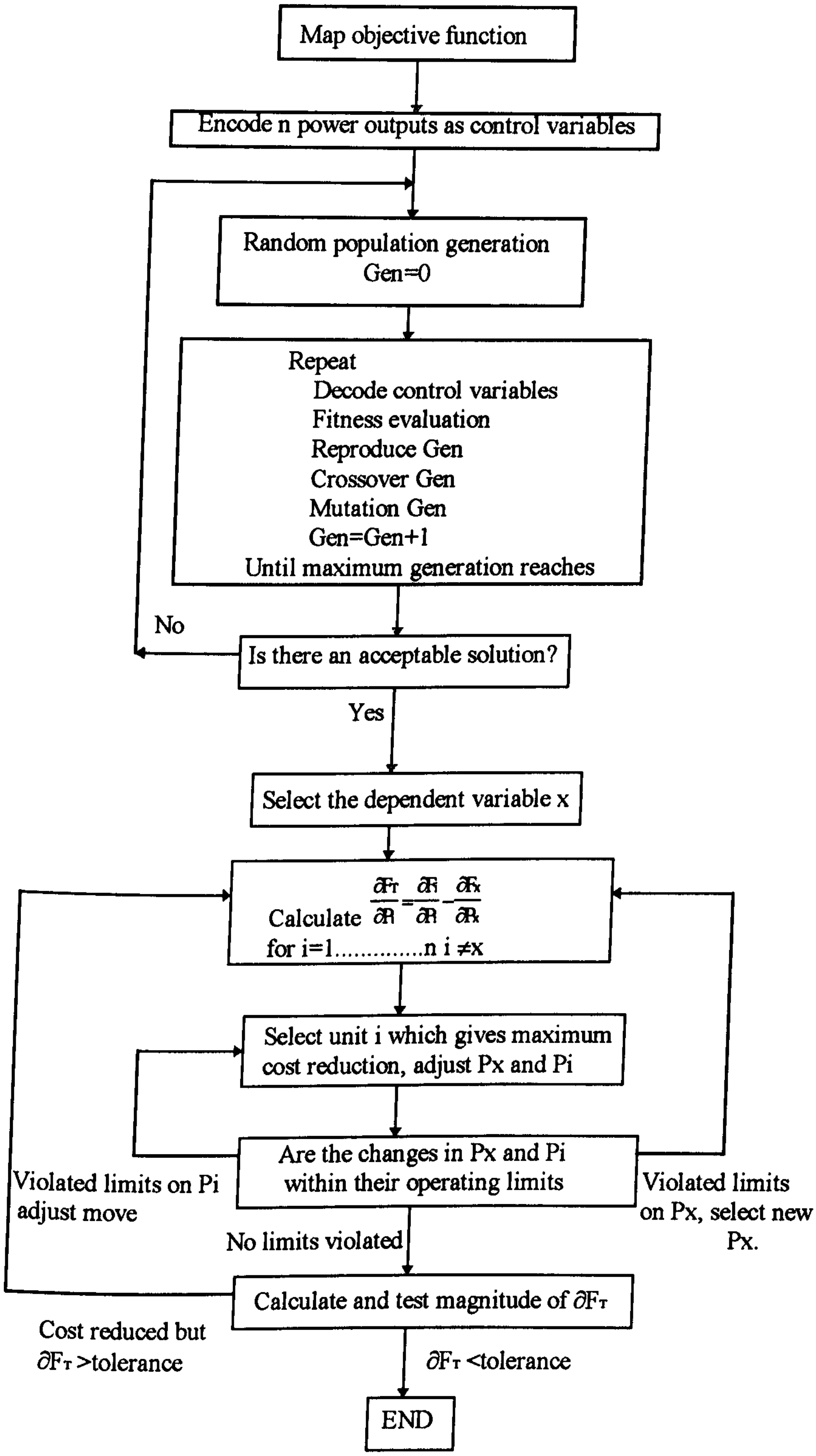


Figure 5.21 A flow chart for the proposed HGA.

5.4.4 AN ILLUSTRATION OF THE HYBRID GENETIC ALGORITHM ON STATIC ECONOMIC DISPATCH PROBLEM

Two HGAs have been proposed in this project to demonstrate their inherent characteristics on the SED problem. The first hybrid scheme (termed as $HGA^{(1)}$) is constructed such that the local search does only one iteration. In this way, the local gradient search technique has a light and constant computing time, which can be ignored when accounting for the total computing time. Under such a hybrid scheme, though the execution time can be approximated to be the same as a CGA, the operating cost is indeed improved. However, the local search technique designed thus may not be able to fulfil the remaining task since the search is restricted by the limited search time. The second hybrid scheme (termed as $HGA^{(2)}$) is designed to further improve the operating cost by fully utilising the potential of local search techniques. The $HGA^{(2)}$ allows local search technique to complete the remaining hill climbing with an extended search time, therefore has better opportunities to achieve or nearly reach the optimal point. Both algorithms are analysed regarding the solution quality and the solution speed. Number of generations for the base GA search is varied for each algorithm in order to provide valuable information in constructing a robust and efficient Hybrid Genetic Algorithm for the ED problem.

Firstly, the test was carried out on the SED problem by the $HGA^{(1)}$. The local search time climbed only one step up so that the search time was limited to 0.22 seconds. With the base GA search changing the number of successive generations from 5 to 35, the resulting operating costs with the $HGA^{(1)}$ are plotted in Figure 5.22. As clearly illustrated, even with a very light local search effort, the technique can improve the cost reduction significantly (up to 0.62%). If the local search time (0.22 seconds) is ignored, for the same computing time (computing time is in proportion to the number of generations), a HGA achieved a lower operating cost (line *a* in Figure 5.22). For the same operation cost, the HGA required a lighter computational expense, as indicated by line *b*. As the number of generations linearly increases, the improvement that the local technique made is monotonically decreased, as shown in Figure 5.23. This occurrence might be explained as follows. Assuming that any base GA search could identify the potential hill, different GAs locate the search at the different levels of that hill. As can be expected, a long base GA search encounters points at the upper region of the hill, while a short base GA search finds the points at the bottom area of the hill. When the search is getting closer to the top of the hill, little improvement can be made. Moreover, small improvements require a great deal of search effort. The bottom region has plenty of room to be improved, and the improvement can be made rather easily.

Secondly, the test was applied to the same SED problem with the second HGA$^{(2)}$. In this case, the HGA$^{(2)}$ provides adequate time for the local search to accomplish the remaining search task so that the search gets better chances to arrive at the optimal point. Again, the base GA search varied its generation number from 5 to 35. The cost improvement thus obtained are shown in Figure 5.24, together with the costs attained by the HGA$^{(1)}$ and the EGA for comparison. The picture clearly shows that the cost can be significantly improved with the HGA$^{(2)}$ (up to 2.67% saving). As the gradient technique is a quick local hill climber, HGA$^{(2)}$ only took slightly longer time than that of HGA$^{(1)}$ to attain much lower costs. The HGA$^{(2)}$ is therefore more desirable in this application.

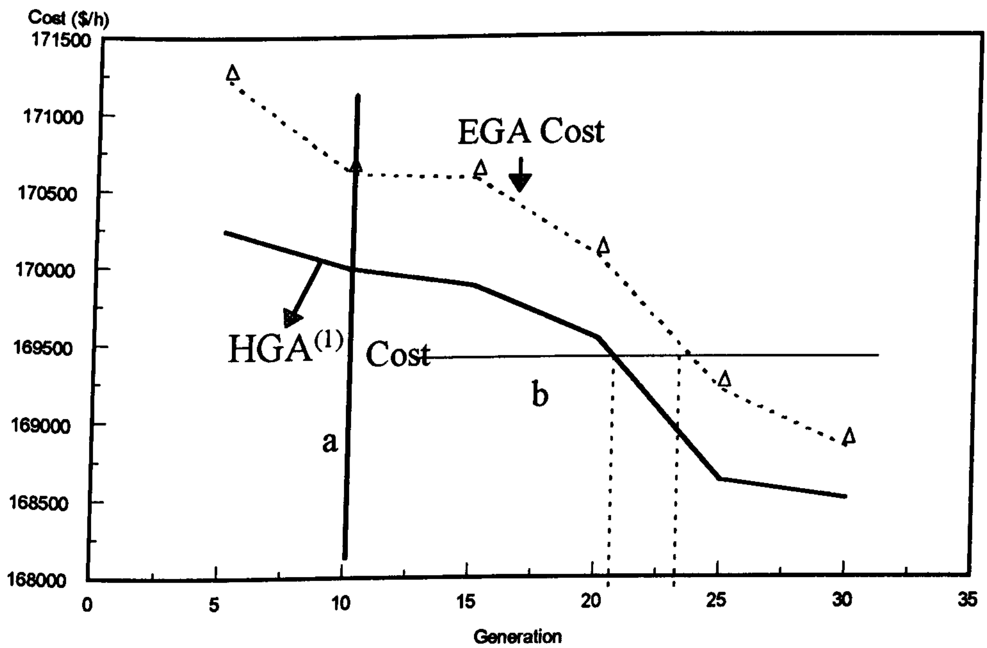


Figure 5.22 Performance improvement of a HGA$^{(1)}$ over a EGA with different base GA search.

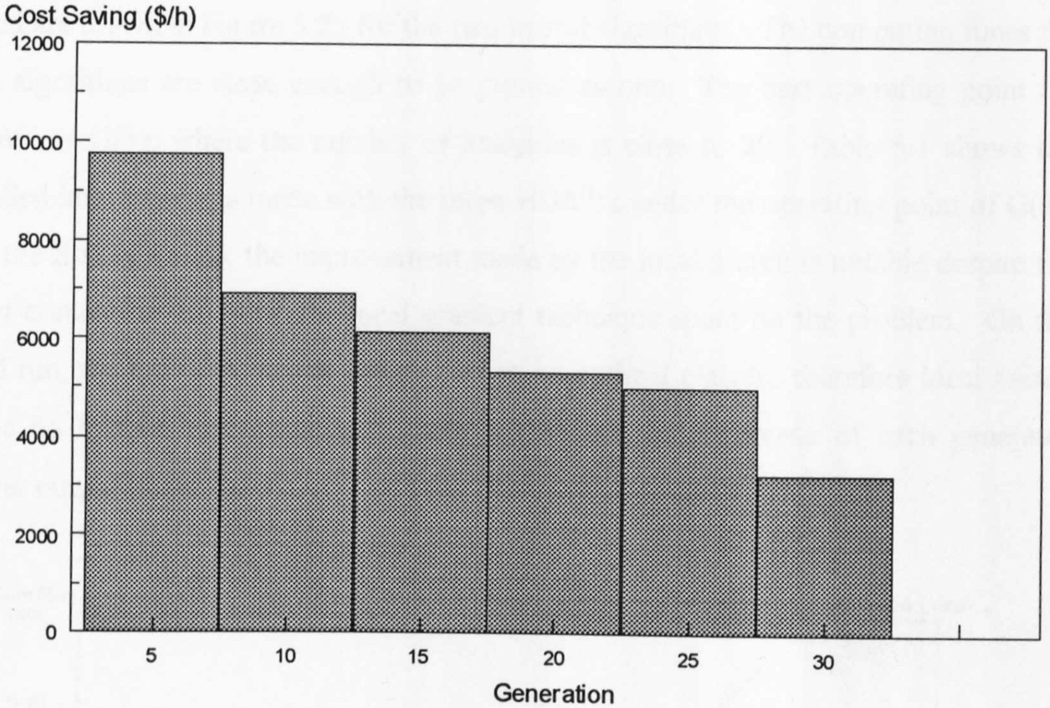


Figure 5.23 Cost saving by HGA$^{(1)}$ with different base GA search.

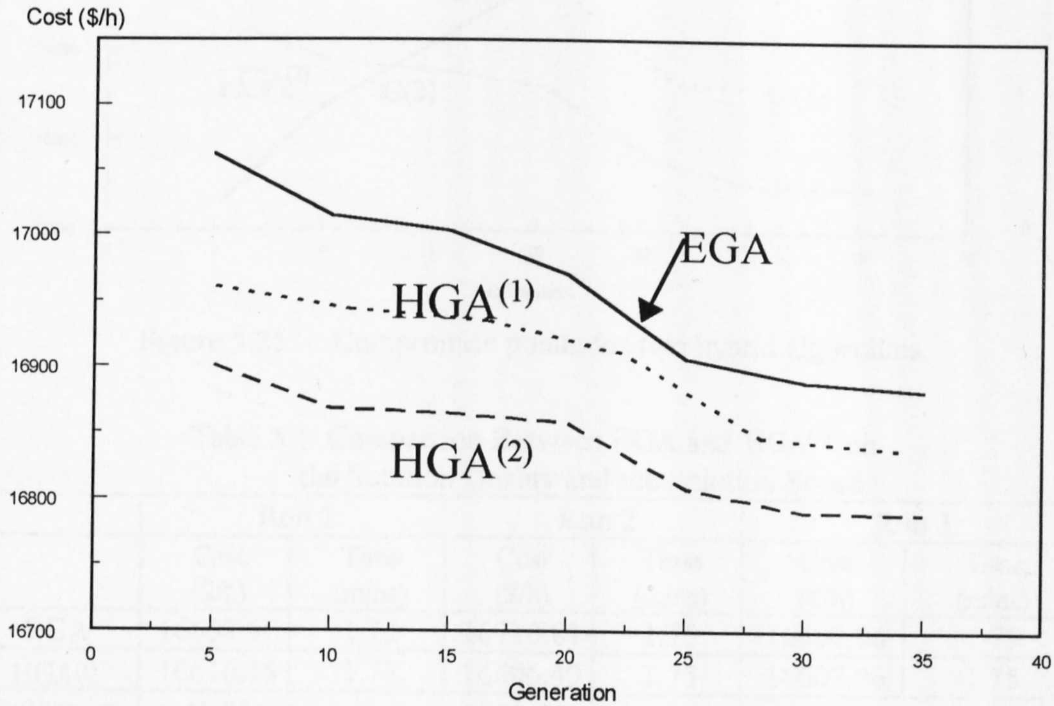


Figure 5.24 Performance improvement of a HGA$^{(2)}$ over a HGA$^{(1)}$ and a EGA with various base GA search.

Finally, the best operating points for optimising the solution accuracy and the solution speed are drawn in Figure 5.25 for the two hybrid algorithms. The computing times for two algorithms are close enough to be plotted as one. The best operating point for HGA$^{(1)}$ is G(1), where the number of iterations is close to 20. Table 5.1 shows the detailed improvements made with the three HGA$^{(1)}$ s under the operating point of G(1). For the first two runs, the improvement made by the local search is notable despite the short computing time that the local gradient technique spent on the problem. On the third run, the base GA search has arrived at an optimal plateau, therefore local search made no further improvements. Table 5.2 shows the difference of each generator power output under the HGA$^{(1)}$ and the EGA search strategy.

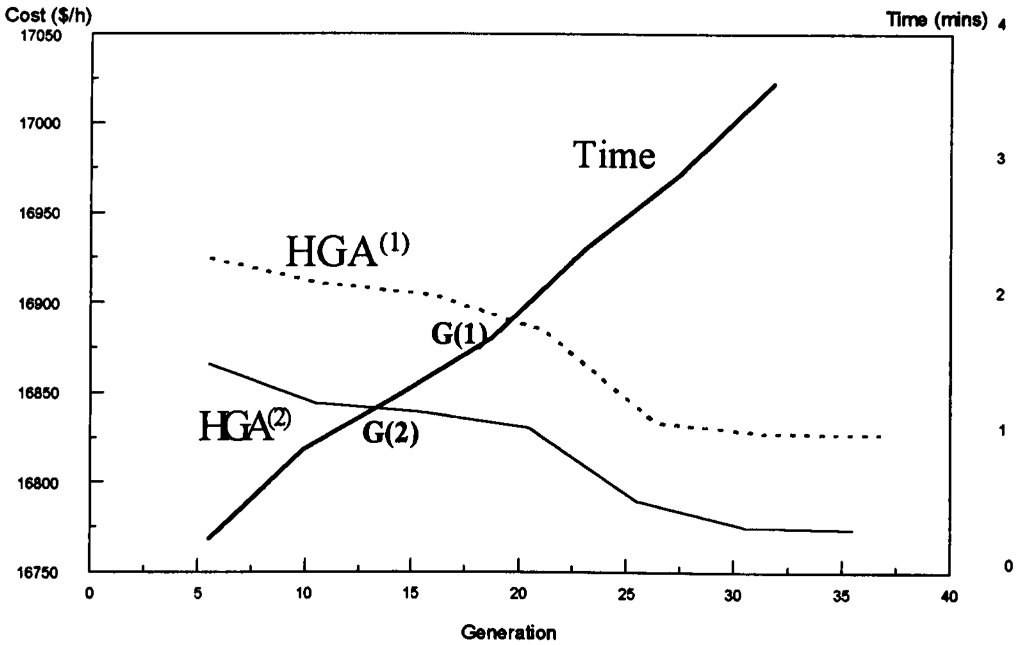


Figure 5.25 Compromise points for two hybrid algorithms.

Table 5.1 Comparison Between EGA and HGA$^{(1)}$ on the Solution Quality and the Solution Speed

	Run 1		Run 2		Run 3	
	Cost ($/h)	Time (mins)	Cost ($/h)	Time (mins)	Cost ($/h)	Time (mins)
EGA	16657.96	1.75	16710.81	1.75	16607.06	1.75
HGA$^{(1)}$	16616.15	1.75	16606.40	1.75	16607.06	1.75
Difference	41.81	0	104.41	0	0	0

Table 5.2 The Difference in Power Outputs for Each Unit Made by the HGA[(1)] over CGA

	Unit 1 (MW)	Unit 2 (MW)	Unit 3 (MW)	Unit 4 (MW)	Unit 5 (MW)	Unit 6 (MW)
EGA	285.72	386.80	60.99	309.35	391.61	365.80
HGA[(1)]	251.59	372.87	83.96	578.65	377.65	135.58
Difference	34.13	13.93	22.97	269.30	13.96	230.22

The compromise point G(2) for HGA(2) has an iteration number of 15. The results attained by three identical HGAs(2) are listed in Table 5.3. The allocation differences are listed in Table 5.4. The HGA(2) showed the obvious advantage by providing a better solution with a short computing time. However, if either the solution speed or the accuracy is of great importance to the application, alternative results would be attained at the trade-off curve. The potential of HGAs has been further verified on the Dynamic Economic Dispatch problem on a practical power supply system in Chapter 8.

