MODELLING LONG-TERM PRIMARY ENERGY MIX IN THE ELECTRICITY SUPPLY INDUSTRY THROUGH GENETIC ALGORITHM BASED OPTIMISATION

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ABSTRACT

The United Kingdom's Electricity Supply Industry (ESI) was commercially restructured when it was privatised in 1990. Its long-term future now depends upon the actions of competing companies rather than the political decisions of a nationalised industry. Existing models of the industry have not included these market effects as the added complexity has proved difficult to include. A new type of model is needed to understand the operation and enable forward planning in the ESI.

There are many approaches to forecasting ranging from individuals' opinions to mathematical iterations and, more recently, computationally intelligent techniques. Each of these methods has a place in different modelling environments as each has different characteristics. The thesis of this study suggests that forecasting the long-term primary energy mix in electricity generation is a large non-linear problem that may be solved by a Genetic Algorithm (GA) based model. GAs use a combination of selection, breeding and mutation to evolve an optimum solution from a population of possible solutions.

This work reported how a global utility function reduced the large set of non-linear equations, that described the ESI, into a single optimisation problem solved by a GA. The GA made repeatable optimisations allowing reliable forecasts of different possible future scenarios. The model was further improved by the inclusion of new genetic operators that reduced volatility and gave the GA a memory of previous generations.

The model was validated by matching an ex-post forecast with actual past data. It was then used to analyse the ESI's sensitivity to changing environments. This was achieved by building a picture of the future environment from the combined results of multiple scenario forecasts. Although there were politically sensitive outcomes to some scenarios, electricity generation met demand in every case.

DECLARATION OF ORIGINALITY

The research recorded within this thesis and the thesis itself is, except where indicated to the contrary, the original and sole work of the author.

Charles Lawrence Silverton

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Finally I am indebted to my Parents, Norma and Victor, my sisters, Francesca and Victoria, and brother-in-law, James, for their love which made the completion of this research possible.

"Although the study of natural evolution and the development of life is new and inspiring, the chaotic complexity of the total system is beyond the scope of today's science. Only the foolish believe that they truly understand all of nature's complexities. So let history serve to warn them, who attempt to alter any single aspect of this grand process, and disturb nature's balance of selection and diversity."

B. Biteabout

Suffolk 1983

To Ingo Trepel.

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1. INTRODUCTION

1.1 Introduction

The UK Electricity Supply Industry (ESI) developed from a few independent privately owned generators at the turn of the century into a centrally controlled interconnected grid system by 1926. Numerous Acts of Parliament were passed to aid and regulate the expansion of the industry which was, until 1947, one third privately and two thirds publicly owned. Energy shortage was the major concern during the post-war period up until the early 1950s and nationalisation was considered the solution. This was the first swing of a pendulum away from the decentralised private sector towards a unified industry which proved to be crucial in establishing the UKs status as an independent nuclear power. The period between the mid 1950s and late 1970s saw great leaps in development and political backing for innovative technologies. British industry performed well during the early part of this period which helped transform the ESI and bring it into the technological age. The belief that commercial competitiveness is the only path towards efficiency has dominated the UK since the 1980s. Privatisation and market forces, rather than nationalisation and central planning have shaped the industry which was privatised in 1990 which is set to be reorganised further in April 2000. Although the objective of privatisation was to reduce government intervention, public opinion against nuclear power and the imposition of international emissions targets have forced the present government to take an active role in the regulation of the ESI.

Governmental policies towards the generation, supply and sale of electricity have played a key role in the recent change in energy trading within the UK. The increase of renewable generating capacity has been the result of extra funding provided by both the Non-Fossil Fuel Obligation (NFFO) in England and Wales and the Scottish Renewables Order (SRO) in Scotland. This government is committed to achieve a target whereby 10% of the UK's electricity is generated from renewable sources by the year 2010. This represents approximately 9GW of renewable plant capacity, over ten times the current value. Although the expanding renewable energies market is becoming more profitable and is fast attracting investment this target will only be met through increased government intervention.

The ESI presently utilises a mixture of primary energies for electricity generation. Each has its ideal place in the industry based upon available resource, economic costs, environmental impacts and the merit of the generation technology. Since the privatisation of the UK ESI the choice of generation method has included market effects which affects company strategy. In order to maintain the most sustainable fuel mix a degree of control over the industry is necessary. The new structure of the ESI asserts that this can only be achieved through taxation and independent regulation, removing government intervention, and its political bias. However the construction and lifetime of electricity generating plant involves time-scales from tens to hundreds of years depending on the technology and the amount of time the plant is on-line compared to its optimum scheduling (lifetime load factor). To regulate successfully in such a long term industry a degree of forward planning is vital based on predictions of the future shape of the electricity market concerned. In addition, competing companies within the industry need forecasts upon which future strategy and plant construction decisions can be made.

Long term forecasts of the variables which describe the UK ESI are readily available to aid planning, speculation or risk analysis. These variables are grouped into economic, environmental, technical, political and market functions and can be described as:

- Economic functions that include plant capital and generation costs, taxation structures and interest rates. They give a financial view of electricity generation and transmission. Forecasts based on these variables alone, such as Least Cost Plan forecasts, omit many of the most critical variables mentioned below.

- Environmental concerns which involve the external costs of generation including pollution, decommissioning and resource depletion. They are manifested as emission taxes and regulatory constraints which can be enforced through heavy financial penalties.

- Technical forecasts that predict advances in generating efficiencies and the rise of new, unproven, generation methods. These variables alter the shape of the economic values associated with existing generation technologies. New technologies can directly replace old technologies although the risk costs of new generation technologies are often prohibitive at their inception.

- Political forecasts which encourage or handicap individual generation methods based upon the predicted influence on votes that the use of these technologies might have. Political influence is usually applied through legislation but has, in the past, involved the direct interdiction of particular types of plant construction. This is the least objective of the variable categories and is therefore given less influence on final outcomes. However, they are especially useful in scenario studies as they allow the analysis of the effects caused by proposed government intervention.

- Market effects cause competitive strategies which ensure that company efficiency will not fall below a critical level beyond which there is a threat of take over. Competition also alters risk avoidance policy by promoting hedging contracts, vertical or horizontal integration and speculative behaviour.

At present the influences of different forecasts are *weighed up* by strategists and a rough picture of a single possible future is estimated. Present modelling approaches offer limited complexity thus many of the key factors that may influence long-term generation mix are omitted, greatly reducing the reliability of results.

A repeatable quantitative analysis of all influential variables under the new and powerful market forces of the privatised industry has, until now, proved unfeasible due to the size of the problem and the non-linear nature of the data. The recent exponential increase in computational power has allowed the application of innovative modelling algorithms that were once considered only as theoretical concepts by both academia and industry. One of these techniques, Genetic Algorithms (GAs), evolve optimum solutions to large non-linear problems using the rules of selection, breeding and mutation found in nature. This study suggests, and goes on to show, that forecasts of the primary energy mix for generation in the UK ESI can be modelled as an optimisation problem. It also shows that optimising by GA can give relatively rapid results when all of the relevant explanatory variables are included.

A Genetic Algorithm starts with an initial population of possible solutions that, in this case, represents the mix of primary energy used in generation on a yearly basis. The solutions survive, die or reproduce due to their ability to satisfy a fitness function made up of the factors that drive the electricity market and political, economic, environmental and technical variables that describe and regulate the industry. This method allows a computer model to explore possible outcomes for feasibility and assesses the probability of these outcomes actually happening. This occurs in a manner which disregards groups of solutions deemed impossible, whilst optimising all the solutions that are probable. The optimum solution is given alongside other solutions which might not satisfy the market functions as accurately as the fittest, but are valid and realistic possibilities. This approach enables repeated simulations of various scenarios without having to re-solve the mathematical representation every time. Such flexibility allows the model to be run and analysed by decision makers, as opposed to professional mathematicians who may not be familiar with the operation of the ESI.

1.2 Statement of Thesis

The thesis of this study is that a reliable long-term forecasting model of yearly generation, energy resource and available plant mix in UK electricity generation can be constructed using a global utility function solved by a Genetic Algorithm (GA) based optimisation.

This has been made possible by:

- A change in the decision making process, effecting generation scheduling, that resulted from the privatisation of the UK Electricity Supply Industry (ESI).

- The recent exponential increase in computational processor speeds that has allowed the application of GA theory to real life large-scale problems.

Although it is not possible to foresee every event in the long-term future the Genetic Algorithm based Model of Electricity Supply (GAMES), suggested in this thesis, will provide both probable and most likely outcomes to suggested future scenarios.

GAMES can be validated through a comparison of an ex-post forecast and actual data since the privatisation of the UK ESI in 1990. The stability of the model can be further assessed by performing sensitivity studies on future possible scenarios and through the analysis of these results.

1.3 Thesis Outline

This thesis suggests the design of a new architecture for energy planning models through an optimisation, by genetic algorithm, that allows a level of complexity that is not currently available in a forecasting model. The first three chapters of this report form the introduction, giving a background to the UK ESI and an outline to existing approaches to forecasting within the industry. The necessity to make forecasts of how electricity will be generated in the future is discussed, highlighting the need for a new type of forecasting model. This is followed by three chapters that describe a new approach to long-term forecasting through a GA based general utility optimisation. The final three chapters explain the application of this new forecasting approach, discuss the results from scenario forecasts, and form conclusions based upon the methodology and how the model performed.

Chapter 2 describes the UK ESI and is divided into three sections. The first gives a brief history followed by the effect of privatisation on the structure of the ESI. It describes the electricity marketplace and trading pool, how the industry is regulated and its future when new trading proposals come into effect. The second Section in this chapter concerns generation in the UK. Each generation method is described from an energy planning perspective. Each technology, its financial costs, resource constraints, environmental impact and political implication is discussed in turn. This includes technologies that are not yet proven in the electricity industry. The final section concerns forecasting in the UK ESI and highlights the differences between forecasting the behaviour of nationalised and privatised industry.

The third chapter investigates current forecasting techniques and their applications in the electricity supply industry. It begins with the old school of opinion based forecasting and the process by which a number of experts' personal views could be averaged to give a single forecast. Modern mathematical methods of trend regression and extrapolation are then explained and their advantages and limitations discussed. This is followed by four prominent computer based approaches to modelling and forecasting in the ESI. The final Section outlines the major Artificially Intelligent (AI) methods which are currently being used in forecasting. Some of these AI techniques are improvements that can be added to traditional forecasting methods and some constitute novel approaches to forecasting. The chapter concludes with a description of a simple GA and explains why this method of optimisation is best suited for large long-term forecasting problems.

Chapter 4 begins the description of a new model of the UK ESI. It shows a clearly defined model structure using exact definitions of functions and data types in order to control the complexity needed to describe the ESI accurately. The assumptions made have been clearly highlighted and proven methods of noise reduction, such as aggregation, are discussed. The chapter moves on to discuss the need for a new type of global utility function to combine the myriad of individual explanatory functions into one large optimisation function. The chapter concludes that due to its size, and non-linearity, a GA is found to be the only method available to optimise, and solve, this global utility function.

The use of GAs in long-term forecasting is new and still developing. This thesis suggests that GA optimisation is ideally suited to solving large forecasting problems and has many inherent advantages. Chapter 5 describes the structure and representation of a forecasting GA and highlights the changes to traditional GA methodology necessary for long-term ESI forecasts. Each of the standard genetic operators is discussed in turn and the final choice of their settings is explained. The final Section in this chapter looks at five advanced genetic operators of which two are new. One of these, Recall, applies a genetic process that stores redundant genetic code for future use. This new step in the evolution of GAs themselves has emerged from this study and could be applied to other GA applications.

GAs operate by the selection, breeding and mutation of a population of parent solutions to create a new population of fitter child solutions that are closer to a global optimum. The selection process depends on how close each individual solution is to being the optimum solution to the model. This is judged by the fitness function which, in this case, is a global utility function that contains all the functions necessary to describe the UK ESI. Chapter 6 discusses each of these fitness function components from operation costs to risk avoiding strategies. Assumptions and limitations are discussed and relevant values referenced or given. The final Section describes the global utility function and the fitness value returned to the GA for each individual solution that has been assessed.

Chapter 7 describes the Genetic Algorithm based Model of Electricity Supply (GAMES) and the algorithms that operate the user interface. This chapter is not an operation manual, but rather a description of the program's data manipulation, genetic operator choices and results interface. It explains the effect of changing crossover and mutation rates, seeding the algorithm and radiating the population. The chapter ends with a theoretical scenario forecast during which programming and graphical interface decisions made during the program's creation are explained.

Chapter 8 discusses the performance of the GA and the forecasting model as a whole. It starts with the results of a feasibility study undertaken before the final model and program were constructed. This simplistic study assumed a scenario where all electricity was generated by gas and coal only. On the basis of these results a full scale model was constructed and its' performance is discussed in detail. Firstly the operation of the GA is assessed, and the merits of each genetic operator and their respective settings is discussed. These are represented graphically as GA convergence graphs, one for each default setting or new operator. The model itself is validated through forecasts. The first is an ex-post forecast from 1988 to 1998 which is used to make a comparison between the forecasted and actual fuel mix used in generation during this period. The remaining results are from five scenario forecasts. Each represents a 40 year forecast of different possible generation environments. Each scenario outcome is discussed in detail with reference to the model's stability and accuracy. When considering these results it must be noted that it is not possible to make single predictions of the exact amount of electricity that will be scheduled by each generation method 40 years from now. However, it is possible to build up a picture of the critical factors through multiple forecasts. For this a quick, large and stable model is necessary. This chapter ends with a summary of how GAMES fulfils this task.

Chapter 9 concludes this thesis. It gives a summary of the new material and concepts that have been developed learnt during this study and outlines the thesis' contribution made to knowledge. It ends with suggestions for future work.

2. THE UK ELECTRICITY SUPPLY INDUSTRY

2.1 Overview

This chapter gives a brief description of the UK's Energy Supply Industry (ESI) and outlines the major technologies used in electricity generation. It discusses the environment that has been modelled, then moves on to give the benefits and drawbacks of each generation method. The first Section starts from the creation of the first nationalised electricity generating board and ends with current proposals for changes in the electricity market. The second Section describes generating methods from the perspective of an energy planner in the existing ESI. The final section investigates the differences that privatisation has made upon forecasting.

2.2 The Market

The ESI has been changing constantly since the first Electric Lighting Act of 1882. This Act aimed to introduce legislation that would protect customers and create a structured environment for the rapidly expanding business of electricity generation, transmission and distribution. The latest Electricity Act, set to be introduced in April 2000, concerns the restructuring of the Electricity Pool and was passed through parliament for the same reasons as the 1882 Act. This is not because it has taken 118 years to find a viable system, but is rather due to the constant evolution of the ESI as it adapts to new technologies, fuels and constraints. Market led policies and new environmental concerns have shaped the present industry and the immediate future will be influenced by new European legislation. However the only certainty in the long term is that there will be continuing change.

2.2.1 The Nationalised UK ESI

The first Electricity Commission was established in 1919 to govern electricity supply in the UK. This was the first of many governing bodies dedicated to the regulation and control of electricity generation and supply. It was replaced in 1926 by the Central Electricity Board which was in charge of promoting and operating a national system of interconnections between generators. By 1947 there were 560 separate electricity suppliers of which two thirds belonged to local public bodies. This publicly controlled privately owned system of generation was difficult to regulate and lacked the co-operation needed for expansion. The Electricity Act of 1947 reorganised the whole ESI by nationalising the remaining private companies and creating 14 powerful Area Boards to control distribution, and the Central Electrical Authority to organise finance and policy[1]. The ESI was reorganised again in 1954 with the separation of the two Scottish Boards. Three years later the Central Electricity Generating Board (CEGB), serving England and Wales, the South of Scotland Electricity Board (SSEB) and the North of Scotland Hydro-Electricity Board (NSHEB) were founded and made responsible for generation, transmission and distribution issues. At its peak the CEGB generated and supplied, through the twelve English and Welsh Area Board suppliers, 94% of its regions total energy requirement. The SSEB and NSHEB performed both generation and supply duties in their regions. Figure 2.1 Shows the structure of the, then nationalised, ESI.

Despite the Energy Acts of 1983 and 1987, aimed to attract private generators back into the ESI, the industry was performing badly. The CEGB was accused of bad policy making, concerning the construction of nuclear plant against public opinion, and poor customer service. Although the CEGB could prove that government intervention was responsible for the nuclear program it was privatised, along with the SSEB and NSHEB in March 1990.