Table 5.3 Comparison Between EGA and HGA[(2)] on the Solution Quality and the Solution Speed

	Run 1		Run 2		Run 3	
	Cost ($/h)	Time (mins)	Cost ($/h)	Time (mins)	Cost ($/h)	Time (mins)
EGA	16696.99	0.98	16596.26	0.98	16663.27	0.98
HGA[(2)]	16361.11	0.98	16468.66	0.98	16217.79	0.98
Difference	335.89	0	127.59	0	445.48	0

Table 5.4 The Difference in Power Outputs for Each Unit Made by the HGA[(2)] over CGA

	Unit 1 (MW)	Unit 2 (MW)	Unit 3 (MW)	Unit 4 (MW)	Unit 5 (MW)	Unit 6 (MW)
EGA	249.56	356.89	103.81	577.24	187.09	325.48
HGA[(2)]	114.91	250.42	93.16	588.72	438.73	314.06
Difference	134.65	106.47	10.65	11.48	251.64	11.42

CHAPTER

6

DYNAMIC ECONOMIC DISPATCH WITH GENETIC ALGORITHMS

6.1 INTRODUCTION

The classic economic dispatch (SED) problem discussed in the previous chapters is a static power scheduling problem, where the customer load demand is fixed, and a single time interval is considered. This well established SED policy is not optimal in terms of security, reliability and continuity of the electricity supply. The SED cannot foresee the trends of load demand over the future time horizon, but schedules the power outputs only with the present load. This makes it harder to meet the actual load demand under stricter constraints, especially when a large load variation is encountered. In practical applications, dynamic economic dispatch (DED) [Ross, 1980] is favoured because it can improve the generation control. The DED strategy anticipates changes in demand through the use of load forecasting to determine the economic allocation of the future power generation. In constrast to the SED which cannot foresee the effect of the present loading on the future generation capability, the DED policy enables a better match between the load demand and the power generation. It uses the knowledge of both present and future loads, and additionally takes system and security constraints into account, such as ramping rate and spinning reserve constraints. However, this increased accuracy comes at the cost of the complexity of the dispatch problem. Many techniques for solving constrained and unconstrained optimization problems have been applied to the DED problem with different degrees of complexity, and as it has been concluded that a better solution can only be obtained from those techniques with natural complexity. As a result, the popular solution methods have to contend with extended computing time and excessive needs for computing storage, which limits their application on larger power systems. This chapter explores the potential search ability that GAs exhibit on the DED problem, and further demonstrates the ease of GAs implementation in solving problems with increased order of complexity.

6.2 DED PROBLEM

The problem of DED aims to determine the economic allocation of committed units by using predicted load trends in order to better track customer load demand and improve the overall generation economics. The dynamic constraint considered in this study is the generation ramp rate (GR) constraint, which is used to ensure the safety of the equipment and the smoother operation of the power systems. This consideration has in turn formed a highly constrained DED problem for the GA to work with.

The mathematical formulation of the DED is stated as:

$$\min \quad F = \sum_{t=0}^{T} \sum_{i=1}^{n} F_i(t) \tag{6.1}$$

Where F is the total operating cost over the scheduling period of T. It is assumed that the forecast load demand remains fixed at each discrete time interval indexed as t=0, 1, 2,.....T, where there are a total of n dispatchable units at time t. $F_i(t)$ is the fuel cost for each generator unit at time t.

Within each time interval, a static economic dispatch is carried out. Both the equality power balance constraint and inequality power limit constraint have to be satisfied.

$$\sum_{i=1}^{n} P_i(t) - P_L(t) - P_D(t) = 0 \tag{6.2}$$

$$P_{imin} < P_i(t) < P_{imax} \tag{6.3}$$

Where

$P_L(t)$: is the transmission loss at time t.

$P_D(t)$: is the constant load demand at that time.

P_{imax}: is the maximum operating capacity for unit i.

P_{imin}: is the minimum operating capacity for unit i.

The additional dynamic Generation Ramping Rate constraint limits the maximum increase and decrease of power output and bounds the neighbourhood state together. This is done by placing additional limits on unit's operating capacity for the next time interval according to the present outputs, which is stated as follows:

$$P_i(t+1)_{max} = \min\{P_{i_{max}}, P_i(t) + UP(t)\} \qquad (6.4)$$

$$P_i(t+1)_{min} = \max\{P_{i_{min}}, P_i(t) - DW(t)\} \qquad (6.5)$$

where UP(t) is the generation ramping up rate and DW(t) is the ramping down rate at time t, which should be kept within a certain limited level for the safety of the equipment.

6.3 GENETIC APPROACH TO THE DED PROBLEM

The flow chart of a GA to approach the DED problem is illustrated in Figure 6.1.

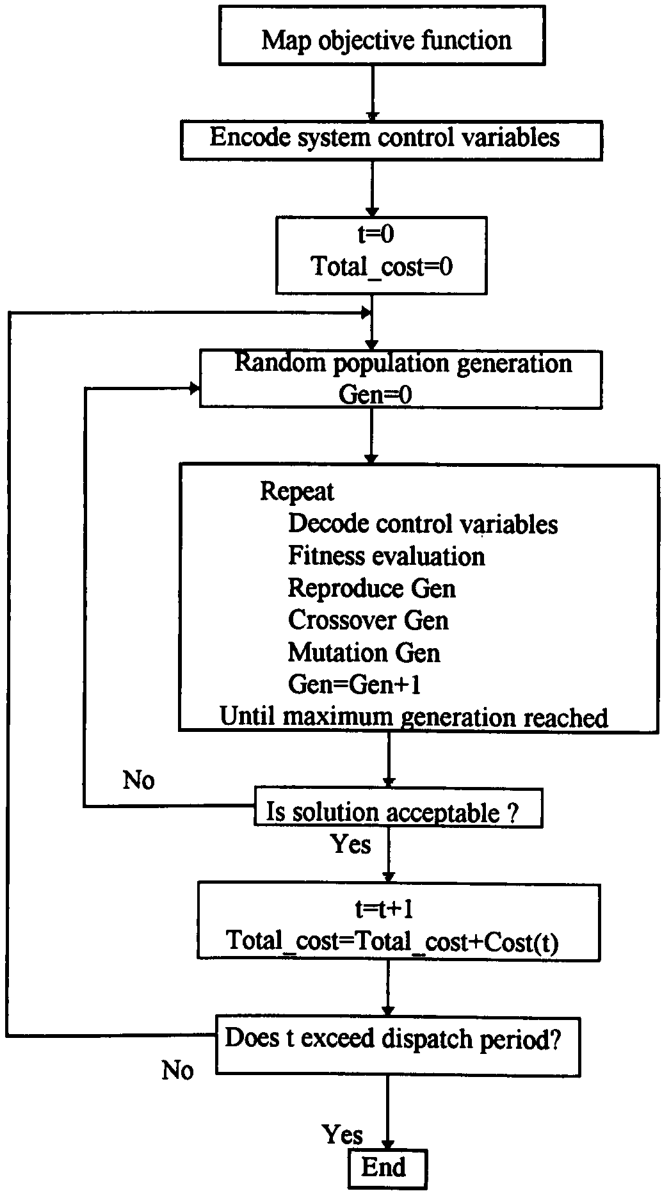


Figure 6.1 GA Implementation procedure on DED problem.

As clearly shown in Figure 6.1, the inner loop of the DED solution procedure at each time interval is almost the same with that of SED as illustrated in Figure 4.1. The only difference is the additional operational limits imposed by the GR constraint which can be handled by a GA inherently. Therefore, within each time interval, the same static ED solution procedure is carried out. The Lagrange approach has been employed again to solve the SED problem by transferring the constrained problem into an unconstrained problem, which is done by adding the constraint equations with a multiplier to the original objective function. This results in the overall objective function for each time interval as:

$$L = F - \lambda\varphi \tag{6.6}$$

where φ is the power balance constraint equation (6.2), and λ is the Lagrange multiplier for the equality constraint. The power limits constraint equation (6.3) and generation ramping rate constraint equations (6.4-6.5) can be easily handled by the GA itself, which is another unique feature of GAs over conventional techniques. Based on the overall objective function, the fitness function is formulated in the same way as that of SED which has been described in equation (3.2).

By performing this static economic dispatch procedure repeatedly until the total dispatch interval is reached, a DED dispatch strategy is obtained.

6.4 THE TEST SYSTEM AND SIMULATION RESULTS

The GA approach to the DED problem is tested on a system with four generator units [Tsuji, 1981]. The purpose of the test is to dispatch the power for each unit to track the customer load demand so as that the overall cost is minimised. The characteristics of the fuel cost consumed by the ith unit has been represented by multiplying the quantity of fuels consumed by the cost, which has the format as :

$$F_i = (a_i - b_i S_i)(\alpha_i + \beta_i P_i + \gamma_i P_i^2) \tag{6.7}$$

Where a_i , b_i are the cost per kcal coefficients, $\alpha_i, \beta_i, \gamma_i$ are fuel consumption coefficients, and P_i is the individual unit's power output.

The data of fuel cost F_i and operation limits for each unit are given below:

F_1 (\$/h) = $(3.065-0.4545*S_1)*(025*10^{-3}*P_1^2 + 2.21P_1 + 148.4)$ $\quad 125<P_1<500$

F_2 (\$/h) = $(3.219-0.3553*S_2)*(025*10^{-3}*P_2^2 + 1.89P_2 + 136.2)$ $\quad 180<P_2<500$

F_3 (\$/h) = $(3.219-0.3553*S_3)*(028*10^{-3}*P_3^2 + 1.99P_3 + 96.1)$ $\quad 100<P_3<365$

F_4 (\$/h) = $(3.248-0.3080*S_4)*(028*10^{-3}*P_4^2 + 1.99P_4 + 96.0)$ $\quad 94<P_4<365$

Where S_i is the sulphur content in fuels for unit i, which is a function of the mix ratio of high and low sulphur fuels. S_i has been kept fixed as 0.5 in this test, while it will change with the customer load demand, in the next chapter, when environmental issue is encountered.

A typical daily load demand curve for the system is depicted in Figure 6.2, which has significant variations over the period of 24 hours.

A GA with the Elitist scheme coupled with the Deterministic roulette wheel selection (described at section 5.3.2) has been employed to solve the DED problem on the 4 generator system over 24 hour dispatch period. The parameter values are based on the Gregenstette's setting with a total generation of 30 for a general good result on the DED problem.

The GR constraints were defined as:

$$80\%(P(t))_i < P_i(t+1) < 120\%(P_i(t)) \tag{6.8}$$

This restriction implies that the maximum increase and decrease of power output due to the demand variation is limited to no more than 20% of the previous power output.

The total cost over 24 hours attained by the coupled Elitist and Deterministic Genetic Algorithm is $1990 per hour. The cost for each time interval is illustrated in Figure 6.3. The power contributions from each unit for the load demand under optimal operation strategy resulted from the GA are depicted in Figure 6.4. As can be observed, the change of a power output for each generator is very smooth, which is the beneficial result from the additional GR constraint. However, a slightly higher cost has to be paid comparing with the relaxed power dispatch.

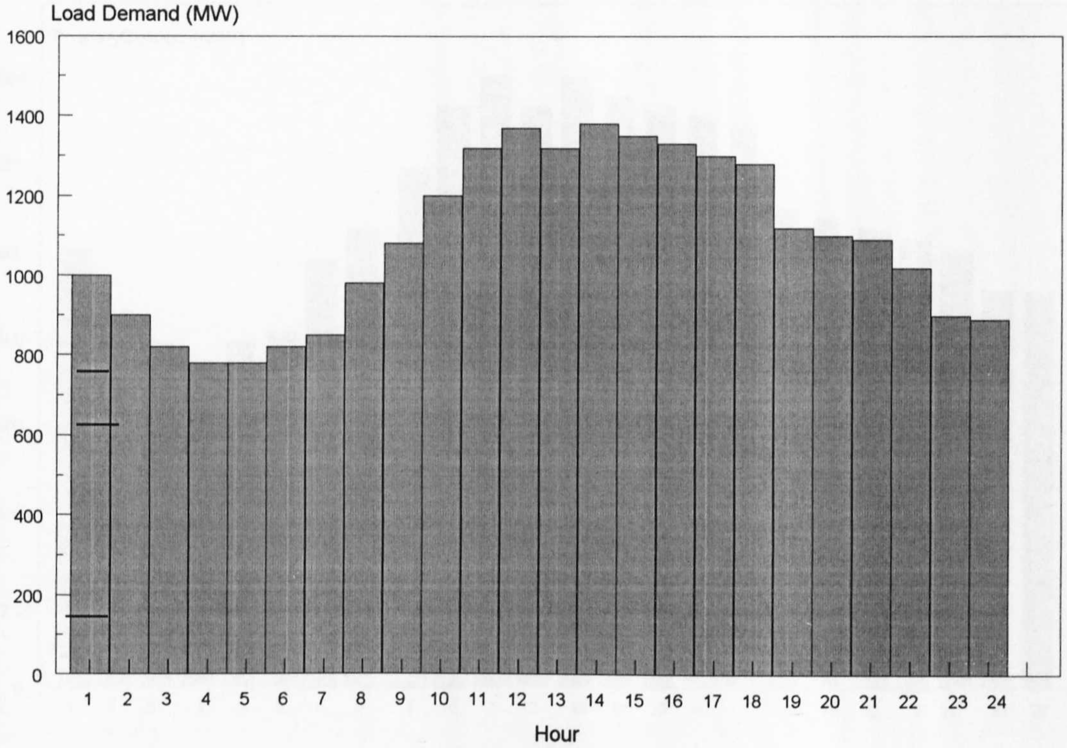


Figure 6.2 A typical daily load demand.

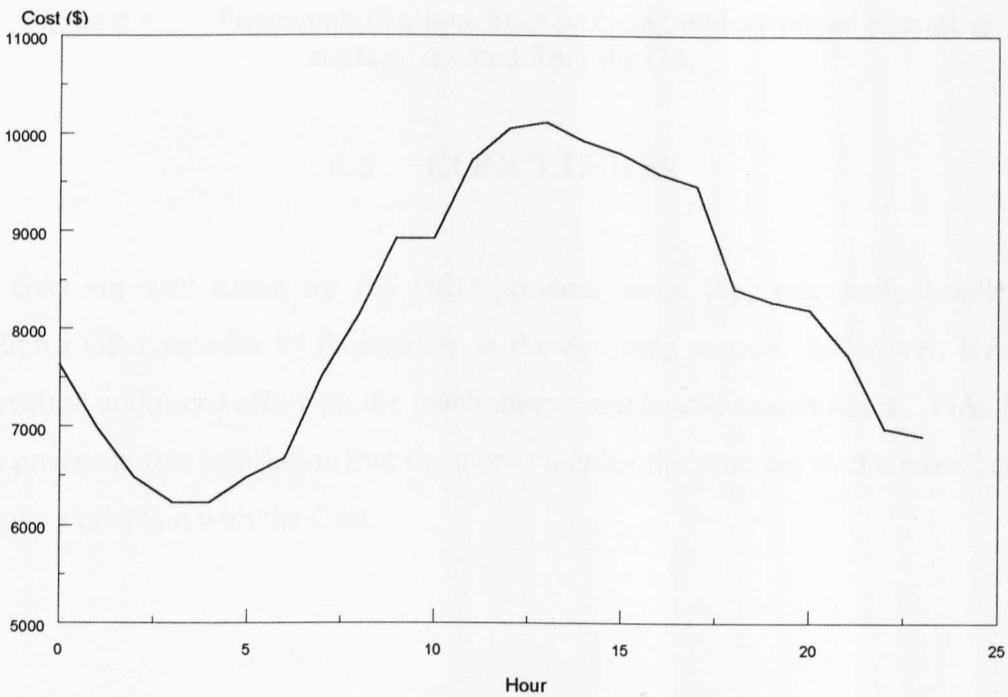


Figure 6.3 Resulting operation cost with EGA.

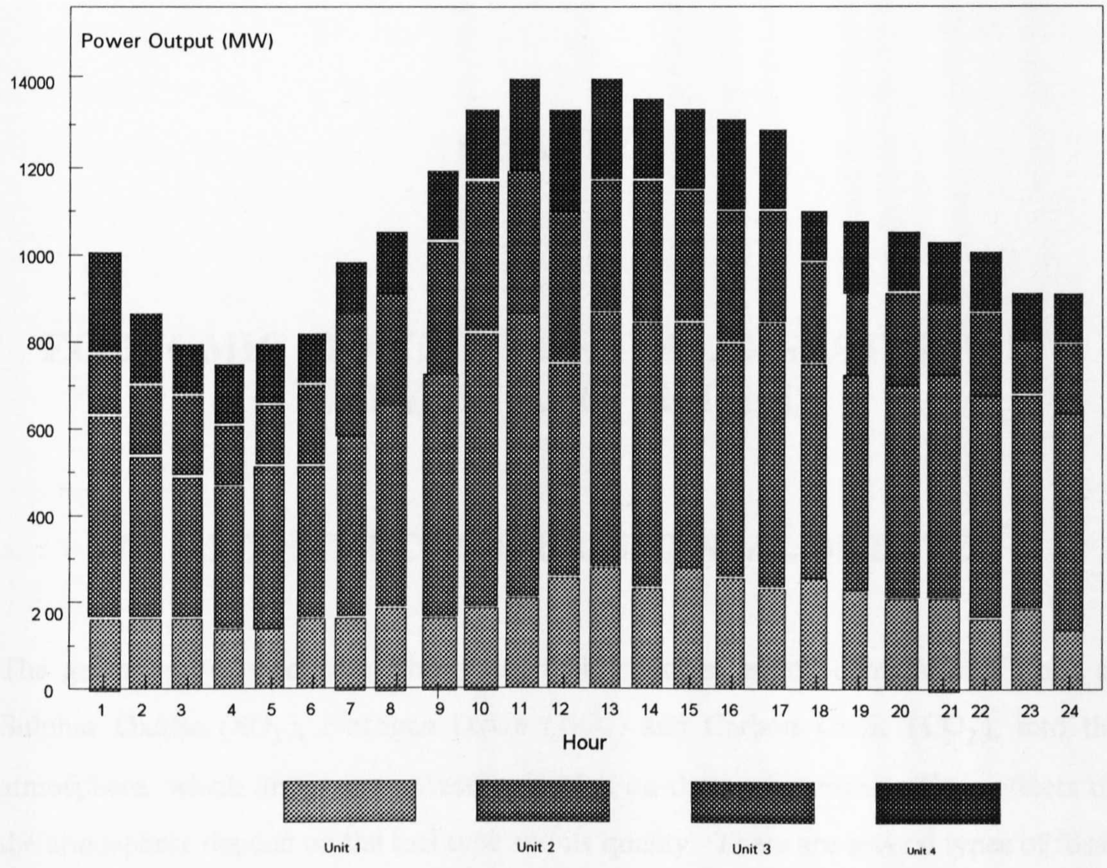


Figure 6.4 Power contributions from each unit under optimal operating strategy resulted from the GA.

6.5 CONCLUSION

The GAs are well suited for the DED problem, since they can easily handle the additional GR constraint by themselves on the decoding section. Moreover, GAs do not require additional effort on the much more complicated search space. GAs have been proven in this application that the more complex the problem is, the more benefit that one can obtain with the GAs.

CHAPTER

7

ECONOMIC - ENVIRONMENTAL DISPATCH WITH GENETIC ALGORITHMS

7.1 ECONOMIC - ENVIRONMENTAL DISPATCH

The generation of electricity from fossil fuels releases several contaminants, such as Sulphur Oxides (SO_2), Nitrogen Oxide (NO_X) and Carbon Oxide (CO_2), into the atmosphere, which imposes a excessive burden on the environment. Their effects on the atmosphere depend on the fuel type and its quality. There are several types of fossil fired electric power plants, using fuels such as coal, oil, gas or combinations of these as the primary energy sources. Coal produces particulate matter such as ash, and gaseous pollutants. The thermal energy dissipated in cooling water raises its temperature and may also be considered as a pollutant. Nuclear plant produces no gaseous emissions, but it does produce waste heat, and in addition it produces radiation, which however is well contained [Bernow, 1991]. Hydro-plants produce no emissions of any sort. Up to now, most researchers have devoted their effort in reducing two most obvious emissions - sulphur oxides and oxides of nitrogen. In this study, reducing sulphur SO_2 emission is considered, because it is probably the most important. Other contaminants such as NO_X and CO_2 can be handled in a quite similar way.

A reduction of the SO_2 emission can be achieved either by system plant-level redesign, or by supplemental control. The plant-level redesign includes processor reconstruction, such as pre- or post-combustion, while supplementary control involves fuel switching and changing operational strategy, which are rather simple ways. Historically, the electric power industries have scheduled their generation at an absolute minimum cost basis regardless of emissions produced. This pure economic based dispatch strategy must be at least partially reconsidered in favour of environmental protection. An alternative strategy has to be raised to satisfy both the economic and the environmental requirements while providing the consumer with adequate and secure electricity. This is known as economic-environmental dispatch (EED), which seeks to shift the load from one unit with high emission rate to the lower emission rate unit. The environmental objective enters the conventional dispatch strategy as a second objective or as an additional constraint.

The complication imposed by such a dispatch strategy is that the cost and the emission functions are two conflicting, incommensurable objectives. Favouring of emission reduction will result in higher operation cost, and vice versa. There is no common term in which they can both be minimised at the same time. When facing this multi-conflicting objective and highly constrained EED problem, many conventional techniques can only seek solutions under the conditions of various assumptions and simplification of the problem. The results thus obtained may not be the best operating strategy. GAs are therefore favoured for their requirement of a raw objective function only, their use of a probability rule to determine a solution, their simple search procedure, and their powerful search ability. These characteristics of GAs, in turn, support the dispatch policy to explore the potential area in an efficient manner in the complex search space exhibited by the EED problem.

7.2 FUEL SWITCHING

The EED approach is an attractive tool for both reducing environmental impact and operating cost. However, EED has the disadvantage that its operational capacities are limited. As a result, the ability of EED to reduce SO_2 emission is restricted. The utilities have to make great efforts to change power generation equipment to meet ever increasing environmental regulations. To avoid such time and cost consuming plant level changes, the fuel switching (FS) technique can be incorporated to get a compromise between system hardware reconstruction and software redesign. The FS aims to switch a fuel with a high content of pollutant but low cost, such as high sulphur fuel, to one of lower polluting potential but high cost. Though the cost is increased, the emission produced from each generator unit is thus decreased. This has long been identified as a cost-effective means of decreasing SO_2 emission, and requires only minor system hardware reconstruction. The FS is therefore another favourable supplementary tool to attain the twin goals of cost minimisation and emission reduction.

7.3 THE PROPOSED TWO-PHASE EED STRATEGY

7.3.1 THE TWO-PHASED PROBLEM STRUCTURE

In practice, it is desirable to meet the environmental restriction without major plant level in avoidance of considerable capital cost and time. It is therefore beneficial to employ both the EED and the FS techniques to maximise the emission reduction capacity, and provide flexibility in attaining the twin goals of minimising fuel cost and reducing emission. To assist a search technique to better fulfil the job, a two-phase dispatch structure is proposed in this project. During the first phase, the cost is minimised and the emission is reduced with both the EED dispatch strategy and the fuel switching techniques. The problem is thus modified to a bi-optimisation function, where unit power output and high sulphur and low sulphur fuel ratio are the two control variables. Based on the optimal fuel mixture obtained from phase one, the second phase, which contains only a single cost criterion, searches for the least expensive solution in the optimal sulphur region. The two-phase problem structure can be briefly concluded as:

PHASE ONE: Min Fs(Fuel Ratio, Power Output)
Bi-variables

PHASE TWO: Min F(Power Output)
Single-variable

The essence of the proposed method is that phase one provides the potential search area for phase two to work with in order to obtain a better overall solution.

7.3.2 THE TWO-PHASED PROBLEM FORMULATION

With both economic and environmental priorities taken into account, and the employment of fuel switching, the objective functions for both phases are expressed as:

PHASE ONE : $$\min Fs = \sum_{i=1}^{n} F_i(P_i, S_i) \tag{7.1}$$

PHASE TWO : $$\min Fs = \sum_{i=1}^{n} F_i(P_i) \tag{7.2}$$

Where S_i is the sulphur contents in fuels for unit i. The sulphur in fuel for each unit is decided by the mix ratio of high and low sulphur fuels. Assuming the percentage of high sulphur content $SU_i(\%)$ is W_i, ($W_i<1.0$), the low sulphur fuel with $SL_i(\%)$ then becomes $(1-W_i)$. The overall sulphur in fuels can thus be expressed as:

$$S_i = SU_i \times W_i + SL_i \times (1 - W_i) \tag{7.3}$$

The additional inequality constraint introduced by fuel switching is the upper and lower bounds upon sulphur in fuels:

$$SL_i \le S_i \le SU_i \tag{7.4}$$

SL_i, SU_i are the maximum and minimum sulphur contents in fuels respectively.

Also, system and operational constraints to be satisfied are:

Power Balance Constraint: $$\sum_{i=1}^{n} P_i(t) - P_L(t) - P_D(t) = 0 \tag{7.5}$$

Power Limits Constraint: $$P_{imin} < P_i(t) < P_{imax} \tag{7.6}$$

Environmental Constraint: $$Q_{AREA} - \sum_{i=0}^{n} Q_i > 0 \tag{7.7}$$

Where Q_i is the SO_2 emission produced from unit i per hour, Q_{AREA} is the total permissible SO_2 emission for the whole area per hour.

For the proposed two-phase structure, the first phase contains two control variables for each unit: power output P_i and fuel ratio S_i. The structure aims to achieve minimisation of cost and optimisation of sulphur content in fuel under environmental restrictions. During the second phase, the sulphur content in the fuel is specified at the level defined by the phase one operation. The objective therefore contains only a single cost criterion, and can be searched in great detail in the optimal sulphur region.

7.4 GENETIC APPROACH TO THE TWIN OPTIMISATION PROBLEMS

The solutions to the problems of both phases are attained by Genetic Algorithms to demonstrate their effectiveness on both single and multi-variable EED problems. The fitness function formulation is the first concern when approaching a problem with a GA, as its value is the only information available to guide the search towards the optimum point. The fitness function for the proposed two-phase EED problem is described as:

$$FN=\frac{Fs}{Fs\max - Fs\min}+\lambda\times\frac{\varphi}{\varphi\max-\varphi\min}+\mu\times\frac{\theta}{\theta\max-\theta\min} \qquad (7.8)$$

Where Fs, φ and θ are the fuel cost objective, the equality power balance constraint and the area emission constraint respectively. λ and μ are corresponding weight coefficients. For both phases, the inequality constraints for control variables of equation (7.4), (7.6) have been handled by the algorithm inherently in the decoding section.

The formulation of the fitness function is the same for both phases; the difference lies in that they contain different control variables. In phase one, two variables are involved in the objective function Fs, namely power output and fuel ratios for each unit. The second phase has only one control variable - power output, where the value of the sulphur content in fuel is specified at the level that phase one has decided.

Each solution of the problem is encoded as a string with 10 bits per unit for both phases. In the phase one genetic search, the first 5 bits represent power output, and the latter 5 bits represent sulphur content in fuel. During the phase 2 search, all 10 bits are used for power output as only one variable is present. This implies that the search is carried out in a much more detailed landscape, which raises the possibility of obtaining better results. The value of genetic parameters are based on the Grefestette's setting for this application.

7.5 SIMULATION RESULTS AND DISCUSSION

The application of GAs to the proposed power dispatch is demonstrated on a 4 generator system as described in Chapter 6 [Tsuji, 1981]. The daily load demand is redrawn in Figure 7.1. The total permissible limit for SO_2 emission per hour is $800Nm^3$ for the system. The solution to the power dispatch problem in this application is to provide the real power generation trajectory tracking the time varying load demand, as well as the optimal fuel mixture for each unit, so that the cost is minimised and the emission produced is reduced to an acceptable level. In order to demonstrate the effectiveness of the proposed two-phase problem structure, the resulting cost over the entire 24 dispatch period is compared with that of the conventional one-phased problem structure. The comparison is illustrated in Figure 7.2, where the phase two results show the obvious cost advantages over the conventional one phased problem structure.

Table 7.1 gives the detailed figure of cost improvement made by using the proposed two-phase problem structure.

Table 7.1 Cost Comparison Between One Phased and Two Phased Problem Structure

	Total Fuel Cost ($) (24 hours)	Cost Ratio
One phase	198,749	100
Two phase	197,435	99.34

The corresponding optimal solutions - optimal power outputs and sulphur contents of each unit, are illustrated in Figures 7.3-7.10. As clearly indicated, when the sulphur content is lower in a unit, it produces a higher output to comply with the environmental constraints.

As the test system is small in scale, a large system is expected to gain even larger financial benefit with the proposed two-phase problem structure when dealing with the power dispatch problem under environmental constraint. The proposed method is proven to be more efficient compared with the conventional one phased problem structure. The ease of GAs implementation makes the technique extremely attractive in this application for its capability and suitability in both single and bi-optimisation problems. GAs can thus offer more problem solving ability over the conventional optimisation techniques.

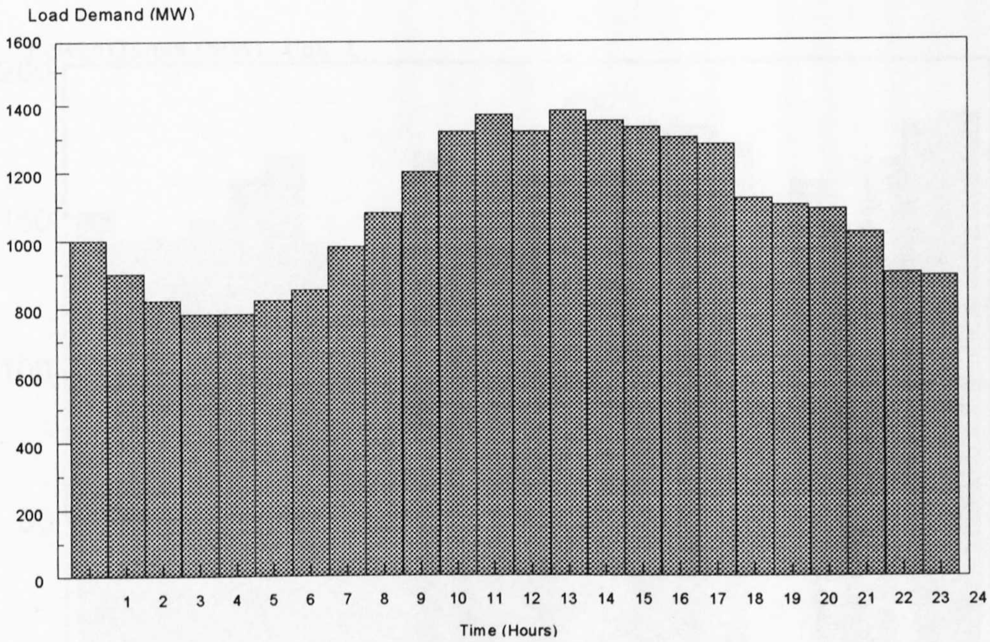


Figure 7.1 The daily load demand curve.

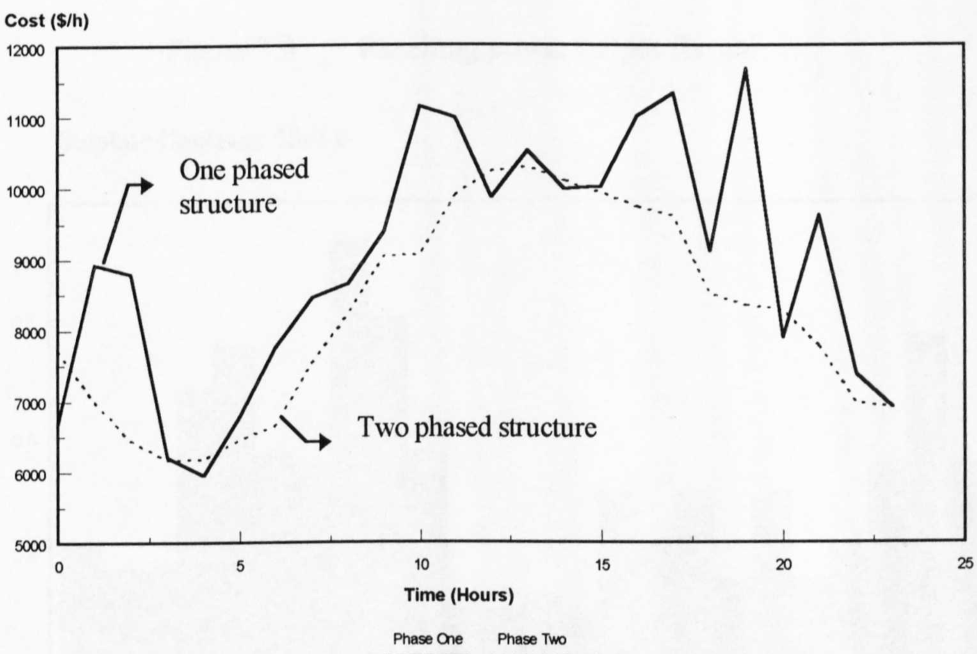


Figure 7.2 Cost comparison for GAs with two different structures.

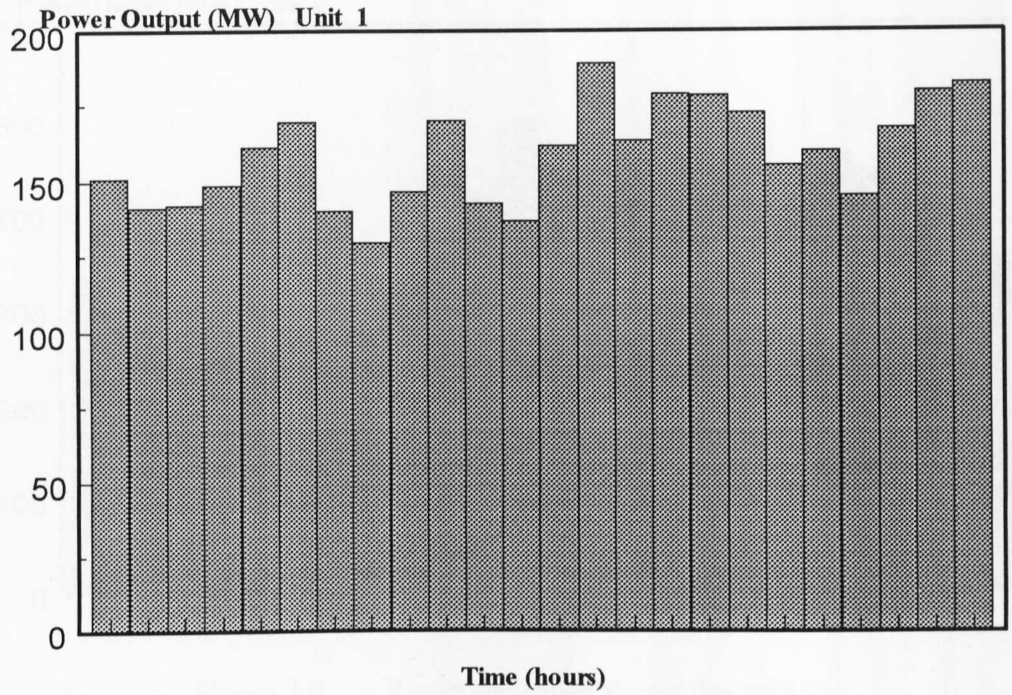


Figure 7.3 Resulting power output for unit 1.

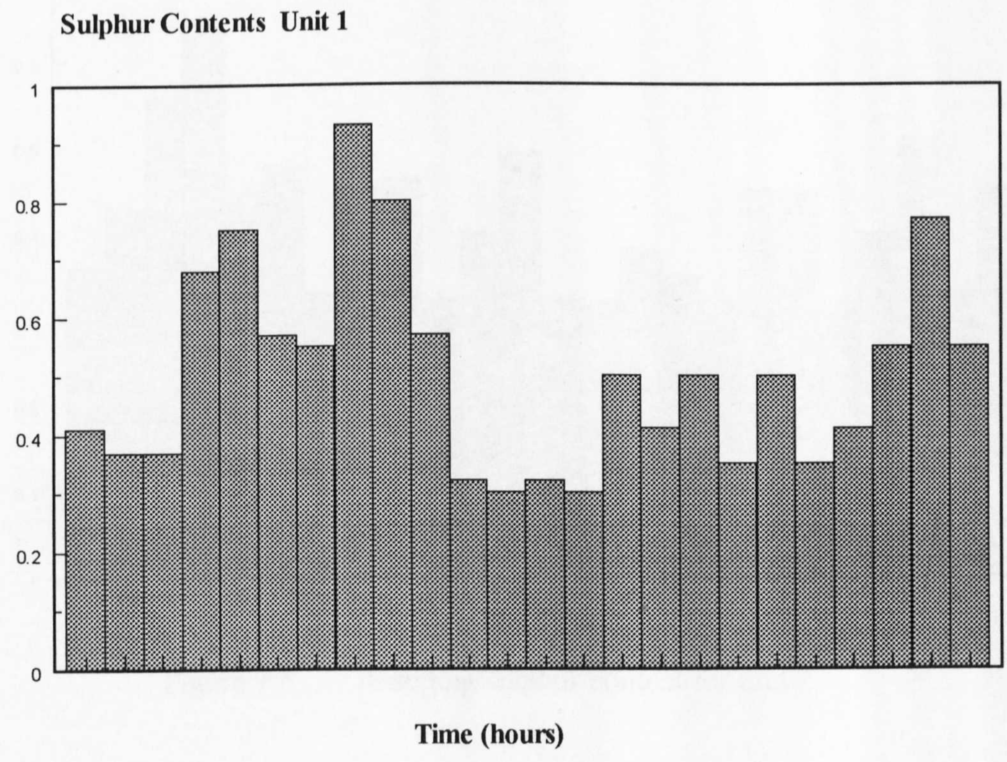


Figure 7.4 Resulting sulphur content for unit 1.