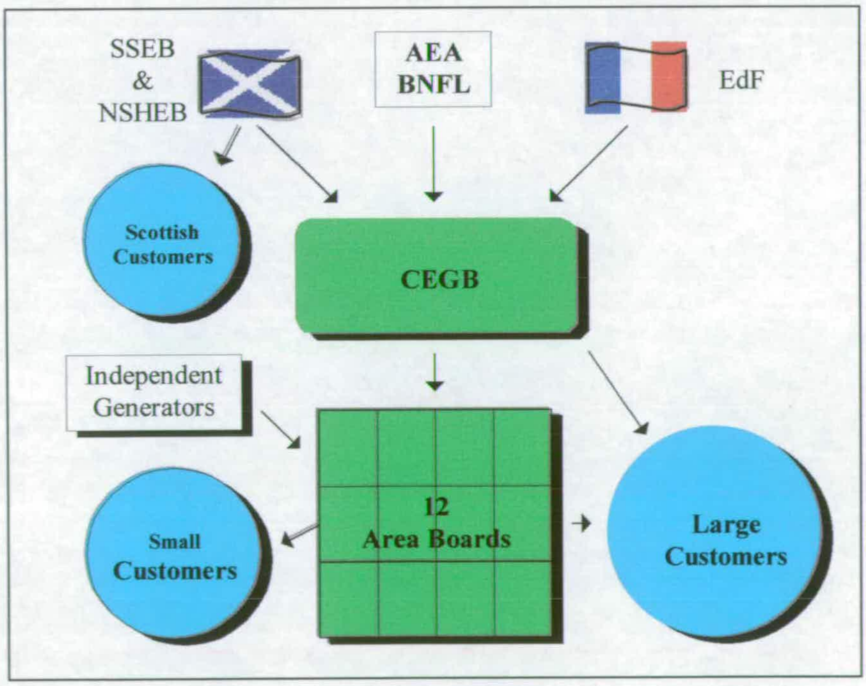

Figure 2.1 Nationalised UK ESI (1989)

2.2.2 The Privatised UK ESI

The decision to privatise the ESI was made to stop the CEGB, SSEB and NSHEB monopolies and prevent government intervention. The White Paper "Privatising Electricity"[2], published in 1988, outlined the UK governments ESI privatisation plan:

ESI supply, excluding Nuclear Electric and Scottish Nuclear, was floated as seventeen companies and generation was put under the charge of two companies, National Power and PowerGen. The twelve English and Welsh Area Boards became the twelve Regional Electricity Companies (RECs). Their role continued as local distribution and supply operators. The RECs and their geographical locations are given in Figure 2.2.

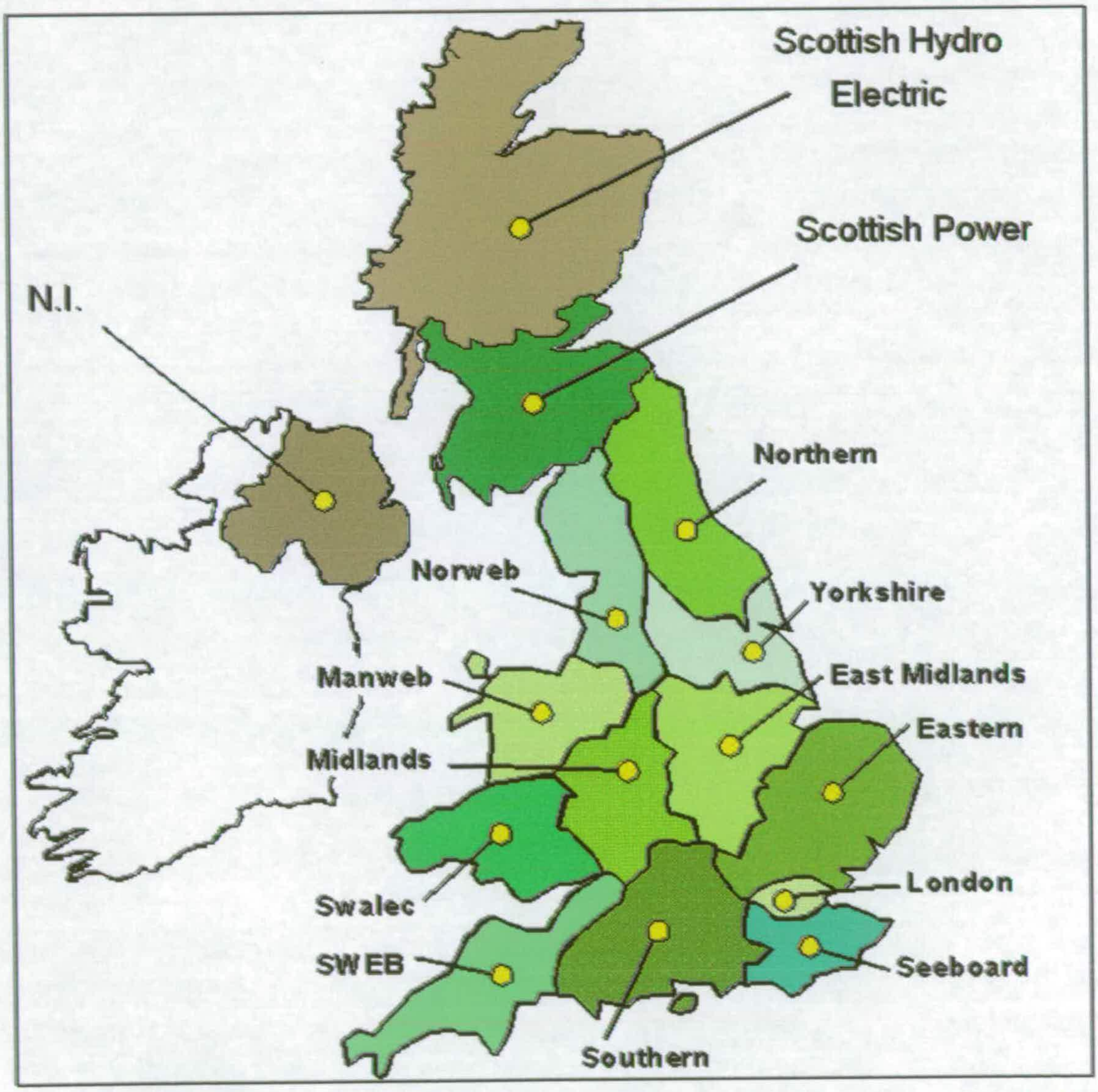

Figure 2.2 UK ESI, showing English & Welsh RECs, the Scottish power companies & Northern Ireland Electric.

The joining of transmission, distribution and supply was originally left to the RECs but, in 1995 the National Grid Company (NGC) was created for this role and floated on the stock exchange. The charge of the NGC was to oversee energy trading along with electricity distribution and supply.

The privatisation of Scotland's equivalent ESI followed a different course. Although joined to the English grid system, by means of an interconnector, it was considered independently. Scottish Hydro-Electric and Scottish Power replaced NSHEB and SSEB respectively and were privatised in 1991. These two vertically integrated companies controlled all of Scotland's electricity generation, distribution and supply. Figure 2.2 shows the geographical control of the RECs, Scottish power companies and Northern Ireland Electric.

In 1994 the National Coal Board, which was still the largest generation fuel supplier, was split into many smaller companies and sold to private investment. Many of these new companies were no larger than single collieries. The sale of Nuclear Electric and Scottish Nuclear came later as their poor assets, huge debts and the uncertain decommissioning costs would have impaired the sale of the whole industry. After much restructuring and debt repayment they were combined and sold as British Energy in 1996.

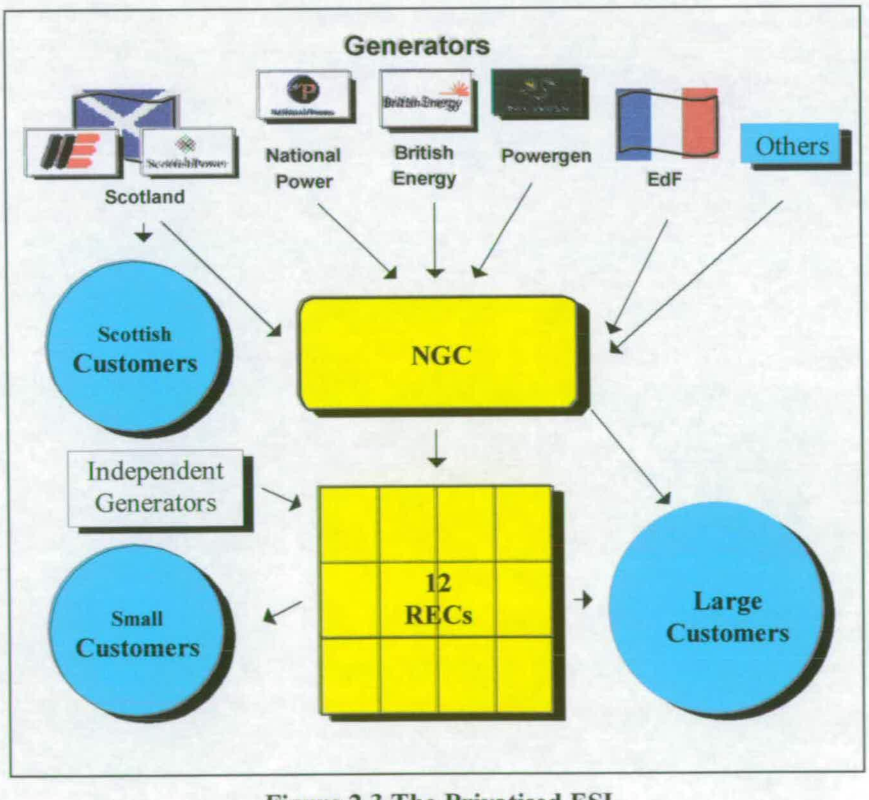

Figure 2.3 The Privatised ESI

Since privatisation in 1990 there have been numerous mergers and take-overs in the UK ESI. Recently the DTI blocked some take-over bids on the basis that competition would be reduced and therefore the customer would suffer[3]. Successful bids have involved companies from outside the ESI, such as Dominion Restaurants take-over of East Midlands Electric in 1997, and companies from abroad such as the take over of Yorkshire Electricity by a 50:50 joint venture between American Electric Power and New Century Energies. However in 1999 Yorkshire Electricity's Generation business sold for £94.9 million to PowerGen, one of the largest players in the UK ESI.

The result of these take-overs and mergers has been a reduction in the number of market players. This has created a market with a small number of very powerful companies which have the ability to control the marketplace. In response the Office of Electricity Regulation (OFFER), which has since become part of The Office of Gas and Electricity Markets (OFGEM), proposed a new electricity market structure which is to come into effect in April 2000.

2.2.3 The Pool

The Pool was set up as the market place for the buying and selling of electricity. It originally provided the commercial link between generators and suppliers but large customers can now buy directly from the Pool. It can be described as a commodity spot market for electricity:

1. Each generator submits a bid one day in advance. The bid contains the plants price for start-up both with and without load, three prices for varying loads, a price for maximum load, a half hourly dispatch availability.

2. The National Grid Company (NGC), who run the pool, create a demand forecast for the following day. The forecast is based on historical data, weather forecasts, large public events, estimates of large customer demand, estimates of interconnector flow and pumped storage availability.

3. An unconstrained (without technical transmission issues) schedule is created from the information in the generator's bids and the NGC's forecasts. It does not include the technical constraints of the transmission network. The schedule is constructed on a half hour basis and consists of lists of plant that must be operational to meet the demand and provide a spinning reserve for each half hour period. The scheduled plant is chosen in price order, cheapest first, stacking up until the expected demand for that period has been met.

4. The operation schedule is the final schedule based on the grid company's forecast. It is derived from the unconstrained schedule but it considers the technical constraints of transmission. Some generators included in the unconstrained schedule are omitted and others included. The price paid for electricity is based upon this schedule.

5. The Pool Purchase Price (PPP) is calculated using the sum of the most expensive generator on the half hourly bid and the uplift cost. This figure then is corrected for the probability of an incorrect forecast and is then given to all the generators chosen, for that half hour, in the operation schedule.

Through this system of bids and forecasts generators compete to sell electricity. Some generators have used bids of zero (bid to supply at 0 p/kW) to ensure they are chosen for scheduling. These generators rely on the need for expensive generators in the same period to raise the PPP.

2.2.4 The New Market Arrangements

In addition to the reduction of competition due to take-overs and mergers the ESI has not become a free market as expected. The first problem was that initially only customers with peak demands above 1MW could choose their supplier. Smaller customers were confined to their own RECs for supply. Competition was therefore limited to the big players who have through growth, mergers and take-overs, become very powerful and influential in the marketplace. The franchise break in 1994 allowed customers with peak demands below 1MW, but above 100kW, free choice of supplier. This was supposed to increase competition among suppliers but it only had a limited effect. The second franchise break, scheduled for 1998, was delayed until 1999. This allowed all customers, including those with peak demands below 100kW, the freedom to choose their supplier. Many new suppliers have arrived on this <100kW market which has helped increase the competitive nature of domestic supply.

Although some customer services have improved, electricity prices have increased. Since privatisation the Pool has raised its selling price from 2.282p/kWh in 1990 to 2.596p/kWh in 1998, an increase of over 12%. Reduced plant capital costs, fuel costs and the introduction of newer, cleaner technologies should have reduced the price of electricity. For example CCGT plant capital costs have fallen by 22%, their thermal efficiency has increased by 8% and the price of gas has, on average, fallen by 53%. The increase in Pool price could be explained by a 12% increase in the System Marginal Price (SMP) during the same period as privatised ESI electricity prices should reflect the SMP. If one should increase the other should follow[4]. However this does not explain why the SMP has increased when the cost of generation has fallen. It has been argued that SMP increased because the amount by which plant capacity exceeded peak demand (or plant margin) decreased. Although a reduction in plant margin could cause the inefficient scheduling of plant, the figures do not correlate; plant margin has been increasing since 1996. Therefore SMP must be influenced by more than the costs of generation and spinning reserve.

The increase in SMP can be attributed to the pricing mechanism used in the Pool. SMP is set by the highest bid prices which come from the mid merit and peak load stations. This category is made up of the UK's coal fired plant, oil fired plant and the older, expensive, gas plant. National Power and PowerGen, the largest of the UK's generating companies, own 90% of these price setting stations. Due to their large market share it is in their interest to keep SMP of all plants, and therefore electricity prices, as high as possible. Other generating companies in the market also benefit from the high profit margins as does the National Grid Company (NGC), which runs the Pool and earns a percentage of the markets cash flow. Therefore there is no incentive to reduce SMP and electricity prices remain high.

By 1998 it was clear that the Pool was not working as intended. One of the root causes was abuse of market power by the large generators[5]. This has been encouraged by the bidding structure in the pool, which is only from one direction (the generators). A total reshaping of the Pool was deemed necessary by the DTI's Review of Electricity Trading Arrangements (RETA) to enable a fully competitive market. In October 1998 the Government accepted the New Electricity Trading Arrangements (NETA) proposed by the DTI. The NETA are set to be introduced by April 2000, and will include:

- A forward and futures market where buyer and seller agree a price today, to be paid on the delivery of electricity, on a specified date in the future. Options on futures will be used to enhance supply security by allowing traders to offset their individual risks.

- A short term bilateral market place where electricity is bought and sold between 4 and 24 hours in advance of each generation period. This will probably be operated via a computerised network based system to ensure transparency.

- A balancing market during the 4 hours preceding each generation period where generation will be matched to the exact demand. This will allow the system operator to use cheap generation by gas, hydro or wind if available, to meet the peaks in demand.

- A settlement process that penalises or rewards market participants depending on how well they met their commitments. This will be measured as the difference between their contractual obligations and their actual generation output.

There are concerns that the NETA will not solve all of the electricity market's problems. Firstly large players will still be able to manipulate the market by controlling the price of futures. Their power to obtain favourable contracts for all of their stations may cause a high market SMP and therefore high electricity prices. Secondly renewable technologies may be forced from the main, futures, market as they cannot guarantee generation at a given time in the future. Finally there are fears that that embedded schemes may suffer as there will be no incentive to include small generators. Their inclusion will add complexity to the system and most suppliers may prefer to enter a single large contract, rather than multiple contracts from a multitude of small embedded generators. The Regional Electricity Companies' (RECs) history of prohibitively large connection charges for embedded generators will also need to be addressed.