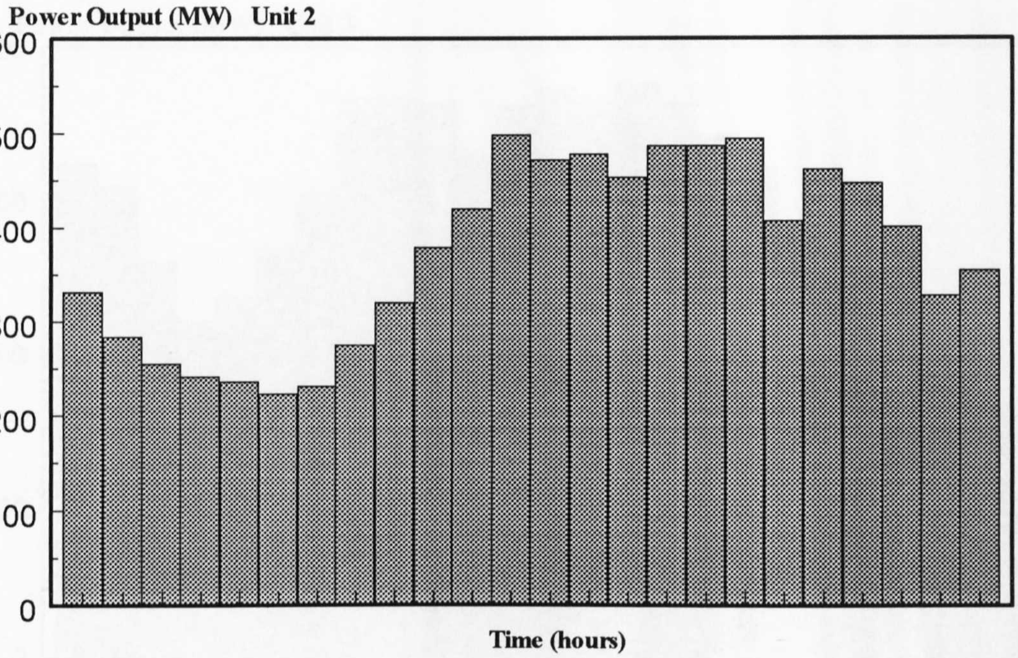


Figure 7.5 Resulting power output for unit 2.

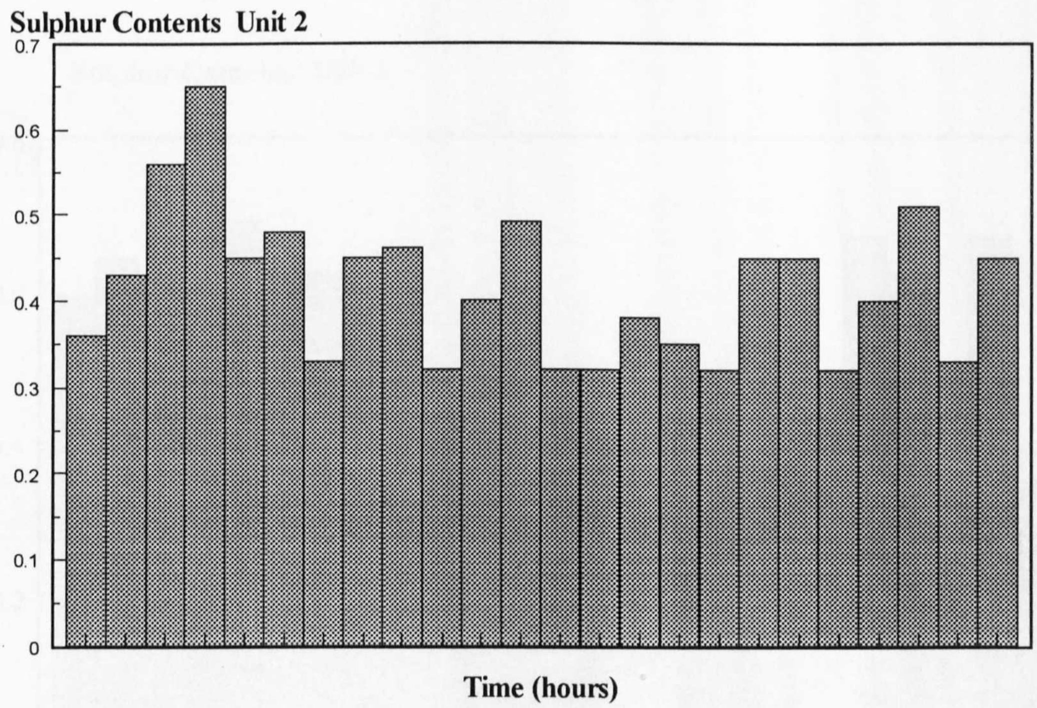


Figure 7.6 Resulting sulphur content for unit 2.

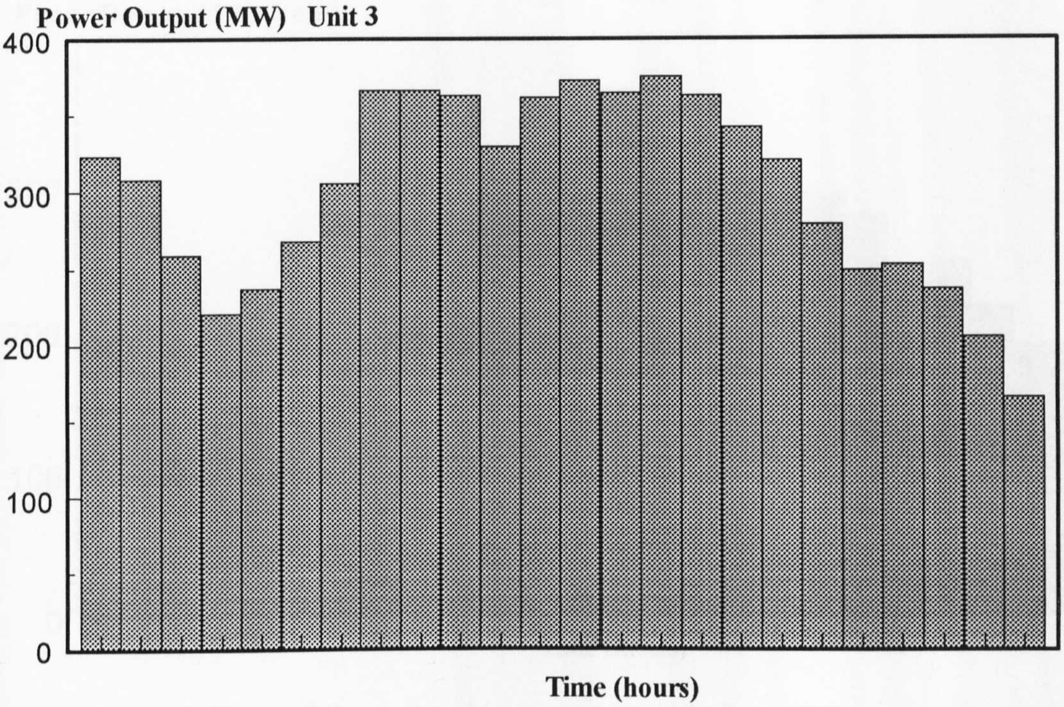


Figure 7.7 Resulting power output for unit 3.

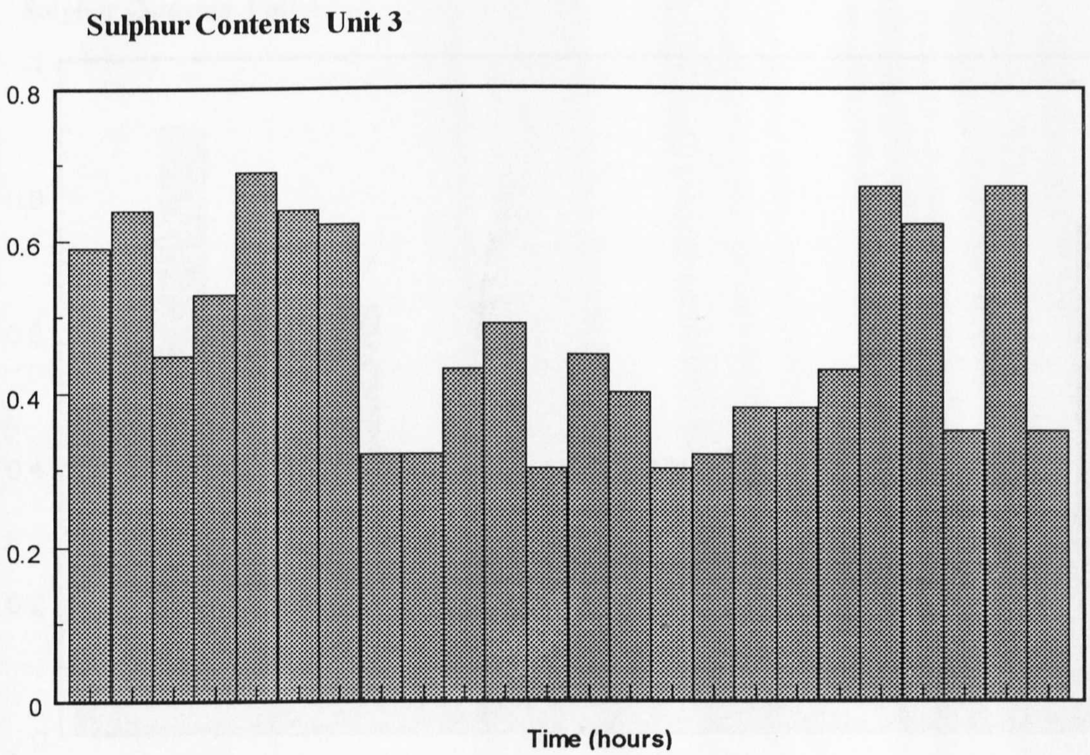


Figure 7.8 Resulting sulphur content for unit 3.

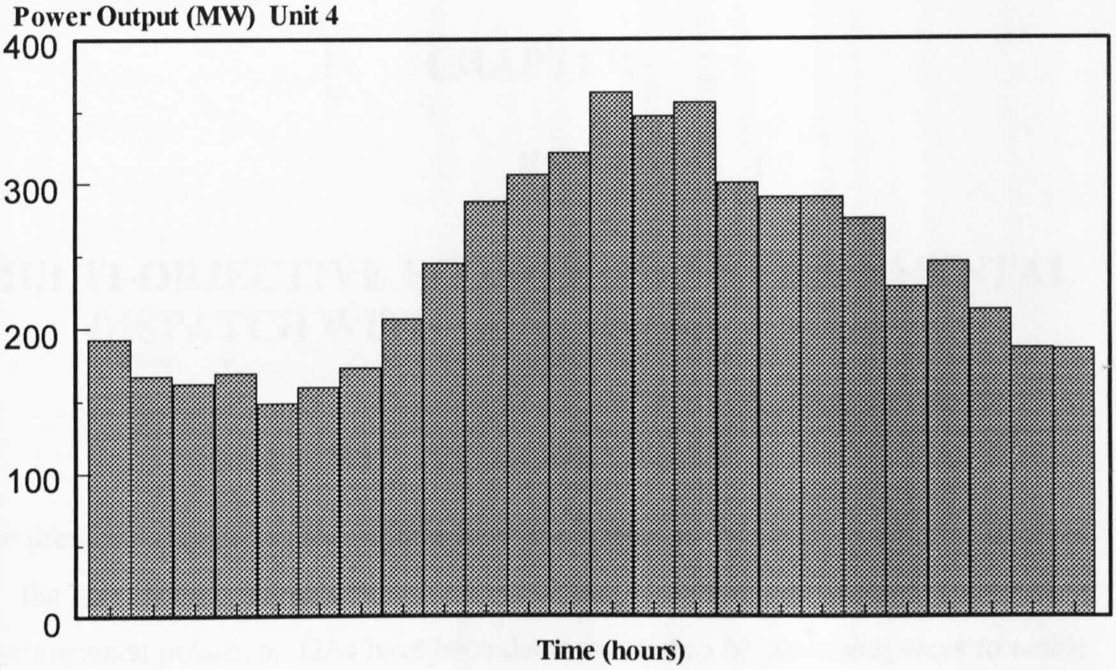


Figure 7.9 Resulting power output for unit 4.

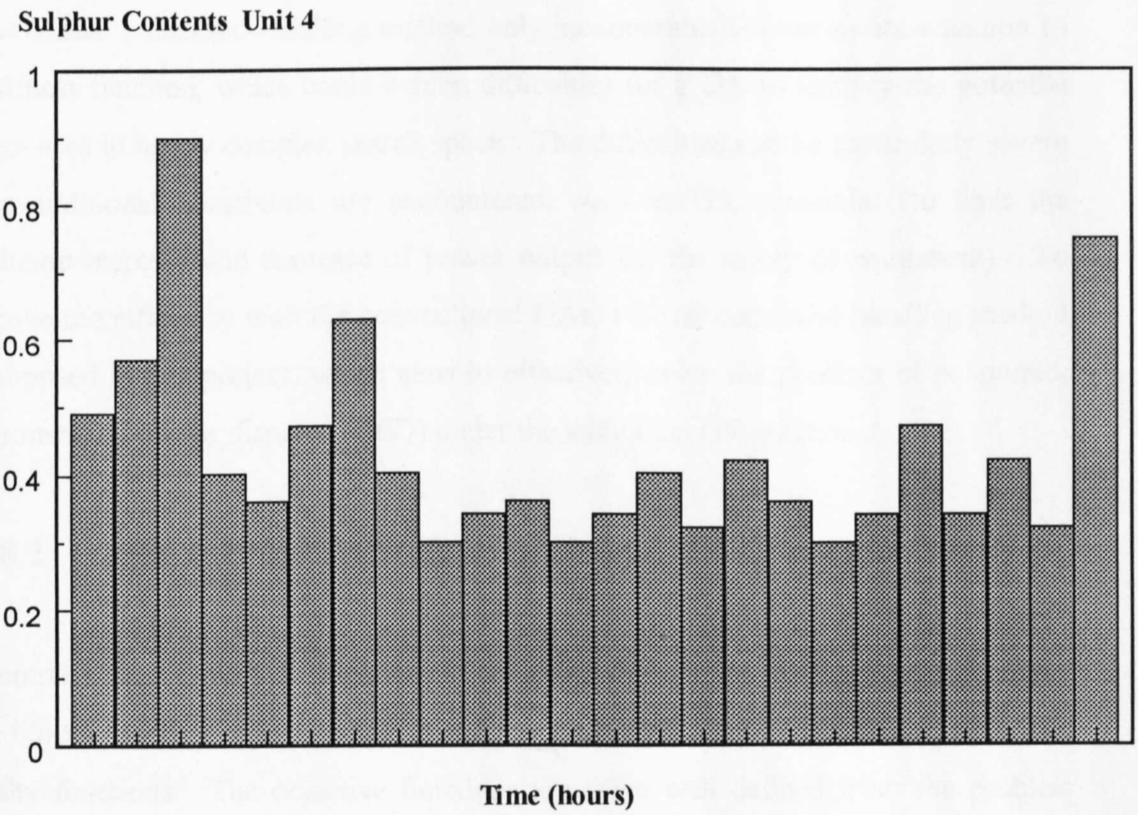


Figure 7.10 Resulting sulphur content for unit 4.

CHAPTER

8

MULTI-OBJECTIVE ECONOMIC - ENVIRONMENTAL DISPATCH WITH GENETIC ALGORITHMS

8.1 INTRODUCTION

The previous chapter has shown that EED is a sophisticated and difficult task because of the conflicting requirements of minimising generation cost and reducing environmental pollution. GAs have been demonstrated to be promising ways to tackle the highly constrained, multi-variable problem involved in the solution and give a better chance of attaining the global optimum. However, the performance is affected crucially by the way a constraint is handled in the GA implementation. The conventional constraint handling method only incooperates the constraint equation to the fitness function, which could exhibit difficulties for a GA to identify the potential search area in highly complex search space. The difficulties can be particularly severe when additional constraints are encountered, such as GR constraint (to limit the maximum increase and decrease of power output for the safety of equipment). To improve the efficiency with the conventional GAs, a novel constraint handling method is proposed in this project, which aims to effectively solve the problem of economic-environmental power dispatch (EED) under the additional GR constraint.

8.2 THE IMPORTANCE OF PENALTY CONSTRUCTION

A central issue of the GA implementation is the formulation of the fitness function. The fitness function is formulated as a linear combination of objective functions and penalty functions. The objective functions are often well defined from the problem itself; it is the penalty construction that creates difficulties in formulating a suitable fitness function. Normally, a penalty function is constructed in such a way that it is a function of the constraint equations, plus corresponding weight coefficients. The choice of the coefficients is a key issue in deciding the quality of the solution. However, choosing an appropriate coefficient for each constraint to balance the search diversity and the pressure for feasibility is a time consuming, sophisticated and difficult task. A common rule has not been developed to determine the weight coefficients optimally. Quite often, they are obtained by experience, or by experiments which require excessive time and effort. Moreover, such weight coefficients are not robust in all cases, as they are sensitive to time and contingencies. Hence, care must be taken when constructing a penalty function for a constrained optimisation problem.

One obvious approach is to construct a harsh penalty function to avoid a solution being obtained in a forbidden search area. As a result, the search is restricted in a much narrower space, which forces the search diversity to be lost. Consequently, if a moderately fit string happens to satisfy the constraints, it immediately becomes a super individual and dominates the whole population. If no action is taken, the search will restrict the opportunity for other potentially fit strings, and end up without finding the best individual. The harsh constraint also works against the foundation of the GA search. The GA technique is able to incorporate partial information from a group of strings, which include both feasible and infeasible solutions. The infeasible solution should not be just thrown away, as it may provide valuable information for the search to progress further. The optimum point might be in the neighbourhood of a highly infeasible solution, and could be reached by recombination operators. Therefore a harsh penalty function must not be generated in order to avoid premature convergence.

On the other hand, an excessively soft penalty function takes too long to arrive at the feasible region, thus giving less time to find the best individual. For the same computing time, the soft-penalty-bearing GA would result in a wide distribution of local minima, or merely a number of feasible solutions, while the harshly penalized GA could reach at least a local minimum. Yet, the softly constrained GA is able to keep the diversity which is desirable to avoid the extermination of potentially desirable characteristics.

For the EED problem, the formulation of a penalty formulation which involves both economic and environmental requirements is especially challenging. It is made more complicated when considering the additional generator rate constraint. Consequently, finding the right coefficients for each constraint is as difficult as solving the problem itself.