2.2.5 Regulation

The Office of Electricity Regulation (OFFER), was introduced in the 1989 Electricity Act. The main tasks of this regulator were to ensure that customer demand was met at a reasonable price and customer service was maintained. It was also responsible for the promotion of competition and energy efficiency. The Regulator's control over the electricity companies was through licence agreements. Operation within the ESI was dependent on these licences which stipulate a minimum acceptable standard of operation. Failure to comply with the licence agreement could have resulted in the withdrawal, by the Regulator, of any of these licences. However the regulator could not change the licences without the holders consent so new regulation was slow to achieve. Rapid intervention was only possible through the Monopolies and Mergers Commission or directly through legislation from the Secretary of State.

In early 1999 OFFER became a part of a general Energy regulator called The Office of Gas and Electricity Markets (OFGEM). The key roles of the new regulator as defined by the Department of Trade and Industry (DTI), were as follows:

- To place a single primary duty on the regulators requiring them to protect the interests of consumers, incorporating the existing duty to ensure that the regulated companies can finance their functions.

- To issue statutory guidance on social and environmental objectives, including energy–efficiency objectives.

- To establish consumer representative bodies on an independent statutory basis, and to create gas and electricity.

- To merge OFFER, the electricity regulator, and OFGAS , the gas regulator, under a single energy regulator OFGEM.

- To provide for separate licences for the supply and distribution of electricity.

- To replace individual regulators by full–time executive boards composed of a chairman and two others.

- To place a duty on the regulators to give collective consideration to matters of common interest.

These directives, published in the DTI's public consultation paper on the future of gas and electricity regulation were intended to improve the consistency of gas and electricity regulation by combining the expertise of both OFFER and OFGAS within a single energy regulatory body, OFGEM[6]. OFGEM's powers under the NETA are yet to be finalised. It is almost certain that the regulator will have increased power through shorter licensing periods, which will increase their influence over the electricity companies, and some direct control over the market controller, which will allow regulation through market changes. It is hoped that regulation through the market, rather than direct intervention, will be able to encourage renewables and embedded generation, whilst maintaining market competition.

2.3 Generation

The most notable recent change in the UK ESI has been the increase in gas generation. This was partly due to new technology but mainly due to government incentives and the *dash for gas*. Figure 2.4 shows the change in generation methods since the privatisation of the ESI in 1990. It shows how oil and coal generation has given way to the new Combined Cycle Gas Turbine (CCGT) technology which has increased from 1% to over 30% in less than 10 years. In addition the renewables, and other fuels like waste combustion, have doubled their proportion of the UK's total yearly generation.

The following Sections, 2.3.1 to 2.3.9, outline the major generating methods that are included within this study. The emphasis is towards issues that influence energy planning and the mechanisms that influence choice between different generation methods. Topics such as efficiency, the availability of resources and environmental impacts are discussed but the data used in the final model, and the detailed analysis of the factors that influence primary energy choice for generation, can be found in Chapter 6.

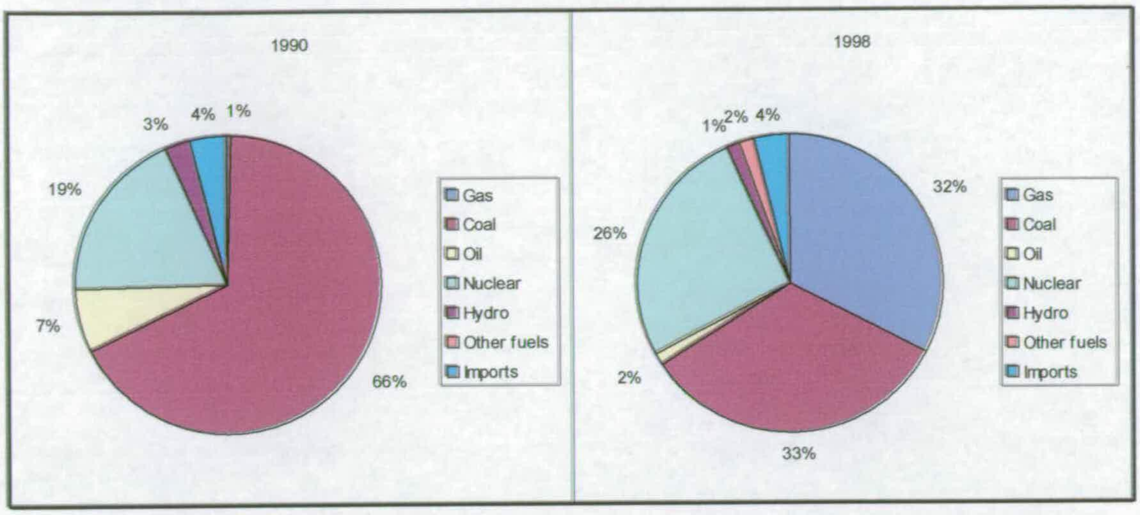

Figure 2.4 Electricity supplied by fuel type in 1990 and 1998 as percentages[7].

2.3.1 Gas

Large-scale gas fuelled generation can be split into two categories, the old style Open Cycle Gas Turbines (OCGT) and new Combined Cycle Gas turbines (CCGT). OCGT generation has served the ESI for many years meeting short term peak loads, providing frequency stabilisation in the grid system and providing restart power for large power stations after black-outs. Over the past thirty years the unit rating of OCGT has increased from 12MW to 200MW and the thermal efficiency of this plant has risen from 22% to 34%. This upper efficiency is constrained by the properties of the Joule, or Brayton cycle which defines a maximum efficiency for an ideal OCGT, if the fresh charge in the compressor due to open fuel combustion in air is neglected[8]. Steam turbine plants have operated with heat recovery boilers to provide in-house power and heat. This practice is known as Combined Heat and Power (CHP). CCGT delivers this steam from the heat recovery boiler to a steam turbine which drives separate steam turbines to produce additional electrical power, without an increase in fuel consumption[9]. This process is constrained by the Rankine cycle which defines a maximum efficiency for an ideal steam engine as approximately 32%[10]. Therefore the maximum efficiency of an ideal CCGT is the sum of both Brayton and Rankine cycles. A modern CCGT plant can obtain efficiencies of over 56%.

Gas powered CCGT and OCGT plant has risen from providing 0.5% of the UKs' annual demand in 1990 to 32.5% of the annual UK demand in 1998. The reason for this is simple; modern CCGT generation is cheaper than competing generating technologies. The costs for new entrants in CCGT generation are presently the least expensive of all the generating methods. Firstly the all-in capital cost of CCGT plant is around £300/kW, approximately one third that of coal. Secondly the fuel is cheap: Running on spot gas, an instant gas pricing mechanism, the fuel cost of generation would be approximately 0.8p/kWh which is less than half that of coal fuel costs which can rise to 1.8p/kWh. Finally maintenance and labour costs are low. Maintenance is reduced by the *clean* nature of gas and the modular design of plant. The high degree of automation has reduced labour to the extent that a modern 700MW CCGT station can operate with less than 30 staff. A modern coal plant of the same size would need a minimum of 80 staff. The total cost of running a new CCGT station at base load could be as little 2p/kWh (0.56p fixed and 1.44p variable). Even running at a 60% load factor costs would not exceed 2.4p/kWh.

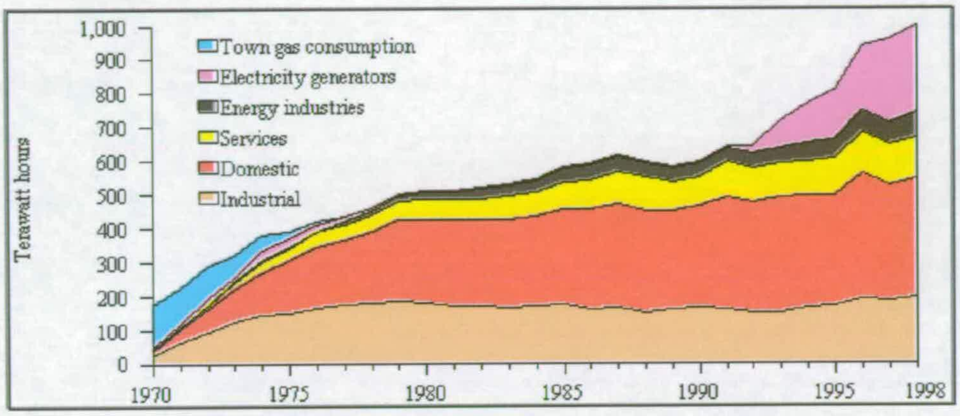

Figure 2.5 UK gas consumption 1970 to 1998[11]

The only drawback is that gas reserves are low. The DTI's current estimate of the UK's accessible gas reserves are approximately 2,000 billion cubic metres. It is presently being used at a rate of 75 billion cubic metres (or 1,000TWh) per year. Figure 2.5 shows the rapid increase in gas usage due to electricity generation, a trend that is not set to end until reserves become scarce. At this rate gas depletion will come before 2025 although some new reserves may be found[12]. Depletion will be slowed by the increased costs of producing gas from remote and inaccessible fields although elasticity in the market may prove stronger than expected.

2.3.2 Coal

Between 1990 and 1998 generation from coal powered plant fell from a level that provided 66%, to a level that provided 33%, of the UK's total yearly demand. Figure 2.6 shows how this 90.8TWh reduction in coal generation was met by a 112.4TWh increase in gas generation. The difference, a 21.6TWh gas excess, contributed to over half of the total generation increase during this same period. These figures show how gas has been a direct replacement for coal. Although the efficiency of CCGT is far greater than that of coal plant this change was not due to technical issues alone.

At their inception National Power's and PowerGen's coal generation divisions were given three year contracts with the RECs to help secure post-privatisation coal generation. These contracts were backed up by take or pay contracts with British Coal in which the generating companies were required to take approximately 70Mt of coal per year at 180p/GJ net, allowing generation costs of around 2p/kWh. Both companies received substantial fees for operating as a pool price cap for the RECs. This risk diverting policy was made possible by good fixed coal price and contracted fuel supply security. The returns were a fixed 3.7p/kWh for the generators within these contracts giving gross profit margins of around 45%. However, when these contracts ended in 1993 a new, a less favourable five year contract was put in place. The new contract was designed to provide a secure market for British Coal after its privatisation. Although as profitable as the three year vesting contracts, the new arrangements only fixed the price for under half the yearly tonnage of coal that was used in the years proceeding 1993. Additional coal was purchased at market rates which were higher than the contracted value; thus reducing the ability for coal powered generation to compete with CCGT generation. Between 1993 and 1998 coal generation dropped by almost 40% and was replaced by CCGT which was more competitive than traditional coal generation without a favourable fuel purchase contract.

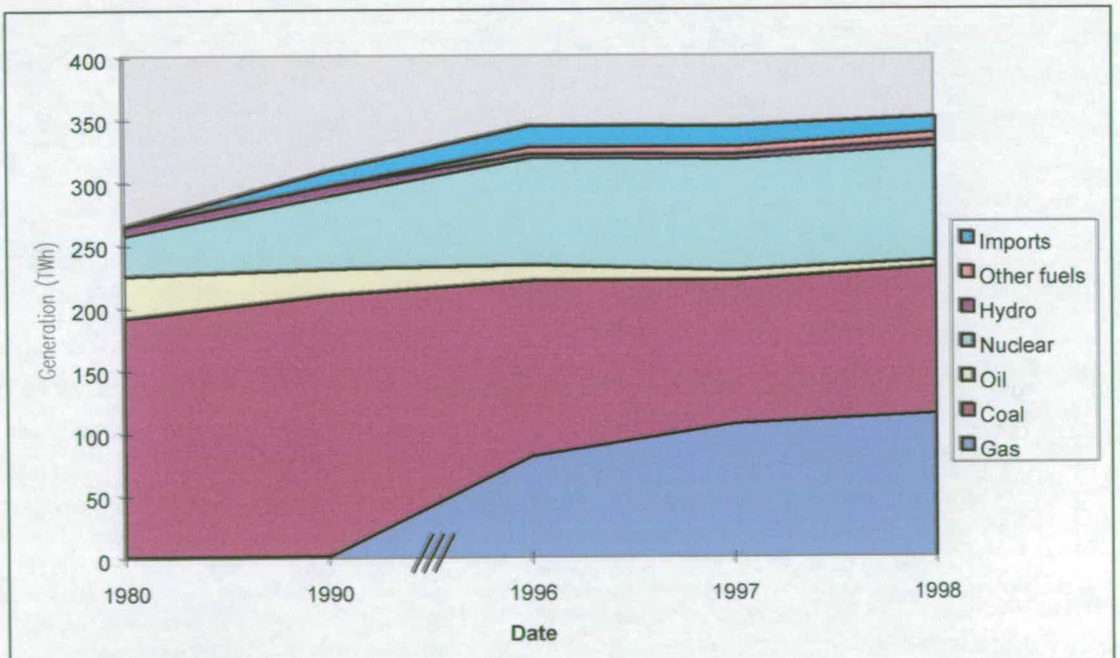

Figure 2.6 Fuel mix in electricity generation from 1980 to 1998.

Environmental concerns have reinforced the switch from coal to gas. The cleanest coal plant produces 36 times the amount of NO_x, twice the amount of CO_2 and twice the particulate emissions of CCGT plant of similar capacity. Gas generation produces insignificant levels of

SO_x whereas coal fired generation produces between 3g/kWh and 6g/kWh of SO_x[13]. Government emission targets will continue to play a significant role in the reduction of coal plant. At the Kyoto summit the UK agreed a further 10% reduction in CO_2 levels by 2010. As CO_2 emissions cannot be *cleaned* the pressure to stop burning coal will increase.

2.3.3 Oil

Generation by oil powered plant has reduced from providing 7% to 2% of the UK's total annual demand between 1990 and 1998. The deficit has been made up by the increase in gas based generation. Oil, like coal generation, relies on contractual arrangements and although oil can be bought on a spot market, the majority of oil purchase involves hedging contracts. These contracts act as futures where, for a premium, oil is guaranteed to be sold at today's price on a future date. This gives fuel supply security and if prices go up during this period, the generator has successfully overcome the price risk associated with the spot market. If the oil price goes down the generator must buy at the arranged rate or face a financial penalty[14].

Oil usage in 1998 was 144.6 million tonnes, higher than in any year since oil was first produced from the North Sea in 1975. This is 44% higher than 1990 production figure whereas oil fuelled electricity generation has fallen. This discrepancy is because oil demand for electricity generation has little effect on oil production figures. The total oil consumption for generation in the UK is 1.8 million tonnes which represents only 0.012% of total oil usage[15]. Unfortunately the large amount of oil used in the UK is rapidly depleting known reserves. Reserves stand at 4,105 million tonnes which gives under thirty years of secure supply.

Along with volatile oil prices and resource constraints oil generation has become less competitive as a result of its high emission levels. Even the most efficient combined cycle oil plant, which could have an efficiency of over 50%, would have high emissions per kilowatt hour of electricity generated. NO_x emissions from oil combustion are almost three times that of CCGT emissions at 0.19g/kWh. SO_x emissions are 0.25g/kWh which is less than coal, but high compared to the insignificant levels produced by gas combustion. Particulate emission is the same as for coal at 0.15/kWh but, again, high compared gas combustion which produces no particulates. Although the total emissions from oil combustion are lower than that of coal combustion the price of coal was only 58% of the price of oil, on a heat equivalent basis, in 1997. This made coal fired generation cheaper than oil powered generation in that year. However this difference was wholly dependent on taxation. Heavy fuel oil used in electricity generation was subject to a 34% tax in 1997 whilst the equivalent steam coal was not taxed at all that year[16]. Until the environmental taxation of SO_x and NO_x emissions penalises coal combustion to a greater extent than the combined environmental and fuel taxation of oil combustion, coal powered generation will remain cheaper than oil powered generation. As environmental taxes are set to rise dramatically in the near future this critical point, where oil combusting plant becomes more competitive than coal fired plant, could occur before UK oil reserves are depleted.

2.3.4 Nuclear

The UK's nuclear program was started as a means of entering the nuclear weapons race independently of the United States. It was continued, and expanded, on the assumption that fossil fuel prices would rise in the then near future. Since 1990 the share of energy produced in nuclear plants has increased by 35% whilst accounting costs have dropped by 30%. This is firstly because of fixed operating costs resulting from the "must take" status given to electricity generated by nuclear power as part of the Non Fossil Fuel Agreement (NFFO). Secondly much of the massive investment cost was written off in order to make the industry attractive to private investment. When the best of the nuclear industry was privatised as British Energy in 1996 it was valued at £1.35bn. With a capacity of 6GW the capital cost for investors was 225£/kW, a value 25% lower than that of new CCGT plant. This figure is approximately one third of the true nuclear capital costs per kW. The low market value reflected the uncertain size of decommissioning and radioactive waste liabilities along with the urgency with witch the government was selling the industry.

Among the many fears about the safety of nuclear power from fission are those of radioactive waste disposal and of a meltdown scenario. A meltdown occurs when the reactor core exceeds a critical temperature and is deformed. Once damaged it is not possible to remove the moderator rods (usually made from Boron). These rods encourage the reaction and their removal is necessary to shut the reactor off. If the reactor cannot be shut down the heat will increase until there is a breach in the reactor and there is a radioactive disaster. Because fission only gives heat when two fissile material are in the presence of a mediator the risks of meltdown cannot be eliminated. The 1996 meltdown at the Chernobyl power station in the Ukraine highlights the problem.

Many are hoping that nuclear fusion will provide the answer to our energy problems. Unfortunately this technology is still only theoretical. However the European Organisation For Nuclear Research is using a particle accelerator to bombard fissile material to make heat[17]. This novel approach avoids the risk of meltdown as the particle accelerator can be turned off an any point in time. A prototype, called the Energy Amplifier, is already running and producing heat. It is possible that this will give a new future to nuclear power.

2.3.5 Hydro-Electricity

Hydro power has been used to provide useful energy since the first century BC. Water mills provided the majority of mechanical power for the Industrial Revolution and the first large-scale hydroelectric scheme in the UK was built as far back as 1860. In 1998 5.1TWh was generated by the UK's hydroelectric schemes, 2.2TWh down on 1980 generation[i]. This represents a drop from 3% to 1% of the UK's total yearly demand. These figures look small against the total estimated hydro power resource of 40TWh per year. However when geographical constraints are accounted for this figure drops dramatically: At less than 10p/kWh, at an 8% discount rate, the feasible UK resource is estimated at 10.8TWh per year, approximately 3.7% of the UKs total electricity requirement in 1997. This can be divided into 6.9TWh, of large-scale, schemes above 5MW, and 3.9TWh of small-scale resource. This leaves an unexploited yearly resource of 3TWh large-scale and 2.7TWh small-scale.

Transmission costs and environmental factors make much of this unexploited potential capacity unfeasible. The 3TWh large-scale resource would either require reservoir storage or is located deep in the Scottish Highlands, far from the centres of high demand. As Scotland already has excess plant capacity it is unreasonable to assume that there will be any large-scale hydro plant construction in the near future. Around 1TWh of the accessible small-scale sites have hydraulic heads below 3m which are uneconomic, unless near an urban population or industrial area. This leaves under 2TWh of small-scale hydro potential in the UK which could be provided by approximately 750MW of plant[18].

The costs of hydro plant can range from £600/kW to £3,000/kW depending on the cost of land, civil works and accessibility. Typically the figure is around £900kWh which, due to the low running costs, makes hydro a viable option. Running costs for existing large-scale plant is around 1p/kWh, whereas new small-scale hydro would need around 2.7p/kWh for a reasonable profit margin due to the high connection, transportation and civil cost per kW of installed plant. Fortunately many new small-scale schemes have come under the Non Fossil Fuel Agreement (NFFO) and Scottish Renewables Order (SRO). The NFFO and SRO require that RECs must take all or a set minimum amount of electricity from the renewables within the contract. The price is also set within the arrangement. This has helped many schemes although more recently the prices set for small hydro schemes have been lowered to converge on the Pool Purchase Price between 2.8p/kWh and 3.4p/kWh. This has made unfeasible many of the schemes being offered these rates as part of the NFFO and SRO.

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[i] As hydroelectric power depends on yearly rainfall resource figures are kept to TWh rather than MW.

2.3.6 Wind

Wind turbines only contribute 0.15% of the UK's annual demand. This figure is set to increase as NFFO and SRO support helps promote the technology. Modern 1MW turbines are replacing the standard older 500kW machines which is reducing the area of land needed for generation. A wind farm of 20 machines presently occupies 3 to 4 square kilometres and although 99% of this area can still be used agriculturally, the visual and audible impact of such thinly spread machines has become the main opposition to this technology.

Wind power has inherent advantages. There are no gaseous emissions, decommissioning is relatively simple and maintenance of modern, modular, systems is cheap. There are also advantages in the load profile of UK based wind turbines. The load factor almost doubles from 22% during the summer months, to 40% during winter when extra load is needed. Also, due to UK specific meteorological conditions, the average daily wind matches daily electricity load profiles. Because of this the government intends to use wind as a major contribution to the 1500MW renewable target which is a part of the drive to convert 2GW of plant to low emission technologies every year until 2010.

Wind power is presently considered an under exploited resource. The total yearly wind generation in the UK is around 0.5TWh which, compared to the accessible resource of 340TWh[19], is very small. Although the environmental impact of exploiting this total resource is inconceivable, it does highlight the possibilities of wind power. Taking account of environmental issues reduces the resource to 40TWh per year[20] which would still represent 12% of the UK's total yearly demand. The UK's wind resource does not end there. If the offshore potential is included a further 140TWh could be generated every year.

The cost of wind power is decreasing as its popularity rises. The annual running costs are only 0.5p/kwh, the remainder is to cover the high capital costs. Presently a wind farm needs to sell at around 4p/kWh to ensure a reasonable profit margin which is noticeably less than 7p/kWh which was necessary in 1995. This reduction in capital costs has been due to the technology becoming more mature leading to the mass production of machine parts, turbine blades and towers. This trend is set to continue.

2.3.7 Imports

The French interconnector has existed since 1961 but was only upgraded in 1986. It now has a 2,000MW capacity which is in constant use. It was supposed to have a two way flow which would offset differences between French and British demand patterns and add the equivalent of 200MW additional capacity to each system. Access to the interconnector is still governed by a protocol originally signed by the CEGB and the French grid operator, the Electricite de

France (EdF). Since 1990 the flow through the interconnector has been one way, from France to England. The UK has imported an average of 16.5TWh per year since 1993, which represents the equivalent of a 0.95 yearly power factor on the link. Plans to further upgrade the link are under development.

2.3.8 Other Generation

2% of the UK's total generation comes from a range of small generators. The largest of these sources of generation include the combustion of biomass, essentially plant-life or organic waste material. It is believed that the combustion of specifically grown forestry could provide a contribution to sustainable generation. Although this would displace food crops and other land use it would not contribute to the greenhouse effect as the CO_2 released during combustion is balanced by absorption during growth. Particulate emissions would cause some environmental damage if the appropriate cleaning technology were not employed.

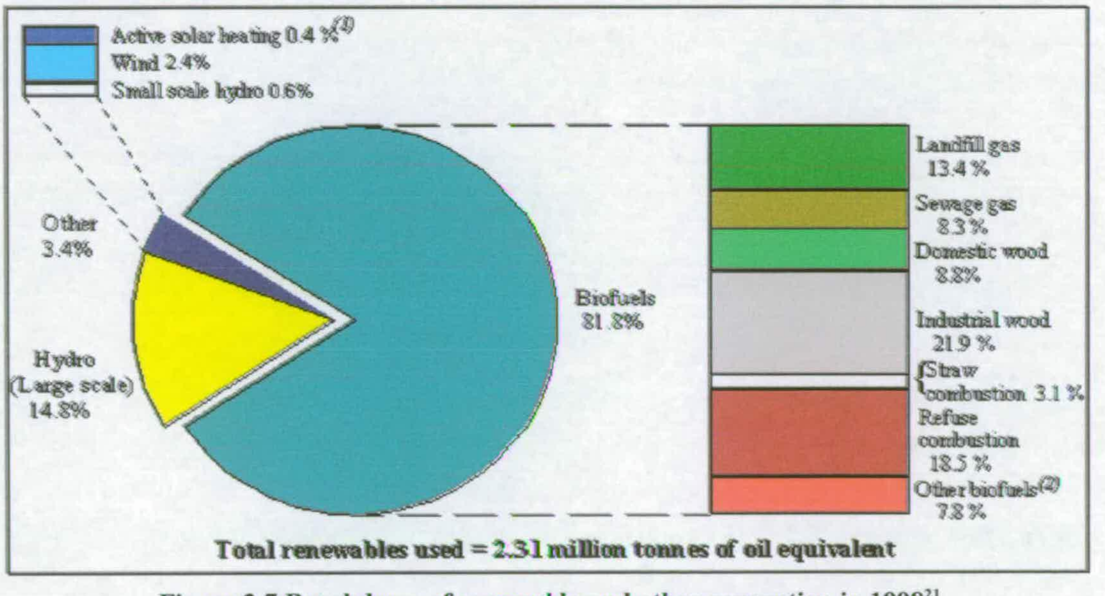

Figure 2.7 Breakdown of renewable and other generation in 1998[21]

Figure 2.7 shows the Energy Technology Support Unit's (ETSU) breakdown of existing biomass based generation. Landfill or sewage gas collection and combustion, for generation, could serve to reduce particulate emissions. However the maximum possible capacity of these technologies is small unless specially cultivated energy crops were to be used. This would involve establishing a radically different approach to land usage. In addition the resulting impact on wildlife and the countryside would be large.

2.3.9 Non-Proven Technologies

The non-proven technologies have been included so that the development, and installation, of new technologies can be invested as part of a long-term forecast of primary energy usage in the UK ESI. The technologies described in Sections 2.3.9.1 to 2.3.9.5 are all currently under development. There are various experimental and theoretical systems, such as super-conducting electricity storage devices or under sea tidal mills, which are not included as it is unlikely that they will be influential in the UK ESI within the next 50 years.

2.3.9.1 Wave

Wave power will soon become a feasible generation option. There are many prototypes that should be operational within the next decade. With an average power of 50kW per metre of wave front across most of Britain's shoreline this technology cannot be ignored. The SRO and NFFO have looked favourably on this technology offering must take contracts at 6p/kW to viable prototypes.

There are two main types of wave device, those that are based onshore and those that are anchored offshore. Offshore devices need undersea cables for electricity transmission which make anchoring a problem. There is also a concern that devices may break loose and cause navigational hazards to shipping. Onshore devices are subject to the full force of storms and therefore need to be very tough in design. The only device of this kind that has managed to withstand the UK's coastal elements is a 180kW prototype on the island of Islay off the West coast of Scotland.

2.3.9.2 Geothermal

There is no potential for the use of hot aquifers' geothermal energy for electricity generation in the UK due to the absence of geological hot spots. However the geothermal temperature gradient found in Cornwall's granite rock bed could be exploited to the extent of 210TWh per year. The process would use "hot dry rock" technology which is still in its experimental stage of design. Two 10km deep holes are drilled into the granite crust and the rock between them is fractured. Cold liquid is pumped down one hole, heated as it passes through the warm fractured rock, and vapour is recovered through the second hole. Some changes would have to be made to existing steam turbines before they could be used to exploit the low geothermal temperature gradients available in Cornwall. The first is that a different fluid must replace water so that vaporisation will occur at lower temperatures. The second is that the number of cooling towers would need to be far greater; approximately ten towers for every one traditionally used would be needed. The environmental impact of pumping 100kg/sec of possibly toxic fluid into the earth through the water table, returning as radioactive vapour, cooled in an array of large towers would probably inhibit the construction of this type of power station.

2.3.9.3 Ocean Thermal

Ocean Thermal Energy Conversion (OTEC) exploits the temperature difference between the sea surface and the sea bed. At present small prototypes are being tested in the tropics where the sea surface temperatures are relatively high. The potential of OTEC in British waters is considered small because of low surface temperatures and the warm, deep-sea, currents along the west coast due to the Gulf stream. The North sea is particularly shallow which limits the OTEC potential of the east coast. However as this technology is researched, and efficiencies are increased, large-scale OTEC generators may find a place in UK generation. However it is unlikely that this technology would have an impact on UK generation within the forecast period of this study.

2.3.9.4 Tidal

Tidal power involves the damming of large tidal estuaries to create a hydraulic potential difference on either side of the barrage as tides rise and fall. This potential is exploited using hydroelectric turbines to generate electricity. There are many potential sites in the UK which, combined, could produce over 54TWh per year if environmental and population concerns were not considered. Due to the site specific nature of the environmental impact of tidal schemes each must be considered on a case by case basis.

The proposed Severn Estuary scheme would produce a peak power of 8,640MW, approximately six times that of a coal fired power station. Opposition to the scheme is based on the environmental impact of removing the tidal nature of the land above the barrage, affecting wildlife, drainage and pollutant concentrations in the area. Fish migrations would also be affected by changes in salinity caused by the reduction in water flow. On the other hand the scheme would create a new river crossing and provide recreational water sports facilities. The final decision on this matter is in the hands of the government who act upon public opinion and its affect on their votes. Therefore the future of the Severn Estuary barrage will not be decided by its technical merits, but by the media's representation of the scheme. Presently public opinion is against this scheme, however if electricity prices increase considerably with the depletion of gas reserves, and the only available options become either nuclear power or tidal power, public opinion may shift in favour of a barrage across the Severn Estuary.

2.3.9.5 Solar

Other than the use of solar panels containing heat exchange units connected to domestic hot water tanks, there are two major active solar technologies. The first is the use of large reflecting units to concentrate the sun's radiation on a fluid to provide heat. The heat is then used in a steam cycle to generate electricity. The second is photovoltaic conversion which originally used photovoltaic minerals that directly convert sunlight into electrical current. Modern devices use artificially produced, single crystal, semiconductor arrays which has dramatically reduced the price of photovoltaic panels. To date small and micro systems are commonplace on satellites, calculators and even for lighting in remote areas. However large systems are still not economically attractive due to the size and cost of large photovoltaic arrays.

The environmental impact of both heat based and photovoltaic generation is minimal except in the construction of photovoltaic cells which is similar to semi-conductor manufacture with its related hazards and wastes. If the environmental problems are solved it is believed that 84TWh could be produced by solar technologies for under 10p/kWh by 2020. Including realistic land constraints reduces this figure to below 5TWh per year or 1.7% of the yearly UK demand. Much of this could provide power for small systems, such as buildings that use air-conditioning during daylight hours. The advantage of using such small-scale DC systems would be that fuel cells, or large battery arrays, could store some of the electric power. This is currently being achieved for street and security lighting in remote areas with no grid connection. Currently the costs of large scale systems are prohibitive. In addition the environmental impact of constructing these arrays is large as they are manufactured by a chemical process.

2.4 Forecasting in the UK ESI

The privatisation of the UK ESI changed more than the ownership of the industry. The new structure, which is now based upon an electricity market, has dramatically altered the incentives and goals which drive the energy companies and the individuals working within them. The result of these changes is that planning decisions now satisfy the company's needs and are only constrained by legislation and taxes. This move away from a ministerial led decision making has made forecasting these decisions more complicated, but quantifiable. Including economic theory, that describes this newly privatised industry, within a model should allow accurate forecasts of possible outcomes to future planning decisions.

2.4.1 Forecasting Within a Nationalised ESI.

Before the privatisation of the ESI, the publicly owned industry aimed to "maximise public economic welfare". This followed from the industry being the agent for, and therefore working in the best interest of, the general public. This implied that it was not in the interest of the industry to let a situation arise that might compromise the interests of the wider public. However the amount and quality of information that the public, decision makers and ministers received was quite varied. These information asymmetries between politicians and voters and between voters themselves meant actions to maximise economic efficiency by politicians were not proportionally linked to electoral success[22]. As promotion within a period of political office was heavily dependent upon the individuals electoral success, ministerial decisions were often heavily influenced by media-led public opinion, rather than on technical, social and economic evidence. This effect was compounded by high levels of political intervention in managerial decisions rather than the arms length relationship between departments and managers that was intended in the 1947 Electricity Act, when the ESI was first nationalised[23]. The decision process was further complicated by the relatively brief periods that politicians held ministerial offices. The lack of long term strategies as a result of this high ministerial turnover led to confused and quite random incentive structures for civil servants. The result was a greater than minimum unit cost of bureaucratic activity. In addition the size of a particular government department's budget, was proved to be proportional to its electoral success[24]. This ensured that decisions which resulted in an increase in the political influence of the relevant ministers were considered successful as this led to increased departmental budgets. This combination of political interference, information asymmetries and varying incentive structures complicated the decision process. Due to the differences in decision making processes at each level of the ESI's hierarchy and the significant variances in the quality of information used in each decision, theories on decision making in the nationalised sector were unable to provide a basis for the analysis necessary for predicting future decisions. This was to change when, in the 1987 Conservative Election Manifesto, a commitment to privatise the ESI was placed high on the agenda.