8.3 THE PROPOSED CONSTRAINT HANDLING TECHNIQUE

To simplify the highly constrained EED problem, this thesis proposes an easy and efficient way to handle the constraints. Instead of using conventionally formed penalty functions, which contain merely a number of violated constraints, the concept of how far the solution is away from the feasible region is incorporated, and from which the weight coefficient is determined. The weight coefficient is monotonically decreased as the distance to the feasible region linearly increases. Moreover, the distance is divided into several stages to distinguish the solutions from the better to the worse. Each distant stage is defined as:

$$N \bullet 2^{N} < d < (N+1) \bullet 2^{(N+1)} \tag{8.1}$$

and the corresponding weight coefficient is:

$$\left(1 - \frac{N}{10}\right)^{2} \tag{8.2}$$

Where N is the different distant region and d is the distance of a solution away from the feasible region. The number of total distance stage, m, is different from one problem to another. Basically, m is decided by the estimated biggest distance d_{max} (to the feasible region) which leads $(m+1) \times 2^{(m+1)}$ to the nearest d_{max}. For instance, if $d_{max} = 750$, the number of distant stage m should be equal to 6 such that $(m+1) \times 2^{(m+1)} = 896$ is greater and closer to the value of the biggest distance - 750. Under this assumption, all possible solutions are covered in the search space, and their feasible distance stage could be any integer among 0 and m. A list of the different distance stages with the corresponding weight coefficient can be found in Table 8.1.

Table 8.1 Lists of Distance Region and Corresponding Weight Coefficient

	Distance Region	Weight Coefficient
N=0	$0<d<2$	1
N=1	$2<d<4$	0.81
N=2	$4<d<24$	0.64
..	..	..
N=5	$160<d<384$	0.25
N=6	$384<d<896$	0.16
..	..	..

The proposed method is a much easier way to design a moderate penalty function to allow a compromise between the search diversity and the pressure for feasibility. Hence, the risk of evaluating illegal solutions or lower quality individuals is greatly reduced.

8.4 TRADE-OFF APPROACH TO EED PROBLEM

In the previous chapter, the EED problem is solved by including the environmental issue as an additional constraint. Alternatively, the environmental issue can be treated as the second objective function to line up with the original cost objective. However, this multi-objective EED policy runs the risk of emission over emphasis or under emphasis depending on the coefficient chosen for the emission objective. It is therefore beneficial to investigate the trade-off relation between the cost and emission to assist the decision maker to choose the optimal operating point which is the best compromise between those two objectives. In the case of emission limits applied, the best operating point will be the least cost point at the trade-off curve where the emission produced is at the permissible level. However, the application of the trade-off dispatch policy can only be applied to off-line study and thereafter for future system planning, rather than be used for on-line applications.

Under the trade-off dispatch scheme, the power dispatch problem can thus be stated as:

$$\min C = \sum_{i=1}^{n} \{a_i * F_i + (1-a_i) * E_i\} \tag{8.3}$$

The EED problem is solved by increasing a from 0 to 1 to cover the entire search region: $a=1$ states the conventional economic dispatch, $a=0$ accounts for minimising emission only. The best operating a is chosen by the decision maker as a compromise between the cost and the emission.

The problem is subject to a number of operational and environmental constraints, as outlined in equations (8.5-8.7). In addition, the generation rate constraint is taken into account in this application:

$$80\%(P(t))_i < P_i(t+1) < 120\%(P_i(t)) \tag{8.4}$$

8.5 SIMULATION RESULTS AND DISCUSSION

The GA approach to the EED problem with the proposed penalty construction is tested on the same four generator units with the same load demand and emission limits being applied (Section 6.4). However the sulphur content for each unit is specified at predefined levels, which is depicted in Figure 8.2. The figure indicates that three fuel switchings are carried out through a 24-hour dispatch period. Ideally the fuels should be switched as often as power output scheduling so as to meet environmental restriction at the minimum possible operation cost. Practically, it is difficult to control the sulphur in fuels as frequently as power output. Therefore, the number of switchings is restricted to a limited number for the whole dispatch period. However, this limited number of fuel switchings will reduce the flexibility of possible emission reduction, and might result in emission over emphasis. The small number of switchings will attain a higher emission reduction, which in turn will result in a higher fuel cost.

Changing a from 0 to 1 results in the cost-emission trade-off curve, which is shown in Figure 8.3. The graph clearly illustrates how the generation cost varies with the produced emission. The best operating point is obtained with $a=0.7$, where the total emission produced each hour is within the permissible level and the cost is the minimum on the trade-off curve. The total cost over 24 hours at the best operating point is shown in Figure 8.4. The resulting individual power outputs are illustrated in Figures (8.5-8.8). Table 8.2 compares the cost reduction achieved by using the proposed method with the conventional constraint handling method in the GA implementation. With the conventional method, only 10% of the final results are within the feasible region, while 90% of the solutions are distributed around the optimal feasible region. The proposed GA technique improved this figure to 50%, which clearly demonstrates the benefit from the additional distance information used in the new technique.

The test has clearly demonstrated the effectiveness and ease of application of the modified GA. Also, the potential financial benefit on the EED problem is clearly indicated. The proposed constraint handling technique can not only pass the constraint information to the fitness function but also provides information on how far a solution is away from the feasible region. The additional information enables the GA to better balance the search diversity and the pressure for feasibility to obtain potential highly fit individuals over the search space. The test results prove that the proposed method is easily implemented in the optimisation problems and can produce more valuable solutions during a course of a GA run.

Table 8.2 Comparison of Total Fuel Cost

	Total Fuel Cost For 24 hours ($)	Cost Ratio
Conventional GA Technique	200002.34	100
Proposed GA Technique	199132.19	99.5

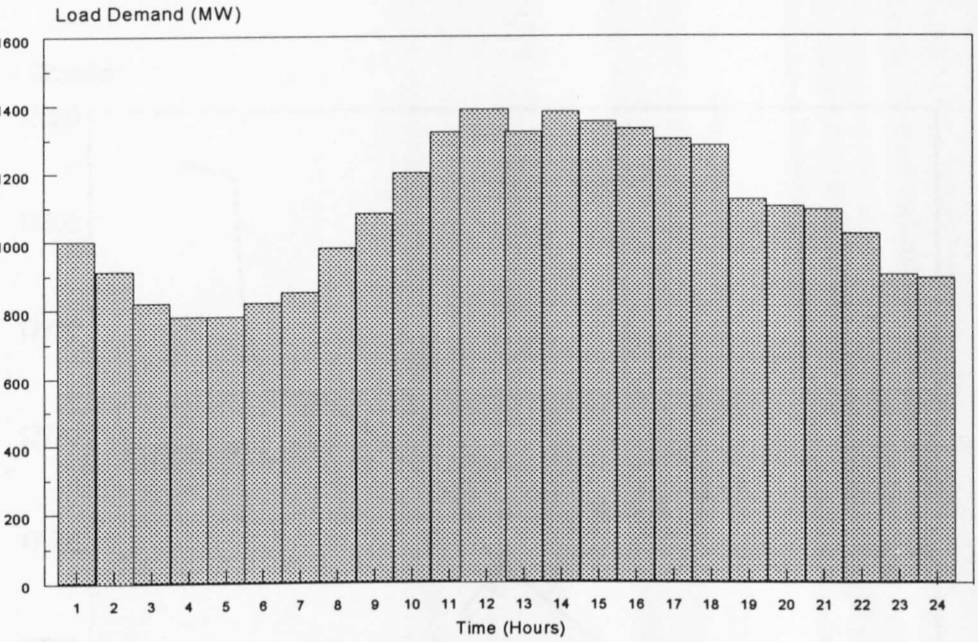


Figure 8.1 The daily customer load demand.

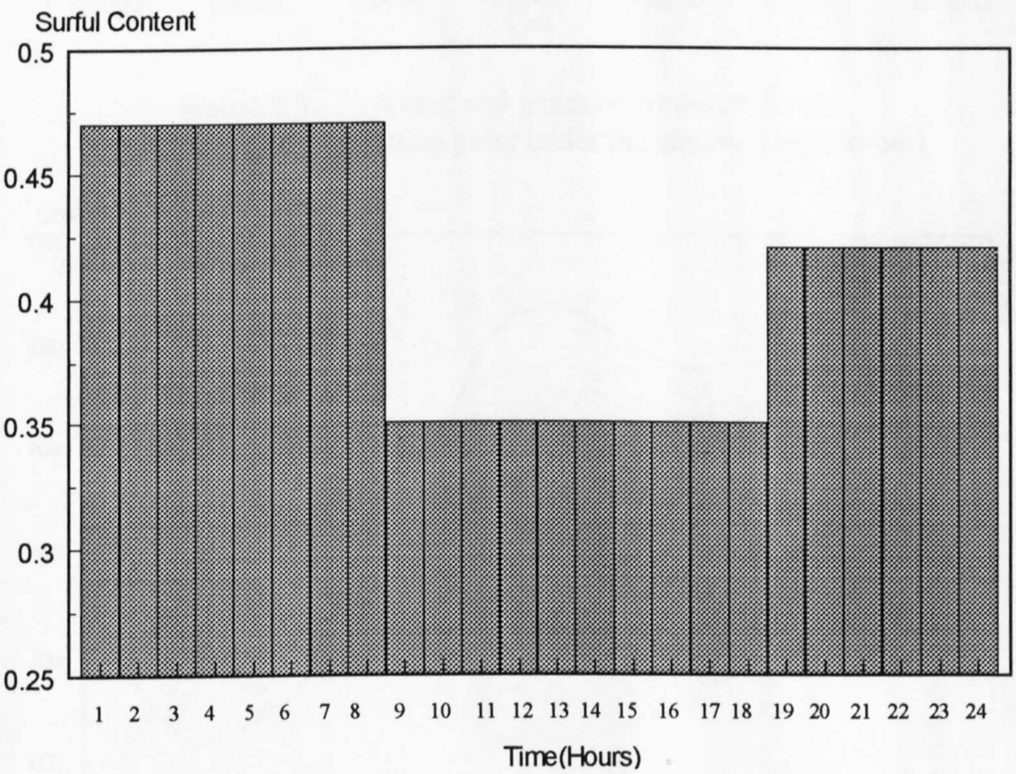


Figure 8.2 Daily fuel mixture for each unit.

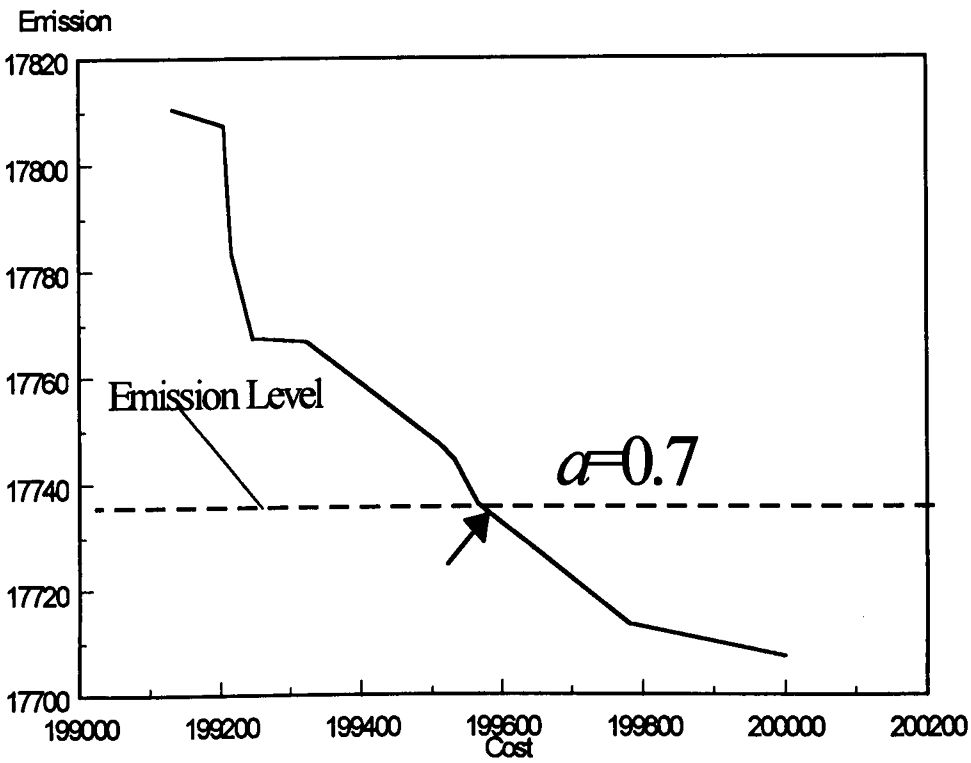


Figure 8.3 A cost and emission trade-off curve.
(a=0.7 is the best operating point under the emission regulation.)

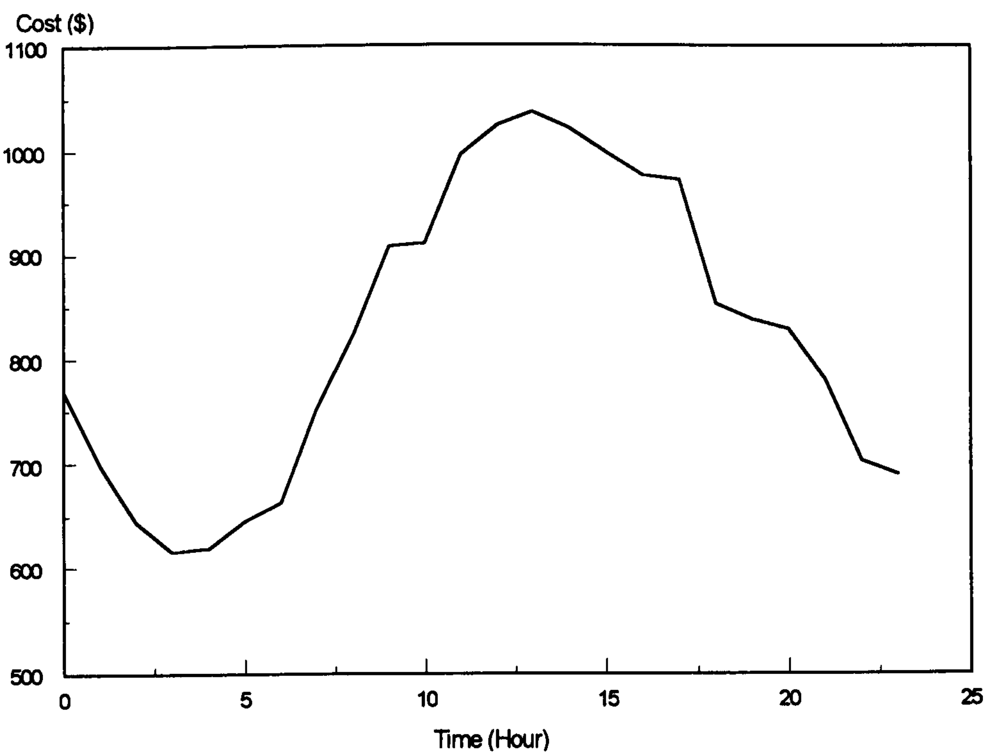


Figure 8.4 The daily cost curve at the best operating point.

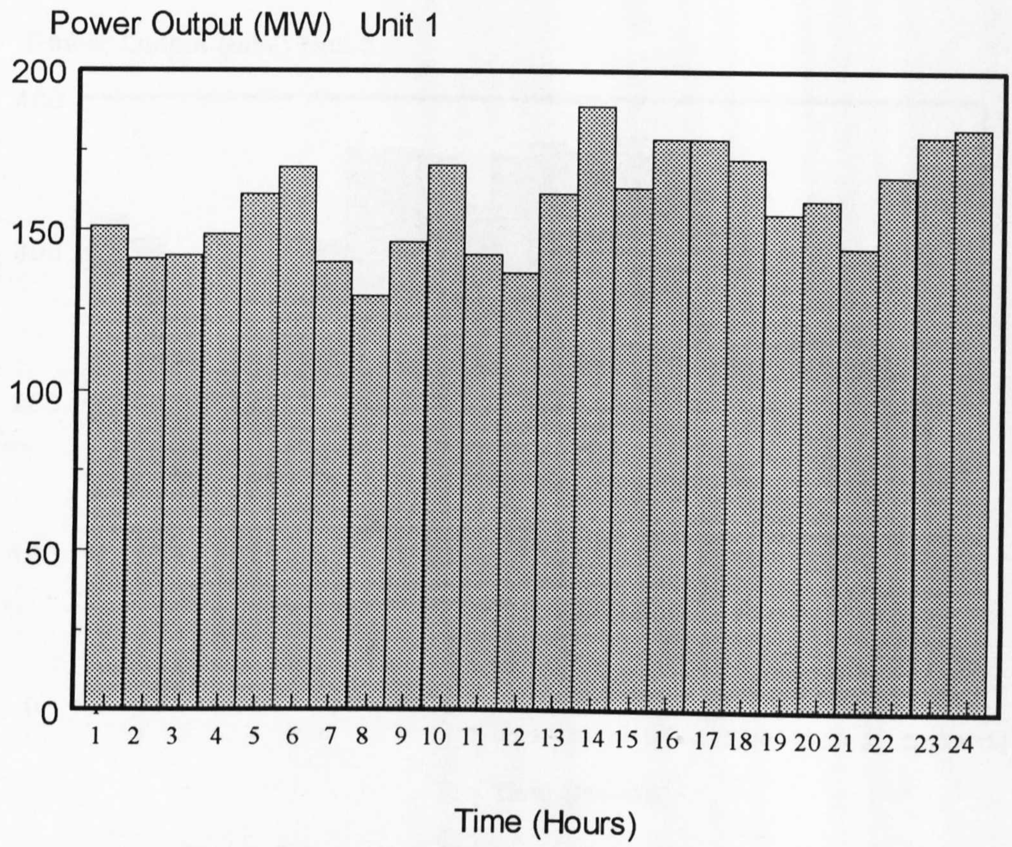


Figure 8.5 Resulting power output for unit 1.