2.4.2 Forecasting Within a Privatised ESI.

Privatisation has been responsible for considerable restructuring within the ESI. As a result of these changes a totally new incentive structure for decision makers has been put in place. In addition the new economic structures of Generators has had an effect, although sometimes only indirectly, on their public policy. It is widely believed that private ownership implies that the firm becomes a profit maximiser, rather than the nationalised goal of creating economic welfare. Many ESI forecasts have used the assumption of the Least Cost Plan (LCP); that decisions concerning the choice of generating technology and how much to generate rely solely on a minimisation of costs in order to maximise profit margins. Although more recently some of these algorithms have included emissions constraints[25], the use of profit maximisation within such constraints has become standard practice. However a study by A. I. Shlyakhter[26] on past forecasts in the privatised US energy sector showed that there was a:

"... *7.5% probability that a value of a parameter predicted by a model would be seven standard deviations above or below the true value.*"

This proves that there is something fundamentally wrong with traditional forecasting methods being applied to the private sector. An example of this is the decision process involved with the construction of new renewable energy plants (REPs). Although many REPs promise future high returns, profit maximisation at present lies in the installation of combined cycle gas turbine generation (CCGT). Profit maximisation would imply that no REPs would be used until they became more profitable than CCGTs. Once more profitable REPs would totally replace CCGTs. In reality companies have become involved in REPs long before they have become the most profitable energy generating method. This is because the basis for decision making is more complex than traditional models assume.

It may be true that all private utilities aim to maximise profit and growth however, as with the public goal of economic welfare, the reality is somewhat different. A closer study of the decision making process reveals economic inefficiencies that are related to the incentive structure of private firms. These inefficiencies are explained using the Principal-Agent theory. The theory suggests that there is a conflict of interests between the Principals, who are shareholders of electricity generating companies, and the agents, who are the decision makers or managers within the companies. The first set of parameters is the agents (managers) contract which must be attractive enough to ensure participation but also must contain constraints that assume that the agent will behave in a self interested manner. The effectiveness of this contract depends on the Principals (shareholders). When there are many shareholders, as in the electricity generating companies, the enforcing of managerial contracts becomes too costly for an individual shareholder as the returns (r) from such endeavours are spread among all the shareholders. An individual shareholder would therefore only interfere in the decision making process if:

$$c < r/n \qquad \textbf{Equation 2.1}$$

where: n = number of shareholders.

c = the cost of enforcing the contract.

However the monitoring of management is left solely to the directors if:

$$c > r/n \qquad \textbf{Equation 2.2}$$

Non executive directors serve as elected agents for the shareholders and enforce managerial contracts. Whilst this does attenuate the shareholder-manager monitoring problem it also introduces further layers of Principal-agent relationships. The resulting amount of managerial freedom within the contract implies a sub optimal managerial utility and therefore the company will not be a profit maximiser. The influence on forecasting is that the agents, when faced with difficult decisions, often chose the easiest path, rather than the most profitable one. There are also two further prime managerial incentives that influence agents' decisions: The perceived threats of take-over and bankruptcy.

The first of these, the perceived threat of take-over, serves in the interest of the Principal in that it sets minimum profit levels. One of the situations in which a take-over will occur is when the capital gain (G) available to the successful raider is equal to:

$$G = n(V - v) - a \qquad \textbf{Equation 2.3}$$

where: V gives the increased value of shares after an optimum contract is imposed
v is the original share value,
n is the number of shares
a is the total cost of acquisition.

As the difference between V and v increases the company will become vulnerable to take-over. Only a perceived threat is necessary to influence the decision maker so that a manager will ensure that $V - v$ is kept small enough that take-over is no longer a concern. This is achieved by keeping the company's earnings per share (EPS) above a minimum value. The EPS is related to profit margins thus a minimum efficiency is created by the threat of take-over. Obtaining a minimum EPS in the ESI often involves high risk, high profit, activities. The drive for high risk technologies and a minimum efficiency level does not imply that there are any incentives to maximise the firm's efficiency. This suggests that private companies are not only profit maximisers. Therefore decision makers in the ESI will not choose the most profitable technology if a simpler solution eliminates the perceived threat of take-over[27].

The second incentive is the perceived threat of bankruptcy. Bankruptcy can be assumed to occur when the market value of a firm's assets (a) falls below the value of its liabilities (l). To avoid the threat of bankruptcy:

$$a > l + f(u) \qquad \textbf{Equation 2.4}$$

where: $f(u)$ is an uncertainty function that ensures day to day losses do not cause bankruptcy.

As with the threat of take-over this sets a minimum level of managerial efficiency. The methods by which decision makers can avoid bankruptcy vary considerably depending solely on incentives. If we assume that the contractual incentives are non-functional and that managerial performance is proportional to effort, decisions would be based on making:

$$a = l + f(u) \qquad \textbf{Equation 2.5}$$

In this case the value of equity would always be $f(u)$ which is far from profit maximisation. To achieve this either l could be reduced or a could be increased. The result of the former would make the threat of take-over prominent whereas the latter could only be the result of managerial efficiencies. By introducing incentive structures such as performance related bonuses, the shareholders can influence the managerial decision to increase a rather than reduce l. Such incentives create a minimum, but not create a maximum, asset value as there is always a critical point where the effort needed to further increase the company's assets exceeds the performance gained from any bonus structure.

In conclusion it is clear that private firms cannot be assumed to be simple profit maximisers. The relationship between Principals and agents not only puts constraints on maximisation but also creates sub-optimum returns. Therefore decisions within a private ESI must rely on a function other than a simple profit maximisation. Functions that describe managerial performance must be added to profit maximisation creating a new function maximising overall utility. This overall utility function could also contain factors which describe the environment, political influence and the electricity markets. This function would provide a base of knowledge covering the theory and experience behind the privatised UK ESI and be used as a base from which forecasts could be made.

2.5 Summary

The ESI has recently undergone major restructuring. Much of this has been due to the privatisation of the industry and the establishment of an electricity market. Although new operating efficiencies have been made, services and electricity prices have not improved as they were expected to. A new market structure has been planned for the new millennium designed to remove the market power that the large electricity companies presently enjoy. The new market arrangements are already subject to much debate as the generators, all of which have vested interests, are divided over the issue of regulation and government intervention under the new system. However none of this is new as the ESI has been constantly evolving since the first generating plants were connected together and synchronised. The industry should therefore be used to structural changes but the current level of uncertainty indicates otherwise. The main difference between the proposed pool changes and historical changes is that the industry is now in private hands, and speculation upon the effect of the new market rules will make or break the utility companies. All of this confirms the need for Regulators, and company planners, to look beyond eight year pay-back periods, into the long-term future and create a stable industry where investment is rewarded and high standards maintained.

3. MODELLING & FORECASTING TECHNIQUES

3.1 Overview

This chapter examines the techniques used in modelling and forecasting demand, scheduling and primary energy utilisation in the Electricity Supply Industry (ESI). Traditionally forecasting was predominantly mathematical in approach, using data assimilation and extrapolation. Section 3.2 discusses the traditional techniques that are currently used in forecasting models. The Delphi method, discussed in Section 3.2.1, is a statistical method of grouping expert opinions. This method does not provide reliable quantitative forecasts and represents the old school of opinion-based forecasting.

Section 3.2.2 looks at the existing purely mathematical models and their various applications to small-scale forecasting problems. These models, which include regression and time series techniques, provide the correlations between explanatory variables, such as weather data, and electricity demand. Extrapolations of these relationships were combined and used in GAMES, a large scale model constructed for this study, to forecast trends in the primary fuel mix that will be used for electricity generation in the UK. This was achieved by using GAMES to perform sensitivity studies on the outcomes to various possible future scenarios bases upon these mathematical forecasts.

The basic computational methods described in Sections 3.2.3.1 to 3.2.3.4 highlight the trend away from mathematical models towards computational methods of simulation modelling. These dedicated programs represent the current modelling and forecasting tools used in energy systems research. These methods can be improved using Artificially Intelligent (AI) techniques and Section 3.3 discusses the uses of AI in the ESI and its possible application to forecasting.

3.2 Traditional Forecasting Techniques

Before the mid 1800s forecasts were purely made upon individual's opinions. The introduction of mathematical techniques, in the 1850s, allowed for the construction of models which could be improved with time and experience[28]. The early models concerned predictions of human behaviour, and their responses to different events, but the concept of mathematically describing a system, that could be extrapolated forwards, has since been proved to be sound. Mathematical models now vary from simple linear equations to complex representations. Extrapolation techniques are equally numerous but the same theory underlies all of these forecasting methods.

3.2.1 Delphi Method

Forecasts can be made with or without a model. The simplest methods are simply predictions made upon a single person's opinion. The disadvantage is that opinions are always biased to some degree. It is not usually possible to compensate for individual's beliefs as they are often hidden or difficult to quantify. The Delphi method was an improvement which used a statistical analysis of a number of experts' opinions[29]. The Delphi procedure was designed in the 1950s to "obtain the most reliable consensus of opinion of a group of experts ..... by a series of intensive questionnaires interspersed with controlled feedback"[30]. The key Delphi elements in the original Delphi method were as follows:

1. The selection of experts, or panels of experts, in the relevant fields.
2. The development of a first round questionnaire by the Delphi team.
3. Transmission of the questionnaire to the panellists.
4. Feedback to panellists of the round's results.
5. The development of further rounds of questionnaires if necessary.
6. Preparation of a final report.

This method proved especially useful in cases where the relevant experts could not be brought together. Initially telex machines were used for distributing questionnaires and their answers, then faxes and email became the communication standard.

During the 1960's the Delphi method was used to formulate opinions on subjects from customer opinion to future energy trends. However by 1974 even the designers of the Delphi method, RAND corporation, had seen the flaws in its application to forecasting and proclaimed: "The future is far too important for the human species to be left to the fortune-tellers using new versions of old crystal balls. It is time for the oracle to move out and science to move in"[31]. The Delphi method may have provided an average opinion from many crystal ball users, but the basis was still personal speculation. New methods that used objective data analysis were becoming more accessible and would soon replace the subjective in scientific forecasting.

Until the ESI was privatised in 1990 Delphi method was used to co-ordinate the opinions of government ministers and the experts within the electricity industry. However this method proved unreliable when applied to long-term forecasting as no individual expert or politician could provide a holistic view of the whole industry.

3.2.2 Trend Extrapolation

Forecasting through the projection of past and present trends into the future is known as trend extrapolation. It assumes that the future will be governed by the same influential factors as the past. This assumption is true in many simple physical cases, such as in small electrical load flow problems, but fails in complex systems where the weighting of influential factors is subject to change. All of the many different trend extrapolation techniques rely on a correlation analysis followed by an extrapolation. Correlation extrapolations of short-term demand forecasts have been derived through regression and time series techniques with varying success. Short-term forecasts, of a few hours to a few weeks, are needed for the economic scheduling of generating capacity, fuel purchase and short term maintenance. The following sections describe the various load forecasting techniques that are currently applied in the ESI.

3.2.2.1 Regression Techniques

Regression techniques are used in the ESI to find correlation between data sets. The National Grid Company, who run the present electricity pool, use short-term demand profiles based on extrapolations of these correlations. The most commonly used regression technique is Multiple Linear Regression (MLR). This finds the linear relationship between independent explanatory variables, such as weather variables, with demand, a corresponding dependent variable. In this case the MLR would take the shape of:

$$y(t) = a_0 + a_1 x_1(t) + \ldots\ldots + a_n x_n(t) + a(t) \qquad \textbf{Equation 3.1}$$

where:

$y(t)$	=	Electrical demand at time t
$x_1(t) \ldots x_n(t)$	=	Explanatory variables such as hourly temperature.
$a(t)$	=	Regression variable (zero mean and constant variance)
$a_0, a_1 \ldots a_n$	=	Regression coefficients.
n	=	Value number

The regression coefficients are found using the least square estimation technique and their significance is determined using a statistical test. In this manner the correlation between explanatory variables and, in this case, demand can be found.

The accuracy of short-term load forecasting can have significant effects on power systems operations, as the daily management of generation and scheduling is based on these forecasts. Large forecasting errors can lead to over, or under, estimations the generation necessary to meet the actual demand[32]. In order to reduce these errors higher order correlations between larger sets of explanatory variables can be added to the forecasts. These added explanatory variables often include weather data, the geographical location of the demand and even television scheduling. Higher order relationships can be represented using a polynomial regression model (PRM). For example the correlation between temperature and demand does not fit a straight line and might benefit from the inclusion of polynomials. In this case the PRM would follow:

$$y(t) = a_0 + a_1 x_1^j(t) + a_n x_n^k(t) + a(t) \qquad \textbf{Equation 3.2}$$

where:

j and *k* = The regression polynomials

Simple non-linear relationships can be found using combined regression models[33]. However, large non-linear models often prove too complicated for such mathematical approaches. In the case of weather, temperature and demand, polynomial functions prove unreliable because the correlation is more heavily influenced by the weather data close to mean weather conditions[34]. Hence deviations from average weather cause the polynomial relationship to fail.

Non-parametric regression has not been used much in the past as it requires a combination of numerous mathematical functions that are time consuming to solve without a powerful computer. Non-parametric estimation differs from parametric models in that, in paramertics, estimates of the assumed function parameters are calculated, whereas non-paramertics estimate the entire function directly from the sample. This is achieved using graphical correlation to calculate relationships[35]. Non-parametric regression allows the weather-demand relationship to be calculated directly from historical data giving an accurate representation throughout the range. This method is robust but computationally expensive and large-scale, multi-layer problems can prove difficult to solve.

3.2.2.2 Time Series Techniques

Time series models are presently popular in short-term load forecasting. Much has been published on this method and its applications including short-term energy usage forecasts[36]. Electrical load *y(t)* is modelled as the output from a linear filter which has a random series input *a(t),* called white noise. The white noise has a zero mean and an unknown fixed variance.

Figure 3.1 Time series model

The linear filter can take can take different characteristics depending on the model. The two filters described in this section, and their permutations, are most common in short-term and very short-term forecasts[37]. Very short-term forecasts, from a few minutes to an hour ahead are needed in the ESI for real-time control and real-time security evaluation. The Autoregressive (AR) model determines its current value by a linear extrapolation from previous values. This gives an extrapolation from data sets that have been derived through the correlation of dependants in historical data. The oldest previous value determines whether the series is positive or negative in order. A positive AR would follow:

$$y(t) = \phi_1 y(t-1) + \phi_2 y(t-2) + ... + \phi_n y(t-n) + a(t) \qquad \textbf{Equation 3.3}$$

where:

n	=	Value number
ϕ_n	=	Autoregression coefficients

A second approach to the linear filter is the Moving Average (MA) process. Here the current value of the time series *y(t)* is expressed as the linear extrapolation of a noise series *a(t)*. The noise series is constructed from the forecast errors, or residuals, when they become available. This corrects the errors in a previous extrapolation and ensures that the next value will be corrected. It takes the form of:

$$y(t) = a(t) - \theta_1 x(t) - \theta_2 a(t-2) - \ldots\ldots - \theta_n x(t-n)$$ **Equation 3.4**

where:

n = Value number

θ_n = Moving Average coefficients

Combinations of AR and MA are often used to self correct whilst extrapolating. This approach is called the Autoregressive Moving Average (ARMA) process. As this method assumes that the mean of the series, and the covariance of its data, will not change with time its application can be limited. However, many real-life problems have data correlations which change with time; for example higher than average temperatures during summer do not affect nightly demand as the majority of domestic heating is already switched off in summer. This type of correlation can be extrapolated using the Autoregressive Integrated Moving Average (ARIMA) which uses the differential forms of AR and MA methods to give an ARMA equation in $\nabla y(t)$. Although complicated, this self correcting approach does give the most accurate very short term forecasts[38].

Simple correlations can be extrapolated over longer time periods using ARMA. Large and reliable historical data sets are needed in order make long term forecasts by this method and the self correction process will only effect the forecasts once new data has been added to the model. This type of data is not available for forecasting long term energy mix decisions due to the restructuring of the ESI since privatisation in 1990. However possible future ESI scenarios can be constructed by combining groups of these forecasts. Each scenario would contain values of fuel prices, interest rates, electricity demand, environmental taxation, generation costs and regulatory constraints over the forecast period. The GAMES model forecasts over a 40 year period and gives sets of the most likely primary energy mix used in electricity generation for each of these scenarios.