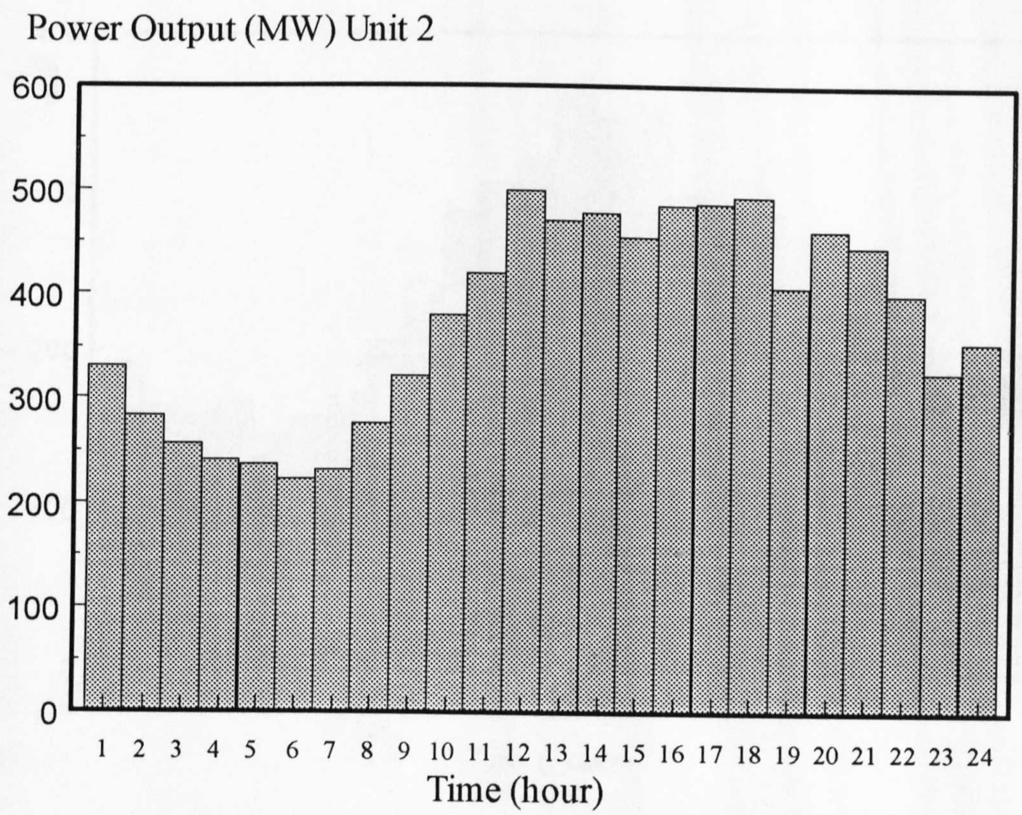


Figure 8.6 Resulting power output for unit 2.

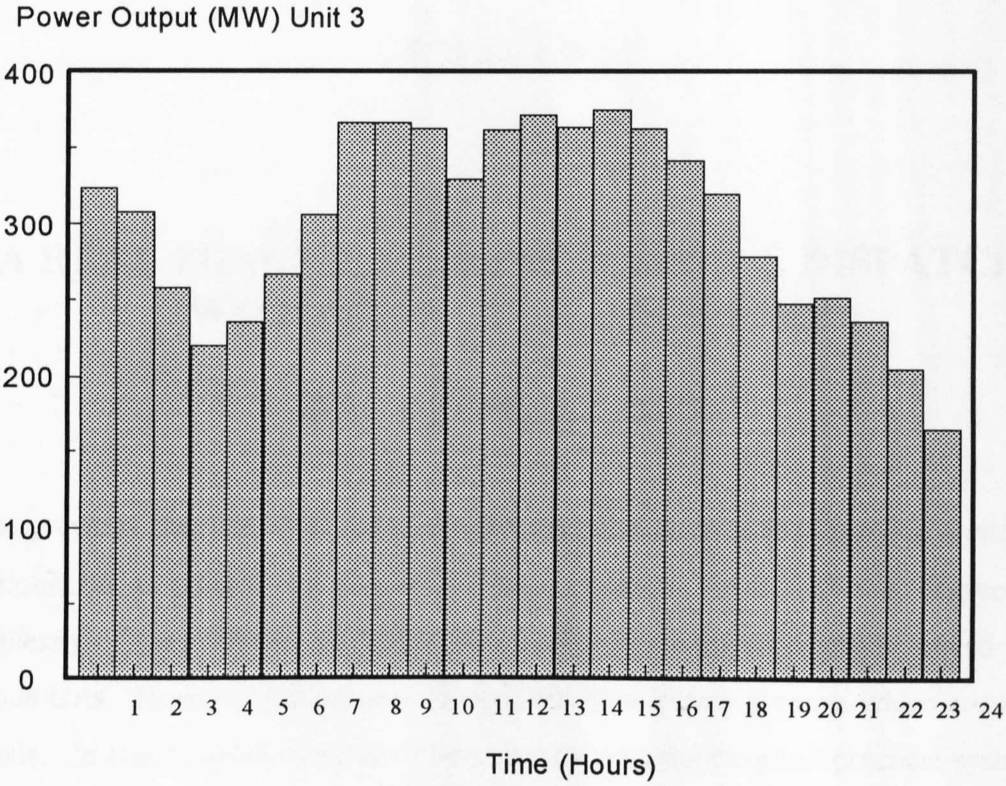


Figure 8.7 Resulting power output for unit 3.

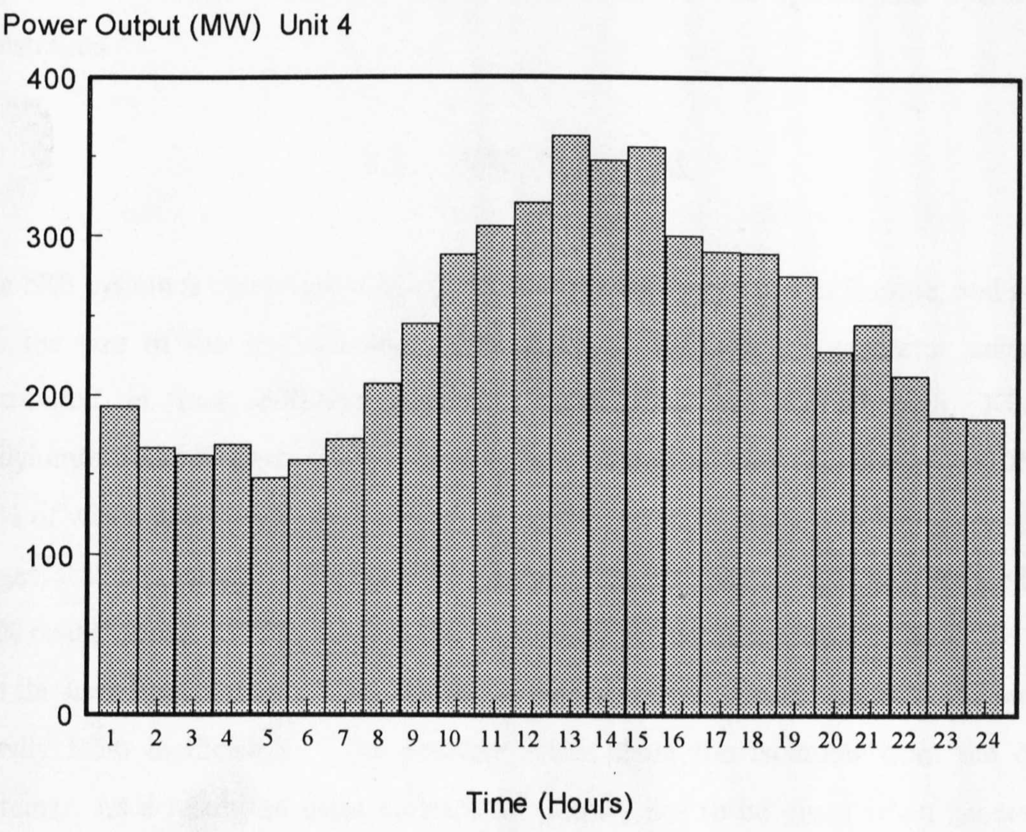


Figure 8.8 Resulting power output for unit 4.

CHAPTER

9

A REAL PRACTICAL SYSTEM POWER DISPATCH WITH GENETIC ALGORITHMS

9.1 INTRODUCTION

In the previous chapters, GAs have been demonstrated to be able to provide promising solutions on a number of power dispatch problems with different degrees of complexity. The problems ED, DED and EED have been successfully solved with various GAs. However, the results are obtained from power systems which are small in scale. In this Chapter, GAs are challenged by a moderate sized practical system - Northern Ireland Electricity (NIE) system - to provide the optimal power generation trajectory tracking the time varying demand under various system and operational constraints.

9.2 NIE SYSTEM

The NIE system is one of the smallest isolated electricity systems in Europe, and is just 3% the size of the England and Wales system. Its total 25 generator units are distributed in four different power stations, they are Coolkeeragh, Kilroot, Ballylumford and Belfast. They contribute to a total generating capacity of 2,320MW, 60% of which is oil-fired. However, Ballylumford is in the process of being converted to gas, which dramatically changed the system's fuel diversity to 40% gas, 20% oil and 40% coal [Moore, 1995]. Despite the restoration of interconnection between the NIE and the Irish Republic after being destroyed by terrorists 25 years ago, NIE still suffers heavily from inefficiency. The problem stems from the isolation from the other systems. As a result, an extra concern of security has to be given when generating electricity. This increased security will undoubtedly result in a higher operating cost.

For security reasons, NIE has to carry a higher margin of reserve which is about 40% compared with that of 25% in England and Wales. Hence, the NIE is a more difficult system on which to achieve the best operational economics, and presents more challenging optimisation problems for a technique to deal with. GAs have therefore the potential to optimise the problem while taking many matters into account. In this initial study, GAs are applied to both the Dynamic Economic Dispatch (DED) and the Economic-Environmental Dispatch (EED) problem, under the additional generation rate constraints. The resulting cost is compared with that of the real figure from the NIE system. In addition, Hybrid Genetic Algorithms (HGA) will demonstrate their effectiveness and efficiency on both DED and EED cases when compared with pure Genetic Algorithms.

9.3 GENETIC APPROACH TO THE PRACTICAL DED PROBLEM

The Dynamic Economic Dispatch (DED) is favoured in practice because it can improve the generation control. The formulation of the DED problem is well defined by equations (6.1-6.7) in Chapter 6. For the NIE system, the additional generation ramping rate constraint has been imposed for the base supply units for this practical GA application, that a maximum increase and decrease of power output over a dispatch interval of 30 minutes is restricted to no more than 20% of the previous power generation. This restriction puts more pressure on the search algorithm by severely limiting the individual generator's operating capacity, which makes the search space much more complicated.

Among the total 25 generators, only one third of the generators are in operation on normal spring days. Furthermore, as many of the generators are identical that they can be drawn together and considered as one larger generator, which reduces the working dimensionality from 25 to 8 (which is a common practice in the power industry, such as National Grid Company). A typical daily load curve in the spring season is depicted in Figure 9.1. The coal-fired and oil-fired generators provide the base load, while gas turbine plant gives peak load capacity because of its quick start-up and quick drop

down characteristics. The dispatch interval is taken as every half of an hour, which results in a total of 48 dispatches over the entire 24 hours time period.
The Lagrange approach has been used to transfer the constrained DED problem to the unconstrained problem by adding the constraint equation multiplied by a weight coefficient to the objective function. The choice of the coefficient is determined by the proposed constraint handling method described in Chapter 8, which adds the information of how far the solution is away from the feasible region. This aims to give a better guidance to trace the continuously changing load demands.

The DED problem is encoded as 5 bits per unit, therefore a string length of 40 results for each solution. A CGA was employed to manipulate the initial guessed solutions for the DED problem with reproduction, crossover and mutation operators. The Grefenstette's parameter settings were used for general good solutions.

Figure 9.2 gives the resulting cost at different time intervals. The overall cost and the computing time are shown in Table 9.1. Given the same problem and same parameter value for a EGA, the resulting cost and the time are listed in the same table for comparison. Obviously, the EGA attained a better cost solution, but takes a slightly longer time. This is because of the technique has no look ahead capability. Therefore, the resulting economic allocation often tends to fully load the large, economic units, and leaves less capacity to meet a sudden load demand in near future. Under such a circumstance, the EGA may not be able to attain a feasible solution unless numbers of genetic searches are repeated, which contributes to a longer computing time compared with a CGA.

Table 9.1 The Solution Results of CGA and EGA on the DED Problem.

METHODS	Cost (£)	Time (min)
CGA	625324.94	0.82
EGA	621349.69	0.96

Figures 9.3-9.4 show the typical base load supply units, which provide 80% of the generation supply, and which are under strict generation ramping rate constraint. In both figures, the dotted line represents the power output with security GR constraint,

and the solid line is that of the power output without the GR constraint. As the GA techniques are blind to the complexity of problems, they give the same search effort on problems with different degree of complexity. Hence, a GA gives the same search efforts for both the relaxed and the constrained problem. Obviously, the constrained problem formulation gives more practical desirable results. Figures 9.5-9.6 represent intermediate and peak load supply. The power generation from these generators are totally relaxed with respect to the GR constraint due to the small amount of power output they produce.

The resulting cost and individual generator output agree well with that of the real dispatch figure from NIE system. The security constrained dynamic economic dispatch problem considered here is simpler than that of encountered in practical operation. Other important constraints, such as spinning reserve, must be accounted for in this small isolated power system. The more complicated power allocation problem encountered in practice should be able to make better use of the potential of the GA search ability.

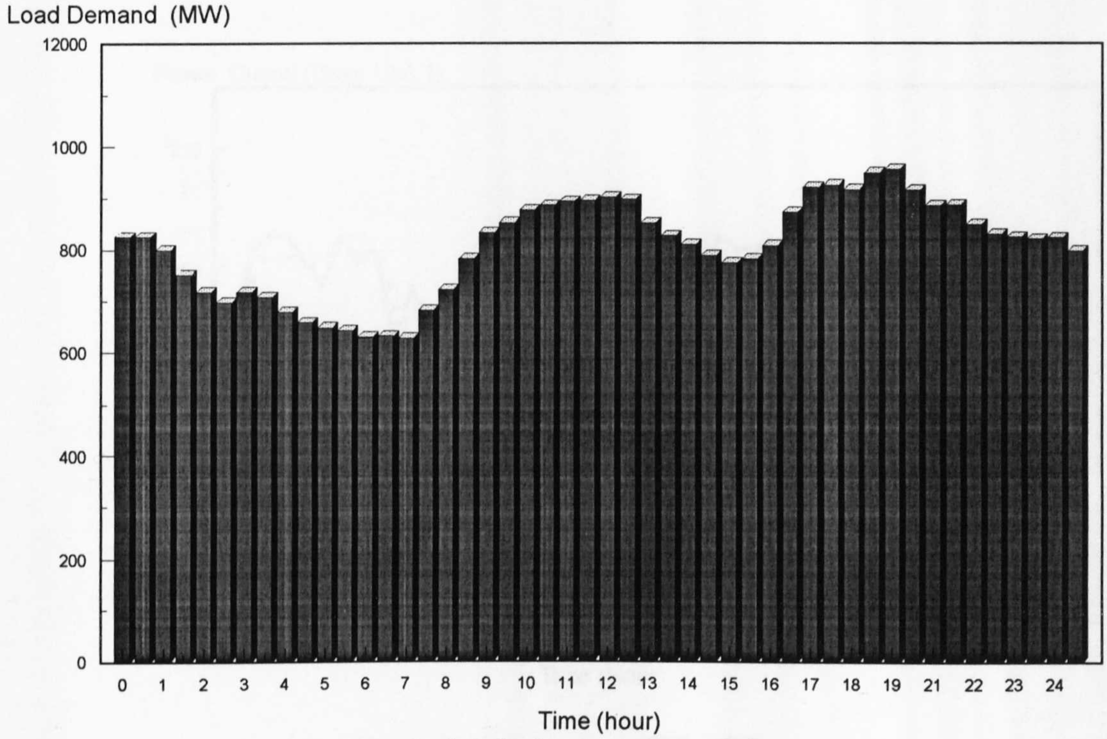


Figure 9.1 Typical daily load curve in spring season.

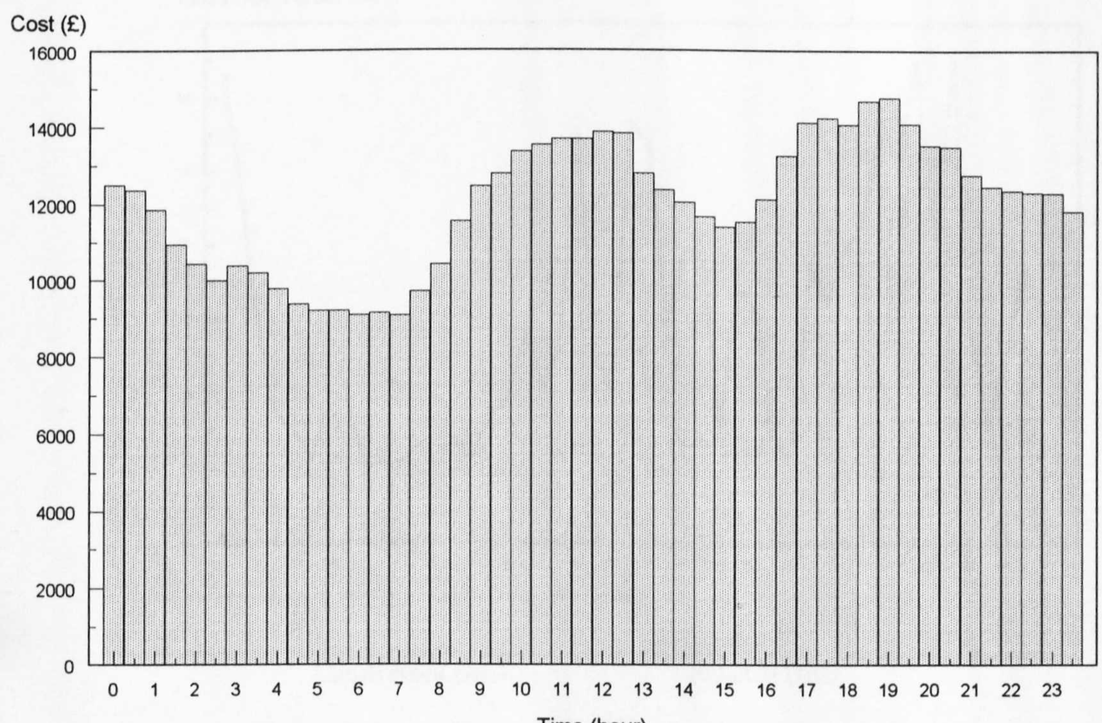
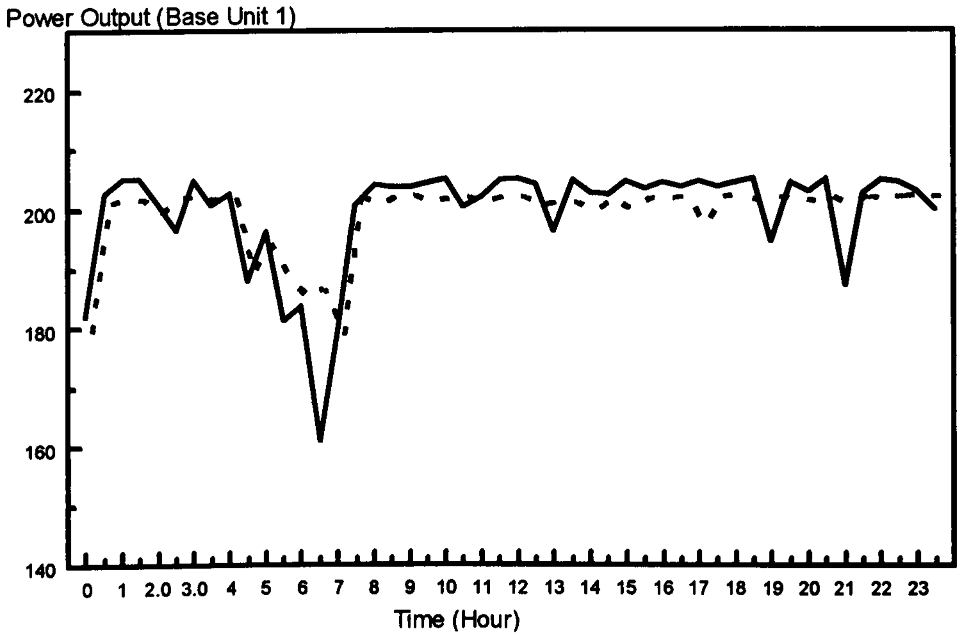
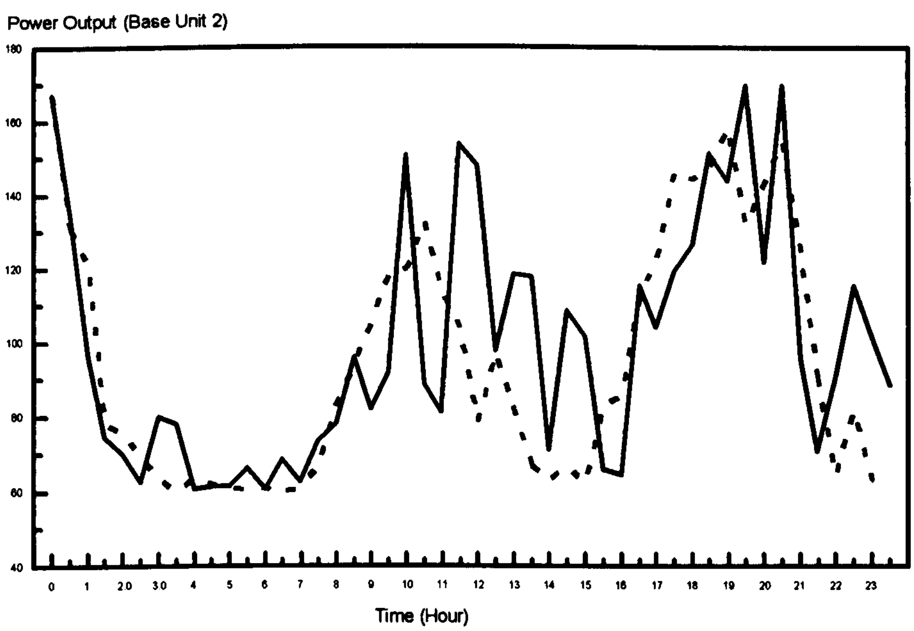


Figure 9.2 The corresponding cost curve.