3.2.3 Simulation Modelling

This category of modelling uses a mathematical description of the environment that is solved using different variable sets. The description is often so large, and complex, that it becomes unfeasible to solve by hand. Computers have made such models possible and through repeated runs, under different constraints, predictions of future outcomes can be made[39].

3.2.3.1 STELLA II

Until recently computers were simply used to help solve mathematical problems through iterative procedures. Now there are specialised modelling languages that allow the creation of a model without a mathematical representation. The latest development in these modelling languages is the iconographic representation model. An example is STELLA II, from High Performance Systems Inc., which can create a dynamic model from a graphical representation of the environment. STELLA II is a general modelling language which has been applied successfully to problems from the spread of epidemics to the modelling of chaotic weather patterns[40]. However this modelling program does have some drawbacks. Because it uses a flow diagram representation the graphics can become very complicated. The UK ESI model contains feedback which adds to this problem. In addition feedback is solved by repeated iteration which gives a good approximation to simple problems but errors can occur in large-scale models with multiple feedback loops.

3.2.3.2 EXTEND

EXTEND is, like STELLA II, an iconographic representation program. It uses a system of graphical blocks, joined by a flow diagram, to describe the model. The graphics are directly converted into code which can be compiled to solve the model. EXTEND has the advantage that it includes separate modelling modules which provide specialised icons for different industries[41]. This serves to simplify the final graphical model. Even the connections between blocks can be altered to improve the model. A balance between graphical complexity and ease of understanding can be found using EXTEND. Unfortunately it still suffers from feedback problems in models with multiple feedback loops.

3.2.3.3 ENPEP

The Energy and Power Evaluation Program (ENPEP) is a specialised modelling program. It was designed by the International Atomic Energy Agency in 1996 and can only be used for power systems modelling[42]. It is made up of separate modules which cover topics from demand forecasting to plant cost calculations. Unfortunately it is a difficult program to grasp, and the 700 page manual does not help. It uses a mixture of prompts and commands which are numerous and abstract. Although ENPEP would greatly benefit from a Graphical User Interface (GUI) it would also need a better representation of results which are given in a raw data format. It also seems to ignore the feedback effects in the system. For example if more gas is burnt today there will be less in the future, conversely if we know that the gas resource is being depleted we will burn less today.

3.2.3.4 ELFIN

ELFIN is another example of a specialised Electricity Supply modelling program. It was designed by the US Environmental Defence Fund[43]. It is more of a language than a program, needing long lists of commands and data strings to create a model. Its advantage is its speed in obtaining results, which are given as output files that need to be edited before they can be viewed on a spreadsheet. ELFIN's input data must be entered manually and extra fields cannot be added. This restricts the explanatory variables to fuel use, marginal energy costs and loss-of-load probability; ignoring the environment, risk strategies, market effects and political weighting. Even with these limitations the European Commission used ELFIN as a basis for sustainability studies completed in 1998.

3.3 AI Forecasting Techniques

This section discusses the main artificially intelligent techniques that can be applied to solve ESI forecasting problems. Sections 3.3.1 and 3.3.2 Consider Decision Support Systems (DSS) and Expert Systems (ES). Both systems are computational subsets of Knowledge Based Systems (KBS), a generic term for information access systems that store and pass-on knowledge. Although useful for the rapid simulation of simple models both DSS and ES fail in three main areas. The first is that they need crisp data and are unable to cope with probabilistic, or fuzzy, data sets. The second is that traditional models are unable to learn actively, and correct errors, from past data. The final problem is that iterative techniques used in DSS and ES limit the size and complexity of the model. Sections 3.3.3 to 3.3.5 look at the AI techniques available to deal with these issues when applied to forecasting and modelling problems. They cover fuzzy logic, neural networks and genetic algorithms which are all currently used in industry.

3.3.1 Decision Support Systems

Decision Support Systems (DSS) are a subset of Knowledge Based Systems (KBS) which simply allow the user to access previously collated knowledge bases. DSS differ in that the knowledge base is in the form of a working computer based model, or set of models. The user has access to some of the variables within the model and can alter them to create the environment in which the forecast is to be made. Access to these variables is normally through a questionnaire styled interface. The answers are used in the model along with internal, endogenous, data to provide either a solution, a set of solutions or further questions.

Decision support systems are regularly used to help address problems and improve design and control in fields from transmission and distribution to turbine design[44]. Their application in power systems planning has been more limited due to the difficulties in creating large models that contain adequate complexity to describe the ESI accurately. A DSS that incorporated expansion planning, power system design and transmission design was constructed to be used in a least cost planning role. This very large model only considered designs and costs and ignored environmental, taxation and political factors. The result of these omissions was a limited forecasting potential[45].

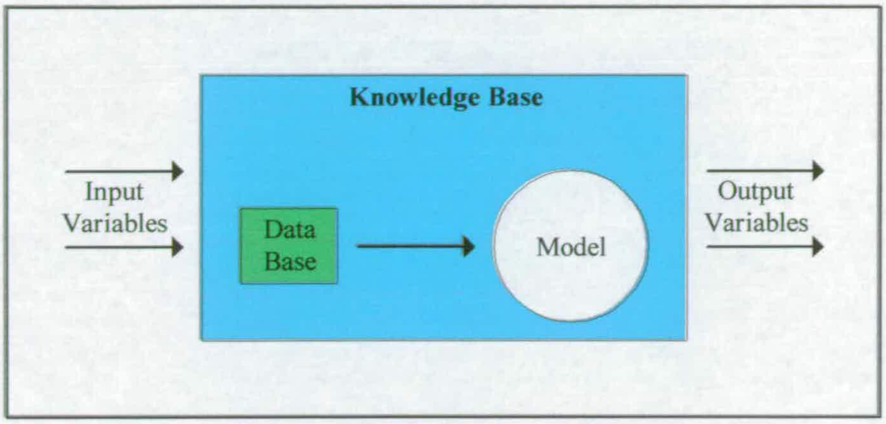

Figure 3.2 Decision Support system

Successful models were designed that gave a smaller range of outputs and so reducing the number of necessary explanatory variables. One of these models, Power Plan, attempted to model the whole ESI using a minimal number of explanatory data sets. The model gave inconsistent results, when compared to existing simulation models, due to the limited complexity of the Power Plan[46]. DSSs can be successfully be applied to small-scale problems such as simulating electrical faults for grid protection assessments, which use a DSS to theoretically test and optimise system protection[47]. Large-scale problems can suffer from feedback and non-linearity problems which make the model difficult to solve. Decision support systems can be improved by incorporating further AI techniques. Sections 3.3.3 to 3.3.5 discuss these approaches and their role in forecasting models.

3.3.2 Expert Systems

Computational techniques, such as ELFIN and ENPEP have been developed and applied to forecasting. They can be described as Expert Systems (ES) as they use a rule base to construct a model to the user's requirements. An ES is similar in structure to a DSS but it uses a knowledge base of rules, rather than a model, to provide solutions. The expert knowledge is stored as a number of strict technical rules and rules of thumb that apply to the problem. Figure 3.3 shows the general structure of a typical ES.

The rules are normally divided into separate data bases, each concerning a particular discipline. The advantage of this is that single database modules can be added or replaced as technology and knowledge moves forwards[48]. The rules are presented to the inference engine as if-then-else statements written in plain language to further facilitate corrections and modifications. These features make an ES simple to test and maintain.

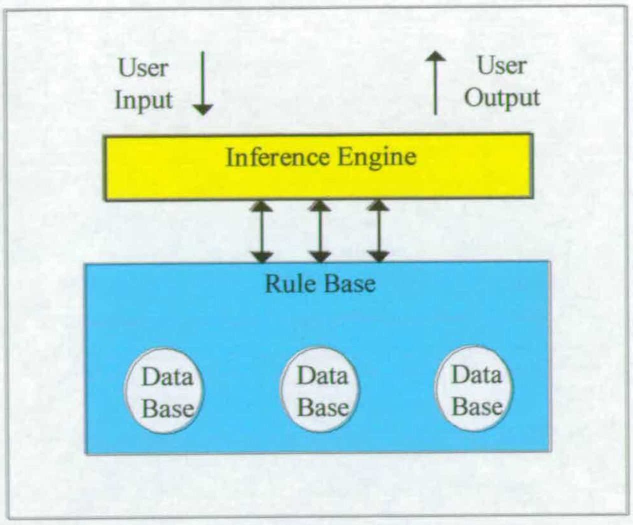

Figure 3.3 Structure of an Expert System

The inference engine is a separate program that uses pattern matching techniques to apply the correct set of rules to the user's problem. This is achieved by matching query information with rule data *switches*. If a good match is found the rule is executed, *else* a different set of rules is sought. The *else* part of the rule base is usually stored as a second part of each rule in its respective data base. The inference engine, which includes the user interface, is the most complicated part of an ES. Two expert systems, with identical data bases, can give different results depending on the inference engine used.

As with decision support systems, expert systems fail when linear data sets are used in the control of digital systems. An example would be the effect of atmospheric temperature on a digital thermostat governed by rules. In addition very large problems, that require a great number of rules, can cause inference engine problems and inefficient rule selection. Problems caused by model size are further accentuated in systems that contain feedback due to the iterative methods employed to approximate such loops. Long-term forecasts of fuel mix in the ESI involve large models that contain feedback. Using an Expert systems to make such a forecast would ignore the feedback causing errors. This type of error has often gone unnoticed as existing Long-term models were rarely validated[49].

3.3.3 Fuzzy Logic

Data classification is one of the largest problems in forecasting. Linear data usually causes a linear response which digital machines and rule based forecasting models cannot solve. For example as oil prices rose during the 1968 oil crisis oil usage dropped respectively. A rule based model can only simulate this in steps defined by indicators and rules:

	INDICATOR		RULE
If:	oil price ≤ £50/tonne	:	Rule *h,* use 20 million tonnes
If:	£50/tonne < oil price ≤ £60/tonne	:	Rule *i,* use 15 million tonnes
If:	£60/tonne < oil price ≤ £70/tonne	:	Rule *j,* use 10 million tonnes
If:	£70/tonne < oil price ≤ £80/tonne	:	Rule *k,* use 8 million tonnes
If:	£80/tonne < oil price	:	Rule *l,* use 7 million tonnes

In reality the response to oil price will be subject to market elasticity constraints, which gives an indication of the change in demand for oil as its price varies. Bread, for example, is highly elastic as it is necessary at almost any price and sweets are highly inelastic. Fuzzy logic is used to blur such data boundaries. It converts linear data into a form that enables logical processing and decision making and then converts it back into a linear form. The two conversion processes are called fuzzification and defuzzification.

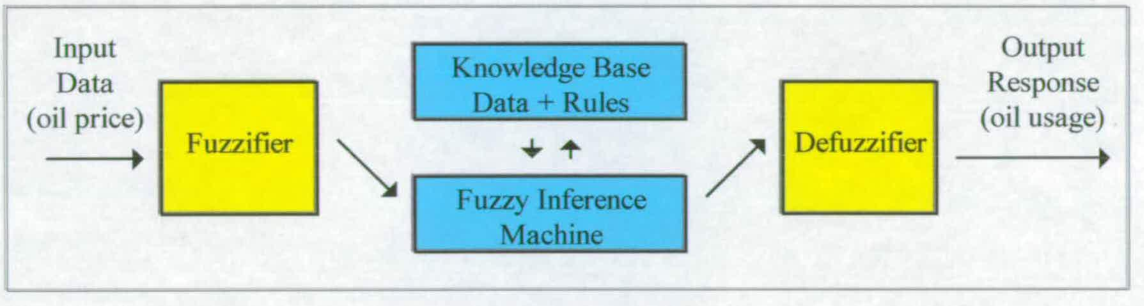

Figure 3.4 Fuzzy Logic Operation

Fuzzification works by grouping the data into fuzzy sets, rather than price blocks which would give the same response to £61/tonne as £70/tonne. Fuzzy sets represent the degree of membership to each of the blocks rather than simply classifying weather the data is in or out of a particular price range.

Figure 3.5 shows the fuzzifier for the oil price example. In this case each fuzzy set is represented as a triangle. The degree of membership to each rule is given by the intersection of oil price and rule boundary. A price of £60/tonne would represent full membership of rule *i* whilst £63/tonne would be a $^{3}/_{4}$ member of *i* and a $^{1}/_{4}$ member of *j*.

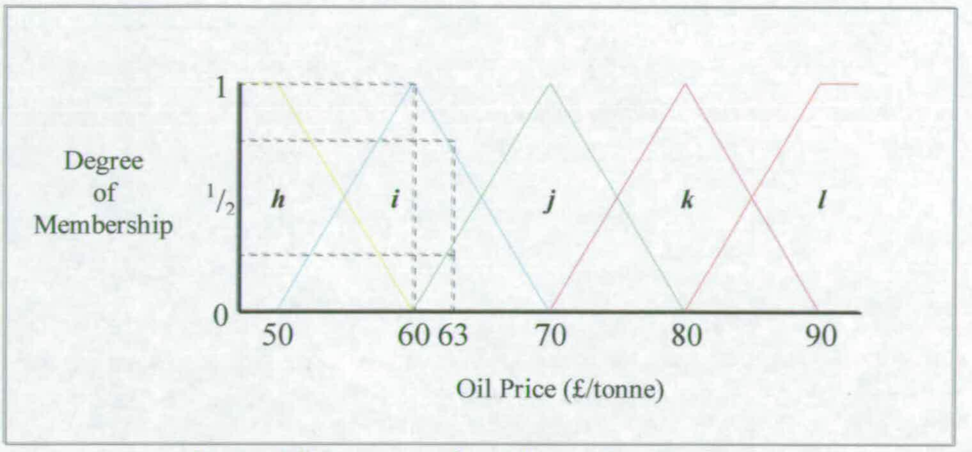

Figure 3.5 Fuzzy membership sets for oil prices

Once the data has been fuzzified it is passed to the inference engine which collects rules from the knowledge base according to the membership of the fuzzified data. All the rules that have a member, however small, are used in the inference engine. The rules are then weighted accordingly. The final step is defuzzification which applies the weighted rules to give useful values. A price of £63/tonne would result in the use of:

$$\left(\tfrac{3}{4}\times 15\right)+\left(\tfrac{1}{4}\times 10\right)=13.75 \text{ (million tonnes of oil)} \qquad \textbf{Equation 3.5}$$

There are many variations to fuzzy logic procedure. Firstly, the sets can be bell shaped, trapezoid, irregular or triangular, as in the oil price example. Secondly the weighting can be based upon area or centre of gravity, rather than simple intersection values. Finally multiple sets of fuzzifiers can be used, and logically combined in the Inference Engine, providing a single output response to multiple data sets[50]. For example electricity demand could be included with oil price to give a more accurate model of oil combustion for generation.

This study did not use any Fuzzy logic as neither the exogenous data used in the forecasting model or the models governing equations were digital, or rule based.

3.3.4 Artificial Neural Networks

A forecast can be split into a description of the environment and a forward extrapolation. Descriptions of the environment can be achieved using a theoretical model or through past data regression techniques. Section 3.2.2.1 outlines some simple parametric regression techniques which create descriptive equations from data trends. Because these methods find trends through iterations, non-linear correlations cause large errors that increase with the size of the model. Non-parametric regression creates a model from the whole data sample which includes any non-linear behaviour.

Artificial Neural Networks (ANN) are ideally suited to non-parametric regression as their learning behaviour is robust. They use a network of nodes that describe the relationships between a system's inputs and outputs. The nodes, or neurons, are joined by interconnectors which have adjustable weights that allow the network to learn. A typical ANN would be constructed in layers as shown in Figure 3.6.

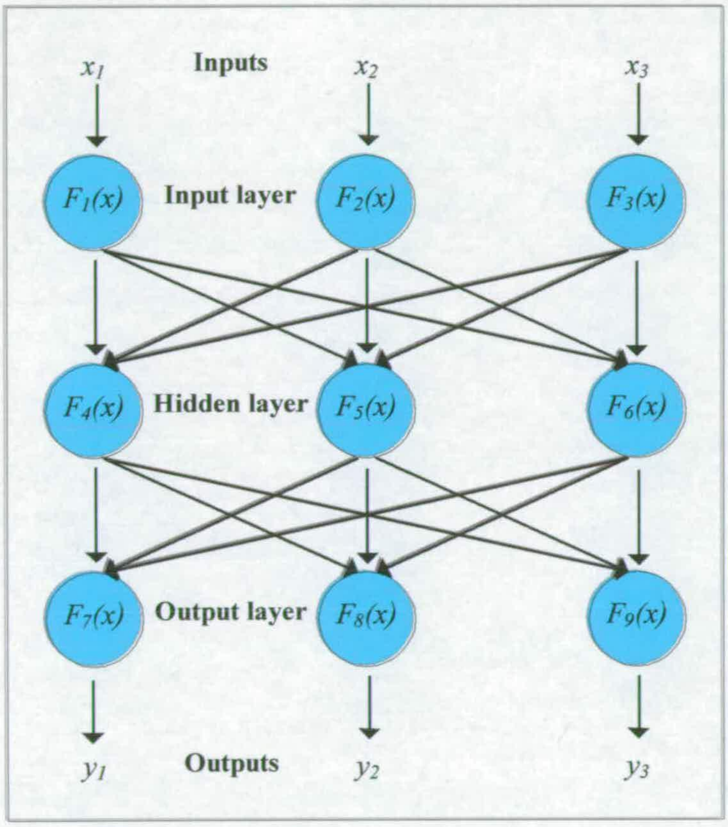

Figure 3.6 Outline of an Artificial Neural Network

Each node calculates the sum of the inputs (x), multiplied by their respective interconnector weightings (w). If this value exceeds the threshold level (T), the node is fired to give an output, otherwise the node's output remains low. A node with n inputs will only fire to give a high output (y) if:

$$\sum_{j=1}^{n} x_j w_j > T$$ **Equation 3.6**

Each layer of nodes in the network can have different transfer characteristics. Instead of the hard limited, or digital, response shown above the output can increase in a linear or sigmoidal fashion i.e.

if :

$$X^{sum} = \sum_{j=1}^{n} x_j w_j \qquad \textbf{Equation 3.7}$$

then

$$y = \frac{1}{1+e^{-X^{sum}}} \qquad \textbf{Equation 3.8}$$

This gives the network a softer response to changes which is necessary when forecasting linear events. This type of transfer function could be used to describe the correlation between oil price and its usage in electricity generation.

The real advantage of using ANNs is that they can be trained on data. In forecasting applications ANNs are used to find the correlations between explanatory variables and the system's response to their change. The ANN finds the correlations by training on past data. There are two training methods, supervised and unsupervised[51]. Both training systems involve data input and the calculation of the deviation between the ANN's response and the actual system response. Supervised training uses this feedback to reduce the weighting of erroneous nodes until the network matches the ideal system response. The disadvantage is that this method can be slow and must be accurate because learning stops after the training period. Unsupervised training does not use a given goal but constantly adjusts to satisfy internal rules. It has the advantage that it adjusts as environments change and should continue to improve with use. There are various training models, such as Backpropagation, Hopfield or Adaptive Resonance, which use different methods of weight adjustment and node testing.

ANNs are adaptive in that they take data and learn from it, inferring solutions and therefore reducing development time. Once they have been trained they can generalise using data that resembles training data providing a tolerance to noisy, or even incomplete data sets. In addition they are non-linear which allows them to capture complex interactions between parallel sets of variables. ANNs are currently being used in short-term load forecasting and their application has proved successful due to their ability to establish non-parametric correlations between large sets of non-linear data[52]. Further improvements have been made using fuzzy neural networks which use fuzzy inputs to an ANN in order to classify data more efficiently[53].

As with most AI techniques ANNs have their limitations. It can be difficult to account for unexpected results as the full relationship between inputs and the derivation of individual outputs is not always possible. Also the quality of training data is critical and unreliable data whilst training can be difficult to identify[54]. Finally long term energy utilisation forecasting using ANNs has not been successful due to the changes in ESI structure since privatisation. The changes have rendered training data invalid and, without training, an ANN cannot be used in forecasting.

3.3.5 Genetic Algorithms

Although the field of Genetic Algorithms (GAs) has been developing rapidly since the early 1970s GAs remained, until the late 1980s, the theoretical tools of a highly specialised computing community. As the understanding of GA theory increased and more powerful computers became more widely available GAs were applied to real optimisation problems. The past five years has seen a widespread acceptance of these algorithms as analytical tools used in industry, finance and academia.

GAs use selection, breeding and mutation to evolve generations of offspring that are closer to an optimum than their parents. They are based on evolution but are similar to bacterial growth, not more complex creatures. Before a GA can be applied a fitness function, that can evaluate possible solutions must be created. If this function, or set of functions, can be solved mathematically then a GA is not necessary. If the function is insoluble due to its size or non-linearity then the application of a GA may be necessary.

The first step is initialisation where an initial population of possible solutions, or chromosomes, is created. Each member of the population is then assessed and given a fitness value depending on how well it matches the fitness function. A number of these chromosomes are selected based upon their fitness value. The higher the fitness of a chromosome, the greater the chance of selection. The selected chromosomes are then bred to create a new population of fitter solutions. Breeding involves the swapping of chromosome segments, or genes, between parents. Each member of the population is subjected to a chance of mutation. Mutation randomly changes a chromosome and helps keep diversity in the population. This is necessary to ensure that all possible solutions are considered. Finally a new population, made up of child chromosomes, is created and the process of selection, breeding and mutation repeats itself. This continues until the fittest chromosome within the population is no longer improving over generations. Temporally high rates of mutation can be used to push this best member off its optimum to see if it will return to the same point and confirm that the global optimum solution has been found. shows the structure of a simple GA.

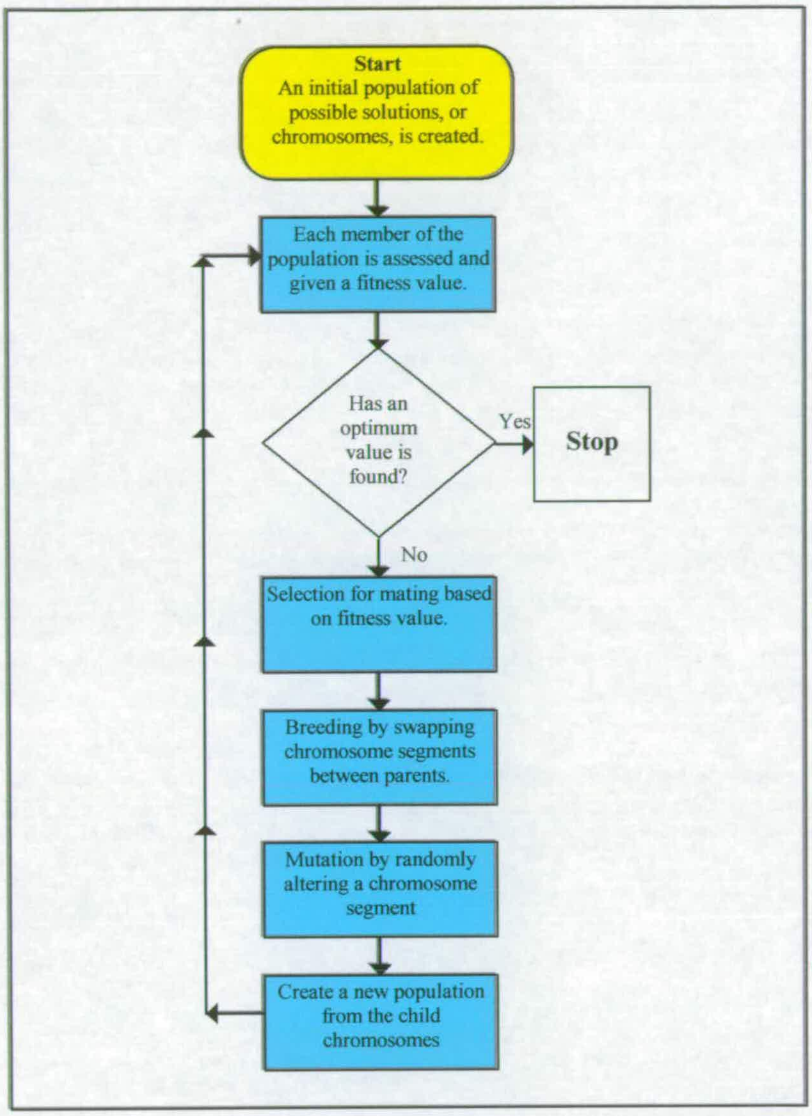

Figure 3.7 Flow diagram of a Basic Genetic Algorithm

GAs have been used in power systems optimisation problems with great success. Complicated despatch problems have been solved[55], corrective power flow planning[56] and turbine design are some recent GA applications. Recently a grid service restoration system was developed using a GA online for the first time[57]. However their use in long term planning has hitherto been limited due to low computer processor speeds. Today's computers have now reached the performance necessary for the application of GAs to very large problems. Chapter 5 discusses the application of GA optimisation to a large long-term forecasting model that describes how electricity will generated in a future ESI.

3.4 Summary

Due to the effects of privatisation, past data on ESI planning issues is no longer relevant. This rules out the use of regression techniques or neural networks in long term energy forecasting as they all need past data for extrapolation or training. GAs, on the other hand, can be used to solve large non-linear models constructed from both theory and experience. Unfortunately, due to their nature, there cannot be a black box GA that can be applied to solve all problems; the programmer must choose the correct GA structure and then adjust it to perform its specified task. Chapter 5 investigates the ideal structure for a GA used in long-term forecasting. Current GA based software can only be run efficiently by operators with at least some knowledge GAs and their operation. The GA suggested in Chapter 5 is pre-set for maximum efficiency over the range of optimisations demanded by energy planners. In addition energy planners with GA knowledge can manipulate the algorithm itself. The aim is to allow the operator to concentrate on the problem being solved and the solutions proposed, rather than the GA itself. To achieve this a new model and GA have been constructed that can include all of the relevant factors that are involved in the future selection of fuels and plant mix in the UK ESI over the next forty years.

4. STRUCTURE OF THE ELECTRICITY SUPPLY INDUSTRY FORECASTING MODEL

4.1 Overview

The proceeding three chapters, 4, 5 and 6, detail the construction of a Genetic Algorithm based Model of Electricity Supply (GAMES). This chapter discusses the general structure of GAMES, a model that is to be used to forecast the mix of generation methods in a future ESI. Chapter 5 explains the GAMES Genetic Algorithm (GA) and details how it solves the large, non-linear and discontinuous model of the UK ESI. Chapter 6 details the functions that describe the ESI and are included within the GAMES fitness function.

A model used as a forecasting tool must be transparent so that assumptions are visible. To achieve this a rigid structure must be adhered to. The types of functions within the model are defined in Section 4.2 and their effects on the model itself are discussed. Because the model spans a time horizon it is dynamic and the effects of this are discussed in Section 4.3. Dynamic models are complex and it is important that adequate calibration and validation is carried out. Section 4.4 investigates methods that ensure confidence in the model is maintained. The complexity of the model is further increased when the concept of a purely monetarist and perfectly efficient market is dropped and replaced with a more realistic theoretical model. A system is put in place that allows the inclusion of these extra, non-linear functions. As suggested in the thesis this system uses a global utility function, defined in Section 4.5, that allows the analysis of all costs and benefits to occur simultaneously which allows for a solution to be derived by a maximisation of utility. Traditional mathematical optimising techniques have proved to be inadequate when used to solve such a large selection of non-linear simultaneous equations. A computational optimisation algorithm based on evolution (a genetic algorithm) is suggested in Section 4.6.

4.2 Model structure

In order to perform a quantitative long term forecast, a model of the system to be studied must be created. The construction of a model involves a balance between explaining the system in more detail, thus increasing the model's size, and keeping the model manageable both in comprehensibility and in computational power needed to derive solutions. Model size is dependent on the proportions of:

- Endogenous variables; variables calculated within the model.
- Exogenous variables; variables provided to the model.

A model with more endogenous than exogenous variables will explain more and be larger. As large non-linear models are best solved by computational methods the inclusion of extra endogenous variables will slow down these iterative processes and reduce the final accuracy of models set to run within a finite number of iterations.

Endogenous variables are calculated by applying sets of functions which often have exogenous variables embedded within them. These functions can be classed in three groups:

- Behavioural functions, that describe the actions of electricity companies in response to market events. For example cheap gas results in an increase in gas fired generation.

- System functions[i], that describe systems such as the market structure, taxation mechanisms and regulation constraints.

- Continuous identities[ii], which are the exact relationships that hold for all points in time. For example the relationship between the electrical output and the emissions from a particular plant.

Each group of functions is described in more detail in Sections 4.2.1, 4.2.2 and 4.2.3 respectively. Behavioural, System and continuous functions rely on high quality exogenous data to provide accurate solutions. Much of the short-term exogenous data that describes the ESI is inherently volatile. A typical example of this volatility would be daily electricity demand profile which can alter dramatically with the weather or even television schedule changes. However Section 4.2.4 shows that it is possible to accurately predict the average yearly demand as the daily deviations can be aggregated. The process of aggregation is fundamental to any macroeconomic or long term model. Section 4.2.5 shows how it increases reliability as well as reduces the model's size.

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[i] System functions are known in econometrics as technical functions. To avoid confusion this study uses the term system function because the term technical function is also used in engineering to describe functions that represent engineering processes.

[ii] Continuous identities are known in econometrics as accounting identities. To avoid confusion this study uses the term continuous identity because the term accounting identity could be confused with economic functions which describe all economic relationships.

4.2.1 Behavioural Functions

Behavioural functions describe the aggregate actions of economic agents such as consumers, producers and investors. These functions are useful in long term models as the averaging of many individual agents' behaviours reduces a model's size. In GAMES they are derived from economic and technical theory and are based on quantitative parameters. An example would be the decision not to construct generating plant that may, in the near future, suffer from fuel resource constraints. Unfortunately the application of some economic theories to empirical models in this manner may be inexact as, in this resource example, some investors would construct plant so long as resources held out beyond the pay-back period. The particular data available that defines the length of pay-back periods may have slight deviations from theoretical values. Many theoretical models do not accept dynamic adjustment and simply fail when faced with the smallest errors of this kind. It is therefore normal for such functions to be validated using statistical evidence based upon relevant data. It is also important to ensure that conclusions about the actions of an individual case are not derived from the aggregate solution as this would be subject to error over time, even if the representative individual were considered to behave consistently[58].

4.2.2 System Functions

System functions approximate institutional arrangements such as taxation structures related to electricity generation costs. They explain the relationships between, and the approximate workings of, these institutional arrangements. System functions in the ESI would include environmental taxation of generation by fossil fuel combustion or the increase in renewable energy generation technologies as a result of NFFO and SRO incentives. They also explain conceptually similar variables that are measured in different ways such as with the electricity pool selling price indexes and pool purchase price indexes. The parameters of these functions are mainly estimated from past data or derived from known system information. As these functions are often approximations, an error assessment of system functions is always necessary.

4.2.3 Continuous Identities

Continuous identities are the exact relationships that hold for all points in time as with expenditure being related to fuel usage in a particular plant or plant efficiency whilst working at different loads. Continuous identities form the core of most models, and they are more reliable than both behavioural and system functions as they are derived from experience and are only subject to exogenous data errors. The links between electricity demand and generation, or fuel costs and generation variable costs are examples of continuous identity.

4.2.4 Aggregation

Behavioural functions, system functions and, to some extent, continuous identities are all subject to aggregation techniques. By averaging the actions of microeconomic systems, such as fuel prices or electricity demand over time, many simplifications can be made. This is obviously useful in very large scale models such as GAMES[59]. The aggregation approach can even be applied to natural effects such as the weather. A long term forecast of the minute by minute temperature, to the nearest ±5°C, of a small town within the UK is simply not possible! However a long-term view of the average yearly UK temperature to within ±3°C is, at present, considered reliable. The GAMES model of the ESI utilises aggregate solutions to give:

- Yearly fuel prices
- Wind speeds
- Rain precipitation
- Temperature
- Electricity demand (Base and peak loads)
- Generation costs or particular plant types

In the case of electricity demand, a yearly aggregate can be made if both peak demand and overall yearly load figures are considered separately. This is because peak demand figures must give the maximum possible figure, rather than an average of peaks.

4.2.5 Model Size

The final size of a particular model is not simply constrained by its manageability but also reflects the methodological approach adopted. Some models, such as the Liverpool (LPL) model of the UK economy, are straightforward, rational and simple, following a monetarist, or neo-classical, view of the world; that most occurrences can be explained by a pure market model. This is reflected in its relatively small size of 11 endogenous and 28 exogenous variables. In contrast the HM Treasury (HMT) model of the same system was much larger, with 509 variables in total, as it was felt by the treasury essential to model the public sector in some detail, including the use of microeconomic theory, to adequately to explain the UK economy[60]. The added variables caused complexities in this model which made it mathematically difficult to solve. Therefore there is a limit to the level of complexity that can be contained within a traditional model.