Constrained DED Relaxed DED

Figure 9.3 Example of base load supply unit 1.



Constrained DED Relaxed DED

Figure 9.4 Example of base load supply unit 2.

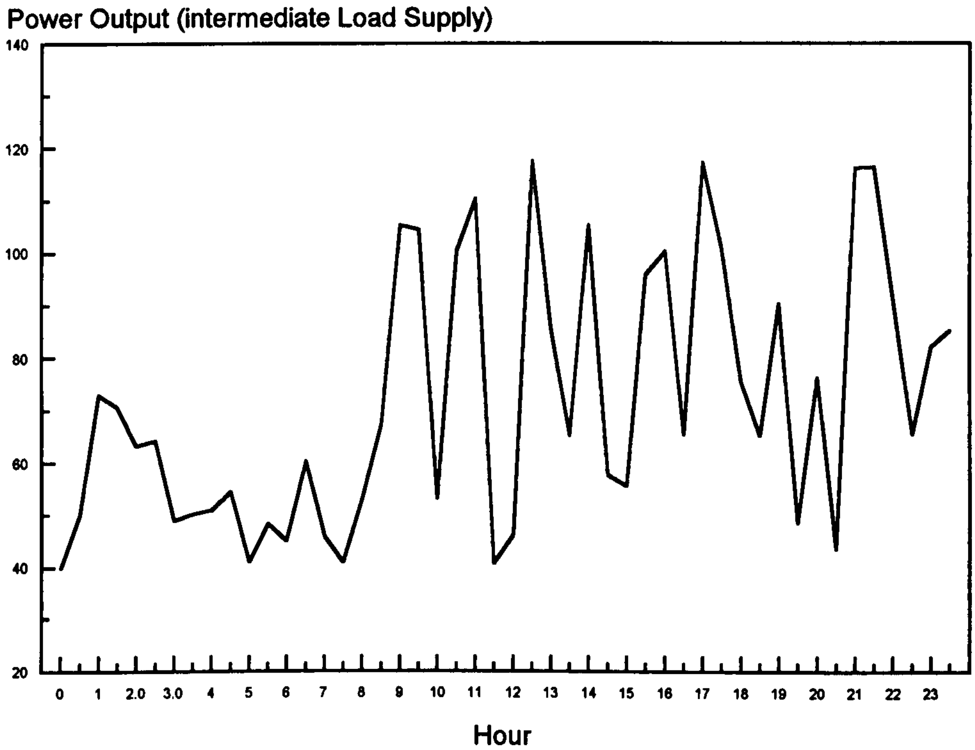


Figure 9.5 Example of intermediate load supply unit.

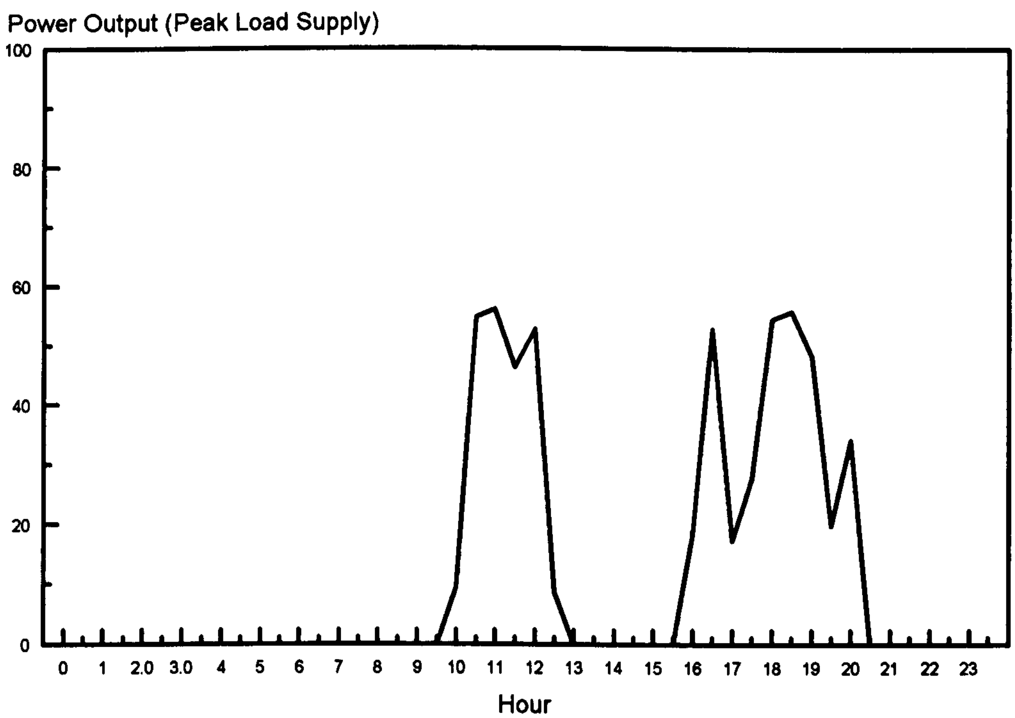


Figure 9.6 Example of peak load supply unit.

9.4 HYBRID GENETIC APPROACH TO THE DED PROBLEM

A HGA which takes advantages of both GAs and local search techniques, showed obvious benefit in solution accuracy and solution speed on the CED problem in Chapter 5. In this section, HGAs demonstrates its effectiveness on the real NIE system.

9.4.1 THE REVISED SYSTEM

Because of the high reserve margin that the NIE system should have for the security reasons, only one third of the generators are in service for a normal spring day, which works out a total of 8 search dimensions. To further test the search ability of the proposed HGA in a larger search space, an example power system is devised from the NIE system in that the load demands are increased by 1000 MW at each time interval and all 25 generator units are in operation so as to comply with the increased demands. The modified 24-hour load demand considered in this application is depicted in Figure 9.7.

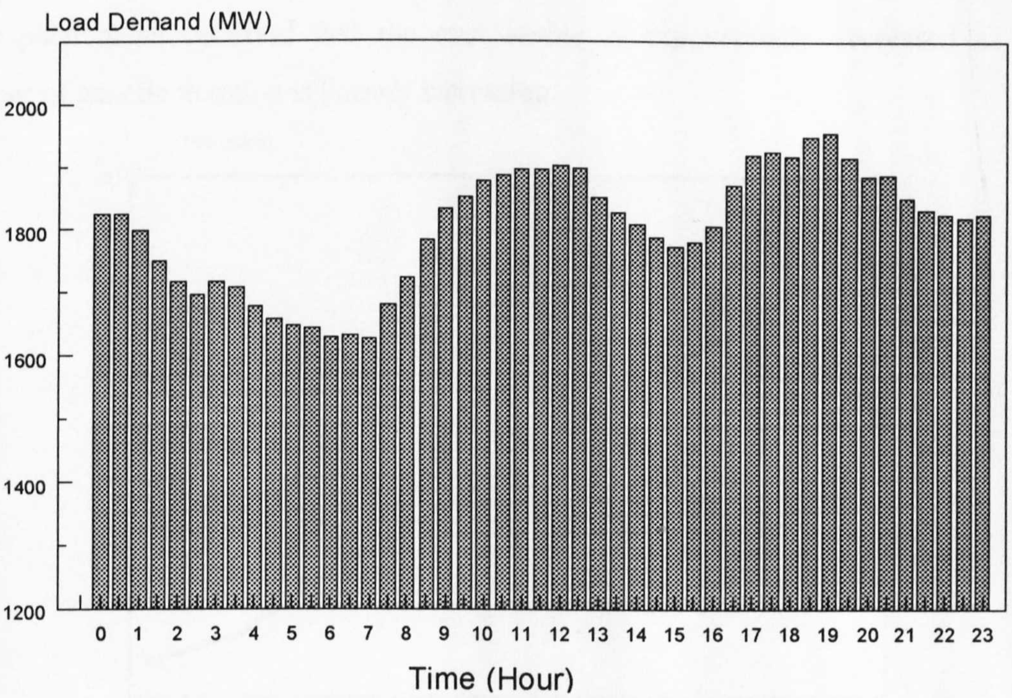


Figure 9.7 The modified load demand.

9.4.2 THE IMPLEMENTATION OF HGAS ON THE DED PROBLEM

The formulation of the DED problem in this section is the same as that of Section 9.3, only the load demands have been increased. A HGA constructed by crossing an EGA with a first-order gradient technique, which is described as HGA(2) in Chapter 5, is employed to tackle the problem.

The base GA is the major influence on computational speed in a HGA search. The computing time for a genetic search increases with the number of iterations. Their relation in the case of the DED problem on NIE system is shown in Figure 9.8. For a short overall HGA search, a base GA search shall take a small number of iterations to complete the search. Yet the base GA search has to be sufficient to identify the potential hill. Figure 9.9 shows the different operating costs for various genetic iterations when population size, crossover rate and mutation rate are set as 30, 0.9 0.01 respectively. Clearly, the HGA made significant cost improvements over the EGA (For instance, the HGA with 20 generations made 1.23% cost saving compared with that of the EGA). The improvements thus made by the local search technique only took 0.27 second, which is a very good investment for cost saving. Again, the same phenomena occurred that the cost saving is exponentially decreased as the number of genetic iteration is linearly increasing.

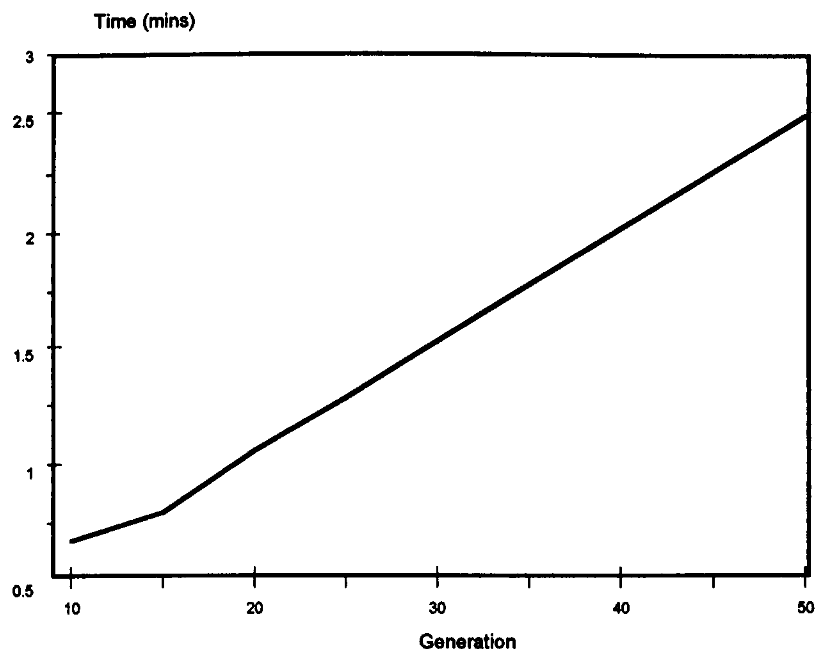


Figure 9.8 Computing time versus the number of generations.

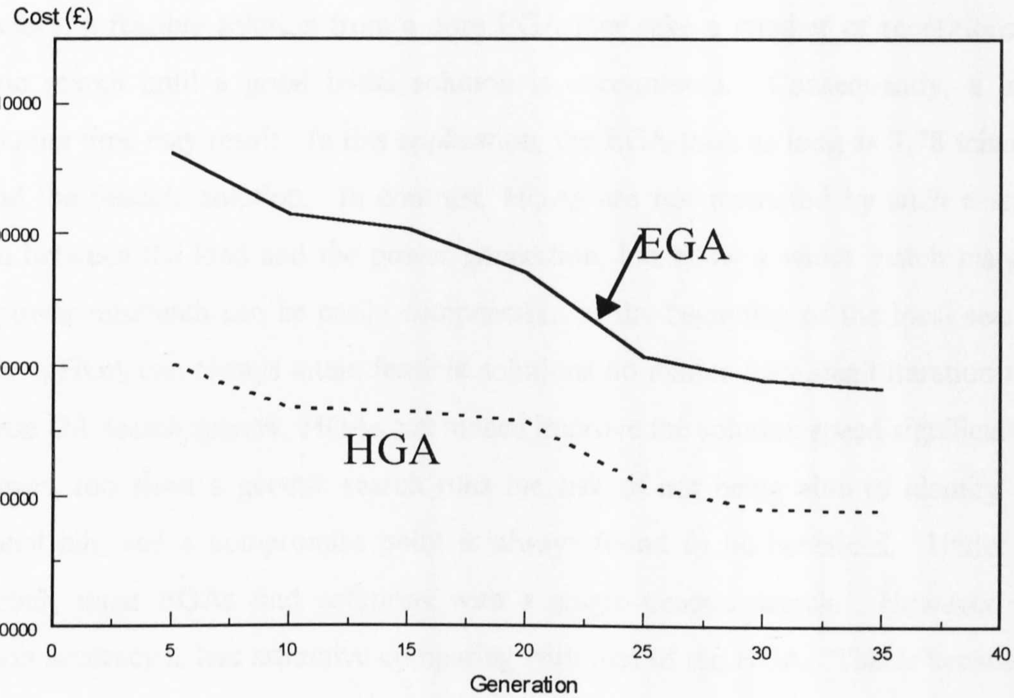


Figure 9.9 Performance improvement of the HGA over the EGA.

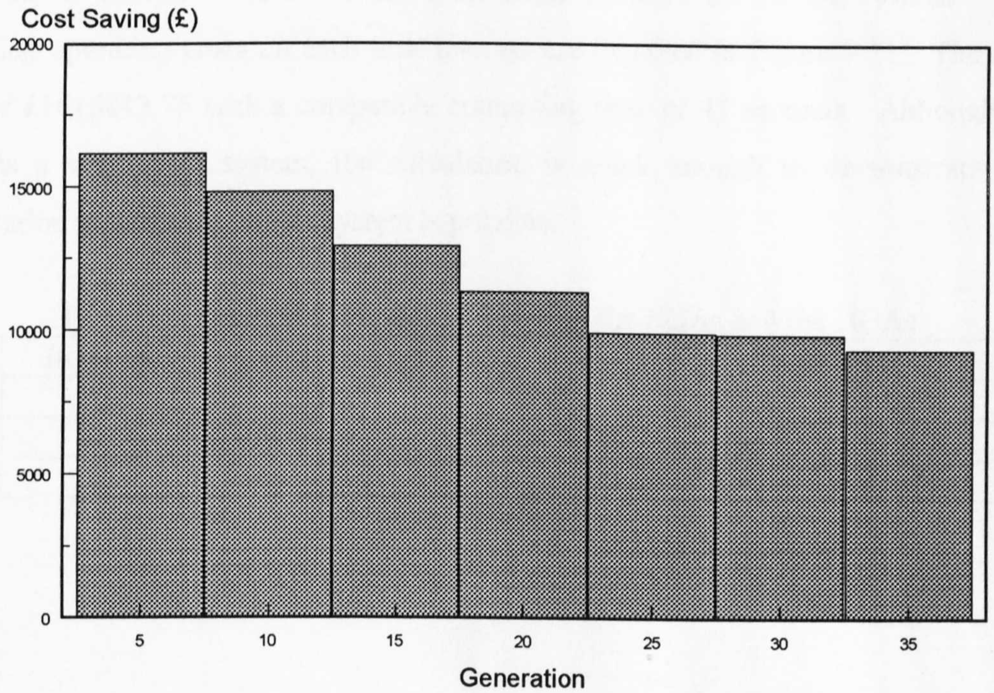


Figure 9-10 Cost saving with the HGA at different base GA search.

A solution comparison between the EGA and the HGA on the NIE system are outlined in Table 9.2. With 10 iterations, most EGAs cannot find feasible solutions (where the load matches the demand exactly) unless the initial solutions are well guessed. Therefore, a feasible solution from a pure EGA may take a number of repetitions of genetic search until a good initial solution is encountered. Consequently, a long computing time may result. In this application, the EGA took as long as 3.78 minutes to find the feasible solution. In contrast, HGAs are not restricted by such a strict match between the load and the power generation, but allow a wider match margin. The power mismatch can be easily compensated at the beginning of the local search. Hence, a HGA can always attain feasible solutions no matter how small iteration that the base GA search spends. HGAs can indeed improve the solution speed significantly. However, too short a genetic search runs the risk of not being able to identify the potential hill, and a compromise point is always found to be beneficial. Under 20 iterations, most EGAs find solutions with a single genetic search. However the solution accuracy is less attractive comparing with that of the HGA. This is because a pure EGA spends much more effort in matching the load and generation than that of a HGA. For a comparable solution speed and solution accuracy, the number of iterations is chosen to be 10 to solve the DED problem on the NIE system. The resulting operating costs on each time interval are depicted in Figure 9.11. The total cost is £1616812.75 with a compatible computing time of 41 seconds. Although the NIE is a very small system, the calculation is quick enough to demonstrate that application to a more complex system is possible.

Table 9.2 Solution Comparison Between the EGAs and the HGAs

Iteration	Cost (£)		Time (min)	
	HGA	EGA	HGA	EGA
10	1616812.75	1638456.38	0.69	3.78
20	1616452.75	1636538.00	1.07	1.05

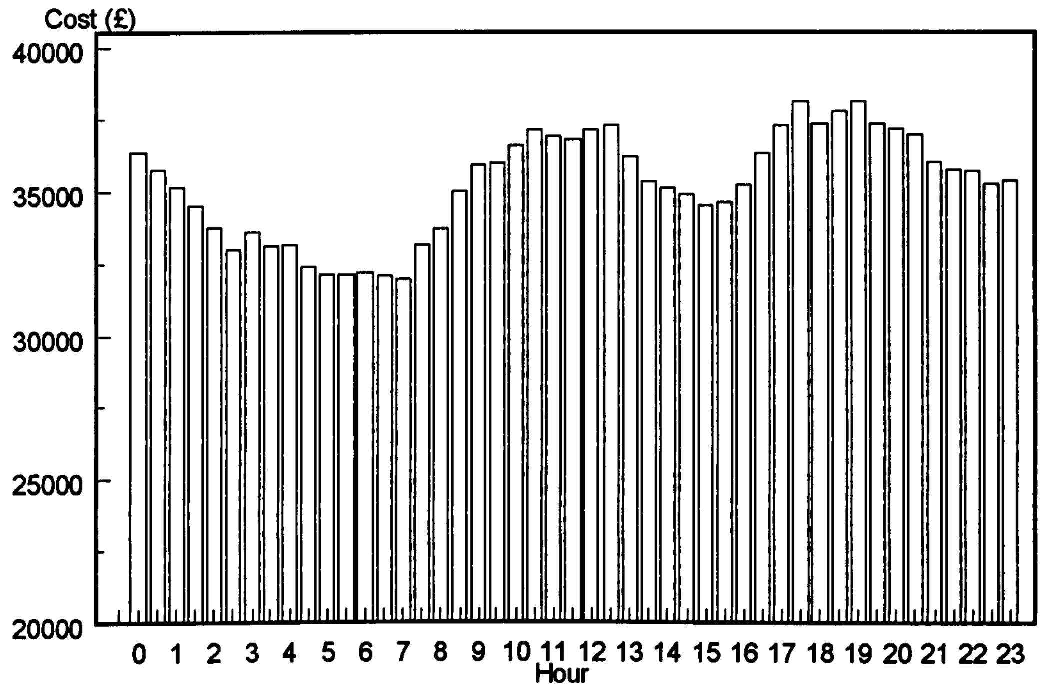


Figure 9-11 Resulting cost with the HGA (the base genetic search has 10 iterations).

9.5 HYBRID GENETIC APPROACH TO THE EED PROBLEM

Economic - Environmental Dispatch (EED) is an increasingly popular dispatch policy in power systems owing to the increasing public concern about environmental protection. EED is a more challenging problem as it takes two conflicting objectives into account, and therefore expected to make better use of HGAs. In this application, the environmental issue entered the dispatch problem as an additional constraint which further complicates the search space. The mathematical formulation for the EED is described by equations 7.2, 7.5-7.7 in Chapter 7. For the revised NIE power system, the permissible SO_2 emission at each hour is 80 Te. The generation ramping rate constraint is set as no more than 20% above or below the previous generator output level.

A total iterations of 15 has been given to the base GA search to provide sufficient search effort, while the population size, crossover rate and mutation rate are kept as 30, 0.9, 0.001 respectively. The resulting cost with the designed HGA is shown in

Figure 9.12. Table 9.3 gives the detailed figure of performance improvement with the HGA under environmental restriction, while Table 9.4 gives the results neglecting the environmental constraint. As indicated clearly in Table 9.4, although large financial benefit can be achieved with HGA under no environmental restriction, it gave no opportunity for emission reduction. Whereas under environmental regulation, the HGA has improved both cost and emission, which is more desirable in practice.

Figure 9.13 and 9.14 illustrate typical power outputs attained by the HGA for a base supply unit and an intermediate unit. The dotted line represents the results without the environmental restrictions, while the solid line represents the results under strict environmental constraint. As the base unit is the most economic one, it tends to produce more power when the environmental constraint does not apply. However, as it is also the most polluting unit, when the additional environmental constraint is imposed, the base load unit produces much less power over the entire dispatch period. The intermediate unit is quite different, as it is a relatively more expensive and clean unit. Without environmental restriction, the intermediate unit tends to produce less power. When under the environmental constraint, it generates more power output.

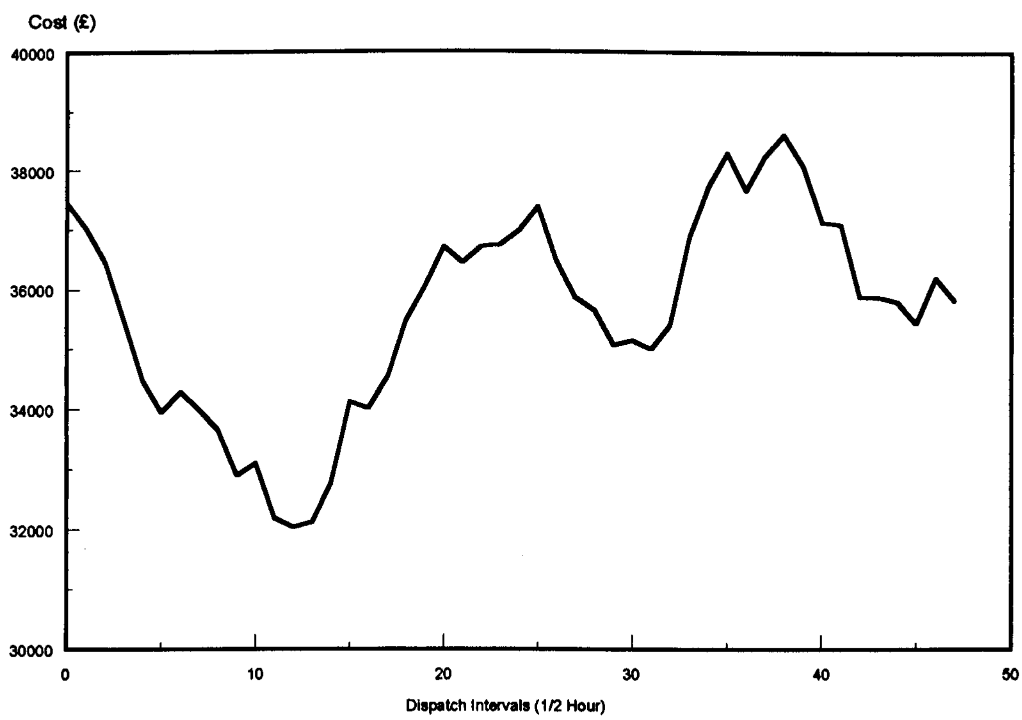


Figure 9.12 The resulting cost at the best operating point.

Table 9.3 The Improvements Made with HGA on Scheduling Problem Under Environmental Constraint.

	Cost (£)	Emission (Te)	Time (mins)
HGA	1710445.62	988.00	4.77
CGA	1712848.50	1038.12	4.55
Improvement	2402.88	50.12	

Table 9.4 The Improvements Made with HGA on Scheduling Problem without Environmental Constraint.

	Cost (£)	Emission (Te)	Time (mins)
HGA	1698817.12	1032.24	4.77
CGA	1705714.12	1032.24	4.55
Improvement	6897.00	0	

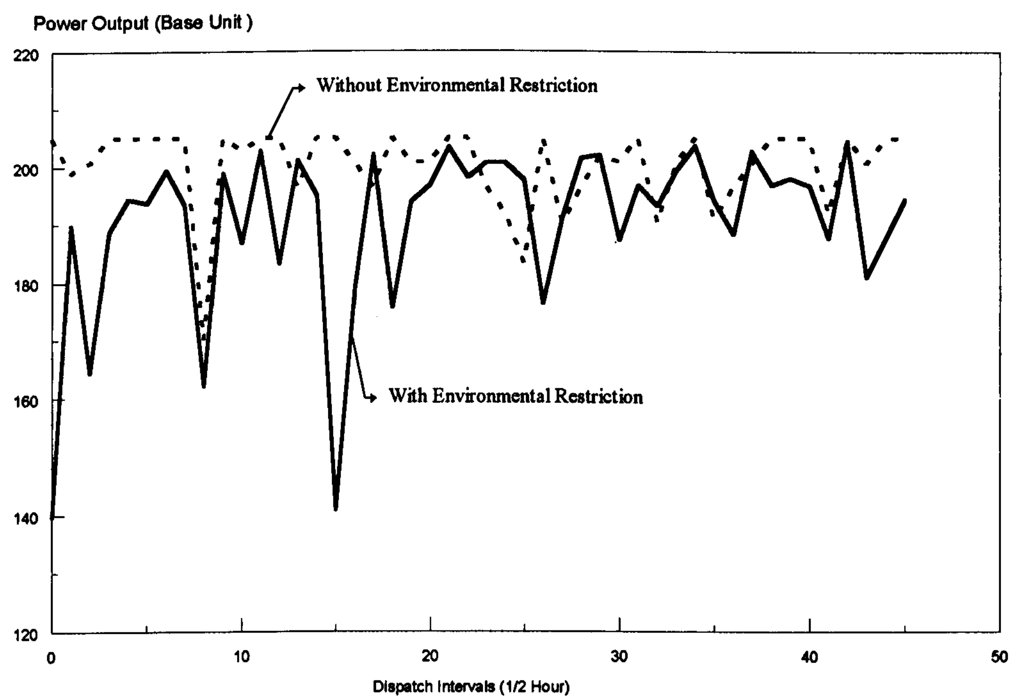


Figure 9.13 Power outputs for a typical base load supply unit.

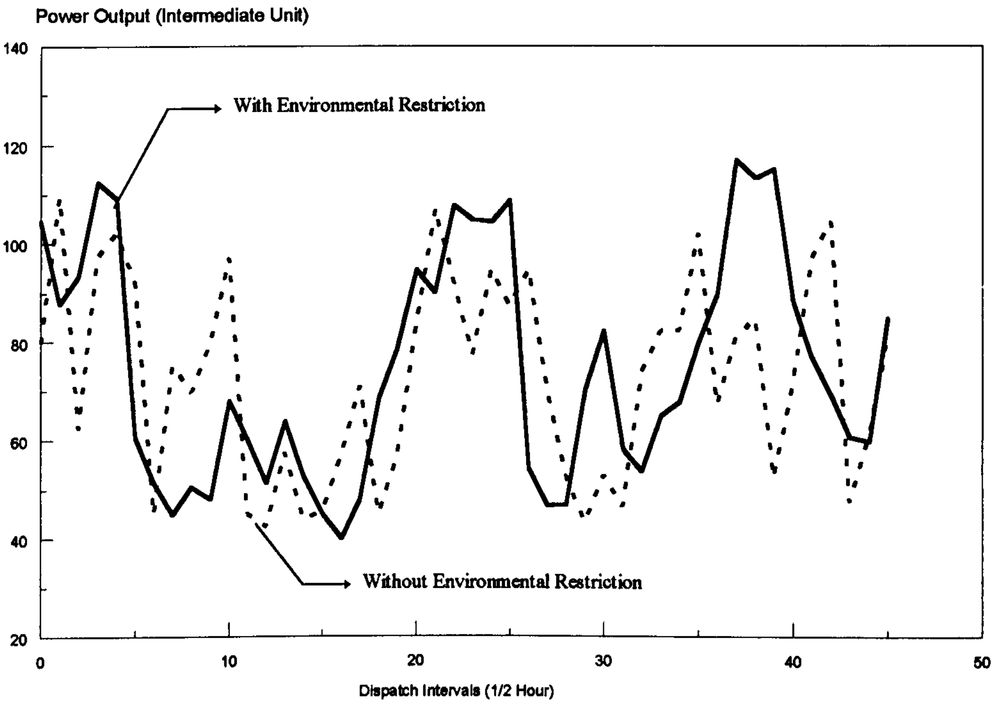


Figure 9.14 Power outputs for a typical intermediate load supply unit.

9.6 DISCUSSION

GAs have been applied to the real power supply system - NIE system for the economic allocation of generation output level while meeting customer load demand. Satisfactory results have been obtained between the simulated results and real data. Moreover, the Hybrid Genetic Algorithms have demonstrated their ability to attain better solutions with a shorter computing time. HGAs are proven to be fast and accurate algorithms to tackle the DED and EED problems both effectively and efficiently on the NIE system. However, HGAs may not be the best algorithms for the multi-objective optimisation problems. This is because a local search has limitations in dealing with multi-objective functions. Therefore, when the GA passes the results to a local search technique to continue the remaining search, a great deal of effort has to be made in reforming the multi-objective problem to a single objective function, which may disqualify the usefulness of the technique in many applications. Such a single criterion objective is less accurate or it may not be possible to constructe such an objective at all. Regarding the search ability of HGAs on multi-objective optimisation problems, further investigation is needed.

CHAPTER

10

CONCLUSION

10.1 SUMMARY

A number of problems in optimal economic operation of power systems have been successfully solved by genetic based algorithms in previous chapters. The problems selected cover a broad range and are of different degrees of complexity, ranging from the static problem to the dynamic problem, from the softly constrained to the harshly constrained, from single objective to multi-objectives, from small system size to large system size, and from simple problem structure to more rigorous structure. The starting point was the static economic dispatch problem on a small power system, and it was then progressively extended to dynamic dispatch and dynamic economic - environmental dispatch. Though the problems are so diverse, GAs consistently produced good acceptable solutions over the wide range of the problem spectrum. What is more, as is evidenced in chapter 4, the more complex the problem is, the more benefit that one can get from GAs. Finally, the feasibility study of GAs and HGAs on a practical power supply system, the NIE system, has been carried out in Chapter 9. The problems of generation allocation for both cost minimisation only and with emission reduction included have been dealt with subject to a number of system and operational constraints. Satisfactory agreements have been obtained between the real figures and the simulated data with the commonly defined GA. Moreover, HGAs showed obvious advantages over the CGA regarding the solution accuracy and the solution speed. In conclusion, in the case of power system optimisations the advantages of GAs over conventional techniques are:

(1) A genetic search procedure is very simple, yet remarkably effective in searching for the optimum or near to it.

(2) The only requirement for genetic search is raw objectives.

(3) GAs are blind to the search space so that they need no assumption of continuity or the existence of the gradient information about the search space.

(4) GAs have the ability to handle inequality constraints imposed on the control variables by themselves which simplifies the search problem significantly.

The early simulation also clearly indicated the shortcomings that a GA embraces which limits it to reach the desired efficiency and efficacy as the theory predicted. There are two major problems associated with the genetic application. One is the problem of the premature convergence due to the difficulties in balancing the two conflicting search efforts: exploitation and exploration. Another is the slow processing speed which stems from GA's population based foundation.

The treatment of the premature convergence problem has been well established, and they mainly fall in the following five categories:

(1) Advanced genetic operator.

(2) Optimal choice of GA parameters.

(3) Suitable evaluation function.

(4) Effective string representation.

(5) Better initial string generation.

Among the 5 possible improvement procedures, this thesis puts special efforts in the first two options to enhance the genetic strategies. It involves two levels of tasks. The bottom or the fundamental level is to select or formulate an advanced genetic strategy, and the top level is to optimally tune the parameter values in order to get maximum efficiency out of the preselected genetic algorithms. It is clearly demonstrated in Chapter 5 that optimally combining those two levels of tasks can have significant impact on the overall system performance. However, it is also clearly indicated that any carefully designed genetic search strategy can only balance the two conflicting search efforts, which implies that the increased solution accuracy must come at the cost of longer computing time, and vice versa. Alternatively, the method for improving both the solution quality and the solution speed is proposed by crossing a GA with other well established local search techniques. Therefore, the advantage of GA's capability in identifying the potential region, and local search technique's speedy search ability can both be utilised. Addition to the optimising genetic strategy, the research has proposed a novel constraint handling method to further enhance the genetic search ability in Chapter 8. The proposed method incorporates the concept of how far a solution is away from the feasible region so that a suitable evaluation function can be set up, and the search can be guided towards the right direction.

It is often suggested that genetic process speed can be improved by using parallel processing to make the inherent parallel genetic search procedure serial. Despite its effectiveness in reducing the computational time, it requires considerable capital cost and involves very complicated system design and implementation. Nevertheless, parallel processing is one of the most effective means to speed up genetic processing. Although HGA can not compete with parallel processing in speeding up the genetic processing, they have the advantages of simplicity in design, ease of implementation and virtually zero - capital cost. Therefore the designers themselves have to choose between the worth of the quality of the solution and the ease of the system design.

10.2 DIRECTION OF FURTHER WORK

Future work can be directed in two trajectories. One is more rigorous problem formulation, and another is further improving genetic processing.

It has been learnt in Chapter 8 that a better problem structure can have significant impact in system performance, which will lead to a cost saving in economic operation. Therefore, a need is always there for more rigorous problem formulation. It is also helpful to integrate the closely related problems whenever possible. Problems such as economic dispatch, emission dispatch and unit commitment are so much coupled that it is more desirable in practice to solve them as a whole rather than solve them sequentially. Parallel to the more rigorous objectives, there is a need to include more operational constraints in practical systems, such as an adequate spinning reserve and power-line capacity, which complicates the power system optimisation greatly. From the previous study, GAs are demonstrated to be promising approaches to the complex, multi-modal, discontinuous and noisy problems, and have the flexibility to include additional objectives and constraints very easily. Therefore, the more difficult economic dispatch problem, such as Optimal Power Flow, which involves several objectives, a number of control variables and some secure and operational constraints, should be beneficial in obtaining solutions with GAs.

Work needs to be done on further effecting GAs' efficiency to better balance the conflicting exploitation and exploration search efforts. The compromise of the two efforts might be well served by some newly inspired genetic operators. Although the HGA appeared to be a perfect solution to balance the two search efforts with comparable search speed, the applicability of the technique in multi-objectives has to be argued. As most of the HGAs pass the GA solutions to the conventional techniques which might only be able to deal with a single objective, require detailed information about the problem domain, and/or need certain assumption on the search space, their application range is severely limited. Therefore, a robust hybrid scheme should cross genetic algorithms with other fast search techniques which have the capacity to deal with multi-objectives and harsh constraints. The investigation of such a fast search technique is both challenging and rewarding.

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