As GAMES was solved by an optimisation process, rather than by a mathematical procedure, added complexity only increased the time needed for the GA to find an optimum solution. Therefore the maximum number of functions and variables was only limited by processor speed which is continually increasing. The balance that was found between necessary complexity and model size in GAMES was based upon a 1996 Pentium Pro 200 processor. Although this balance allowed the inclusion all relevant environmental, technical and economic functions new faster processors, which are already currently available, will allow the inclusion of additional functions. This will allow sensitivity studies to investigate the effects on the ESI of obscure relationships, such as the correlations between global warming and electricity demand.

4.3 Dynamic Modelling

A model where all endogenous variables respond immediately to changes in exogenous variables is described as static. An example of a static model would represent a particular phenomenon at a particular time, such as the distribution of electricity demand in the UK. Such a static model could give the energy demand or even the rate of change of demand for every town or village, for a given year, in the UK. A dynamic model, such as GAMES sets out to describe and analyse the process by which the phenomenon occurred. It would give the change over time, or the rate of change of energy demand. Thus the demand and the rate of change of demand could be given for a set of years rather than at a singular moment of time. To achieve this endogenous variables must adjust to changes in both exogenous and other endogenous variables over several time periods. This process is referred to as lagged adjustment. The presence of lagged adjustment makes the model less simultaneous in nature, since the result of each function may not depend on current endogenous values.

GAMES is a dynamic forecasting tool as it projects exogenous data into the future. The result for a particular year depends on these projections along with the solutions from previous and possibly future years. This vastly increases the model's complexity and causes non-linear and discontinuous relationships that are impossible to solve analytically[61]. Section 4.5 explains how a general utility function is used in GAMES to transform the discontinuous mathematical model into an optimisation problem that can be solved by an artificially intelligent search technique. Section 4.6 highlights the advantages of using a Genetic Algorithm (GA) to solve this optimisation problem.

4.4 Model Based Forecasting

Forecasting does not necessarily need a formal model. Many forecasts are made by experts who have an in-depth knowledge of a system and can use this knowledge to find and forecast trends in the same system. A model of the system is necessary when the system is interdisciplinary and no single expert can make a forecast or when the system is simply too large or complicated do be understood as a single system. In such cases a model is constructed which can be used as a forecasting tool. GAMES, which gives a long-term forecast of the means by which electricity will be generated in the UK, is very powerful as such a tool as it involves a wide range of disciplines: These include technical, economic, environmental analysis and an understanding of the effects that market and policy changes have on the ESI.

Model based forecasts can be distinguished into two types, ex-post and ex-ante. Ex-post forecasts are predictions by the model for a time period for which there is known data and are used for calibration, validation and some sensitivity analysis on the system. Ex-ante forecasts are made for a future period where the exogenous variables are unknown and have to be projected based on other forecasts or models. In general ex-post forecasts are used in the validation of the model and ex-ante forecasts are used to predict future outcomes to possible future events. All ex-ante forecasts rely on exogenous variables that have themselves been derived from forecasts. The quality and continuity of such data is important to the validity of results. Although there are methods by which the quality of exogenous data can be assessed, any assumptions made during the derivation of such data must be highlighted. Section 4.4.1 discusses these assumptions in detail.

A combination of ex-post and ex-ante techniques are often useful in a single forecast as the single set of results can provide the error in the forecast which should be applied to any predictions of future events. Some of the error can be reduced through the use of residual adjustments which can be calculated using the data from dedicated ex-post forecasts (Section 4.4.2). The final forecast is made based on sets of results from a calibrated model. Each set of results has its place in the forecast and can be divided into three groups.

1. Calibration to set residual adjustments.
2. Validation to test confidence in predictions.
3. Predictions of possible outcomes to different scenarios.

Any temptation to hold a single set of results as a form of prophecy can only lead to a reduction of confidence in the model and the validity of forecasts based on that same model.

4.4.1 Exogenous assumptions

A primary issue in exogenous data collection is continuity. Ideally all data should come from one source which would ensure that the same assumptions are applied to each data field (Even slight variations in, say, the applied discount rate can give rise to continuity problems). Unfortunately this is not possible as the range of exogenous data needed for the GAMES model extends across many fields, from interest rates to the environmental impact of transmission. To overcome such problems a strategy of data grouping and adjustment is adopted:

1. The exogenous data must be divided into groups that can be filled from one primary data source. In GAMES this has to include the following data:

   - Economic (taxation, interest rates, electricity and fuel prices)
   - Technical* (fixed and variable costs of electricity generation)
   - Energy (remaining resource and electricity demand)
   - Historical (existing plant of different types and its expected life)
   - Externals* (The environmental and social costs of generation)
   - Risk* (The costs associated with reducing risk)

   *(must be adjusted to link with economic)

2. The groups must be adjusted so that they are matched chronologically.

3. The groups must be adjusted so that they match in standard units.

4. The fiscal groups must be adjusted so that all discount rates are standardised.

Forecasts that consist of a combination of ex-post and ex-ante techniques provide further difficulties as historical data is rarely found with forecast data. This problem usually only involves standardisation which can be solved using the relevant conversions.

A second issue concerning exogenous variables is the common assumption of unchanged energy policy. Forecasts that adopt this stance assume that present policy will be maintained through the forecast period. This is a big assumption that can result in large forecasting errors. It is not possible to make direct long-term predictions of energy policy as a proportion of government policy making is based on public will, which is complex and difficult to predict. The solution is to either explicitly incorporate policy reactions to events, or to compile sets of forecasts from different policy scenarios. The explicit method involves using reaction functions which model the authority's reaction to deviations from their policy objectives. These functions can be as part of the residual adjustments or as separate entities. GAMES does not assume that policy objectives will remain constant and therefore does not rely solely on the explicit method. Some of the explicit reaction functions included are:

1. Proportional increases in fuel price as resource is depleted.
2. Penalties on excess emissions.

Although the fuel price is predominantly market led, the taxation of fuels for electricity generation is soon to become a policy control. GAMES includes a range of exogenous fields by which policy scenarios can be simulated.

4.4.2 Residual adjustments

Residual adjustments take account of expected factors that are not included within the model and are used to calibrate the model against known events in the past. In addition they are often used to re-calibrate an existing model where the re-estimation of individual functions is not feasible due to instability problems in the old model. The re-estimation of individual functions within GAMES is not a problem as it is a newly created model with internal functions that have been coded with stability, easy access and manipulation in mind. Residual functions within GAMES are therefore only necessary for calibration purposes.

Residual adjustments are determined by the type of model. If a residual is needed to calibrate an ex-post forecast a simple multiple of the result may suffice. This may be constant or vary over time. In GAMES most social and economic factors are included directly and therefore need little or no residual adjustment. Residual adjustments have been made within the model for the calibration of extreme, *what if*, scenarios where the effects of massive price shocks or resource depletion could make the model unstable. If adjustment was needed during a set of forecasts it would most likely be the result of errors in the exogenous data used in the political, technical and economic risk functions. The political risk data field, which should normally be set to zero provides an adequate facility for an end user of GAMES to make additional residual adjustments. It must be noted that use of residual adjustment for any other purpose other than calibration, such as including the opinions or bias of the forecaster, can lead to the forecast becoming a derivative of the forecaster' judgement. Although the forecaster's judgement may be valid, such changes can disguise problems with the data or even with the model itself.

4.4.3 Forecast Evaluation

There are numerous methods of validating a forecast model. The majority of these methods involve the comparison of ex-post forecasts and historical data. Formal test procedures use either a mean absolute error (MAE) or a root mean square error (RMSE) to make this comparison.

$$\mathbf{MAE} = \sum_{i=1}^{n}(h_i - f_i)/n \qquad \textbf{Equation 4.1}$$

$$\mathbf{RMSE} = \sqrt{\sum_{i=1}^{n}(h_i - f_i)^2 \;/ n} \qquad \textbf{Equation 4.2}$$

where:
f = ex-post forecast
h = historical data for the same forecast period.
n = Number of data points

As GAMES is a dynamic forecast model, that involves errors spread over a time period which are themselves subject to lagged adjustments, standard RMSE evaluation would not give adequate information of the error variation over time. Error variation shows the stability of the model and gives the errors in trends which GAMES is designed to forecast, rather than indicating the residual adjustment error. To incorporate this into error evaluation a time-series approach can be used. Applying a time-series model to the RMSE gives:

$$\mathbf{RMSE}_{\textbf{(time series adjusted)}} = \frac{\sqrt{\sum_{i=1}^{n}(h_i - f_i)^2 / n}}{\sqrt{\sum_{i=1}^{n}(h_{i-1} - f_{i-1})^2 / n}} \qquad \textbf{Equation 4.3}$$

To ensure that this method of forecast evaluation is valid two criteria must be held:

1. The historical data must be reliable and continuous.
2. The historical data used in RMSE evaluation must not be the same as that which was used to make residual adjustments as this would only give the calibration error.

In addition to testing a single forecast, this form of forecast evaluation can be used to compare different forecasts of the same period against each other. To achieve this h and f should be substituted to represent the two different forecast results.

Unfortunately changes due to the recent privatisation of the ESI have diminished the value of relevant historical data. It is still possible to evaluate the GAMES forecast model using a time-series adjusted RMSE, however some judgement is needed in the interpretation of the results. To distinguish between modelling errors and data discontinuity an in-depth understanding of the differences between forecasting in a nationalised and privatised ESI is essential. Chapter 2 discusses these differences in more detail.

4.5 Utility Optimisation of the ESI

To model decisions in the ESI the working system must be defined. Chapter 2 shows that simply assuming that technologies will be chosen solely on their profit maximisation potential is unrealistic. A function of company efficiency must be included within the model. This efficiency function ($f(e)$) can be based on knowledge of how Principal-Agent theory affects the decision structure in the ESI. There are also resource ($f(r)$), transmission ($f(t)$), political ($f(m)$) and ecological ($f(E)$) constraints which must be included along with the advance of technical possibilities ($f(T)$). The question of how to include all these functions into a single model needs to be solved. The solution is found in a theory that has formed the basis of modern economics, the Utility Theory, which asserts that:

"*...actions are right in proportion as they tend to promote happiness, wrong as they tend to produce the reverse of happiness. By happiness it is intended pleasure, and the privation of pain*"[62].

The theory goes on to state that these are the only considerations in the decision making process. If this is true then the path chosen by a single decision is the one which results in the maximum pleasure (P) and minimum pain (p). This can be described as an maximisation of utility (U):

$$U = F(\mathrm{P} - \mathrm{p}) \qquad \textbf{Equation 4.4}$$

where

$$\mathbf{P} = P(e)+P(r)+P(t)+P(m)+P(E)+P(T) \qquad \textbf{Equation 4.5}$$

and

$$\mathrm{p} = p(e)+p(r)+p(t)+p(m)+p(E)+p(T) \qquad \textbf{Equation 4.6}$$

The utility function is case specific and contains all relevant information known at the time of the decision. Within the ESI factors such as the expected capital costs, operating costs, energy resource and market structure are most influential in the determination of P and p. Each of these factors can be further broken down into constituent parts: interest rates, materials and construction costs are needed to determine capital costs and operating costs are dependant on fuel costs, maintenance and load factor. Each of these case specific factors are derived using economic theory, tested on previous cases, and projections of exogenous variables. As it is true that a decision can be defined as an optimisation of exogenous variable projections constrained by sets of known laws, the optimisation of this utility function will give forecasts of decisions made in response to future environments.

In addition to economic, environmental, political and technical forces, the utility function contains two other factors. First is the management of risks associated with increasing the use of each generation method. A high risk reduces P and the probability of a high p is increased. Risk is included within the function as a set of constraints that vary depending on the probability of a future event. These constraints, for example, ensure that there is some horizontal integration of Generators by increasing the probability of a high p in any technology that becomes too dominant in the market. This creates a further problem; future events will be altered by a preceding decision so forecasts used to make the decision must be adjusted as each option is considered. This loop creates non-linearities that traditional optimising techniques find difficult to solve. The use of Genetic Algorithms to optimise non-linear functions is discussed in Section 4.6.

The second additional factor is the moral, or judgement, variable. For example the decision not to store radioactive waste near a town centre includes more than a simple fiscal optimisation. Before the privatisation of the ESI these questions were answered as part of a single decision making process. The consequence of this was that important moral decisions were often left in the hands of a single ministerial office. With the high ministerial turnover in the UK there was no standard guide to acceptable behaviour. Privatisation has created a separation between moral decisions and utility maximisation. Government legislation is imposed on private firms through a system of regulators, removing much of the moral responsibility from the firms.

Assuming that all actions within the laws and rules of energy trading are considered to be acceptable and any unacceptable behaviour within the law is allowed, with the only constraint being negative publicity, it follows that company policy and legislation can be considered separately as long as company policy remains within legislation. This separation of company policy and legislation has allowed forecasters to use economic theories, within the constraints of known legislation, to predict the outcomes of future decisions.

GAMES combines all the functions that describe company plant choice decisions in the UK ESI within a global utility function. The optimisation of this single function gives the most likely outcome to these decisions on a yearly basis.

4.6 Model solving

Using a global utility function to combine all the discontinuous and non-linear functions that describe primary energy usage decisions in the UK ESI transforms this insoluble set of simultaneous equations into a single optimisation problem. The optimisation involves finding the most likely outcome from the many possible combinations of 8 methods of generation over a 40 year period. An unconstrained model would have 10^{640} possible solutions if each method of generation was an integer representing between 1% and 100% of demand. However as the GAMES model assumes that generation will always equal demand the number of possible combinations is constrained to 4×10^{416}. Within this large number of possible solutions, or search-space, there are many local optima which are often far from the global optimum. In addition primary energy usage decisions are very non-linear with many discontinuous feedback loops. Traditional optimisation techniques, such as Lagrange's Method, use mathematical algorithms to climb gradients or match graphical plots[63]. These optimisation methods suffer from:

- A limit in the size of the search space. Traditional methods involve many calculations per variable so as the number of variables increases the optimisation becomes slow.

- Local minimum / maximum problems; where localised optima are confused with global optimum.

- Non-linearity assumptions; where non-linear problems have to be assumed a combination of linear problems to be solved.

Another, quite different, approach could be to use a computer to search the whole search-space for the optimum. Unfortunately even the constrained model would take months on the worlds fastest computers. However a constrained search of the search space, using an algorithm trained to find an optimum based on a pre-defined objective, would reduce the size of the problem. If such an algorithm had a built in random search function the problem of local optima being assumed as global optima would be overcome. Evolutionary algorithms will provide these attributes, specifically a genetic algorithm (GA). GAs are inspired by natural evolution, their structure is similar to the decision process and is therefore ideally suited to the application of forecasting decisions. A GA consists of populations of possible solutions (chromosomes) from which the fittest, or optimal solutions are combined to make new, fitter populations. A system of mutations is used to ensure the whole search space is covered. Using a fitness function based on economic theory and past data this optimisation method could quickly cover the large number of possible permutations that describe technology and resource utilisation in the ESI.

4.7 Summary

In order to make reliable forecasts of possible future scenarios a model with a clear structure is needed. Continuous identities, system and behavioural functions and all their aggregated exogenous data can be combined into a single utility function that describes decisions in the ESI. This single, non-linear function cannot be solved mathematically, but can be optimised using a GA. This gives a number of near optimum solutions along with the global optimum. This is beneficial in real life forecasting because it gives possible deviations from a single predicted solution. The actual outcome will lie within the distribution of near optimum solutions.

5. GENETIC ALGORITHM BASED FORECASTING

5.1 Overview

This chapter introduces the genetic algorithm (GA) and then, in Section 5.2, describes its place in forecasting the ESI as stated in the thesis of this study. After outlining the GA's structure in Section 5.3 the workings of each generic and advanced genetic operator is discussed individually in Sections 5.5 and 5.6 respectively. The actions of the genetic operators vary with the method by which the ESI model is represented in the GA. Section 5.4 discusses the representation used in creating the GAMES GA. Correct representation is critical to the success of the evolutionary process and care must be taken to ensure that the model itself is not destabilised by the GA.

5.2 Program Structure

The general structure of the ESI forecasting model is shown in Figure 5.1. Specially created data forms are used for the exogenous data input that helps set up the ESI model within the fitness function. The GA uses this function to evaluate the fitness of possible solutions within the evolving populations.

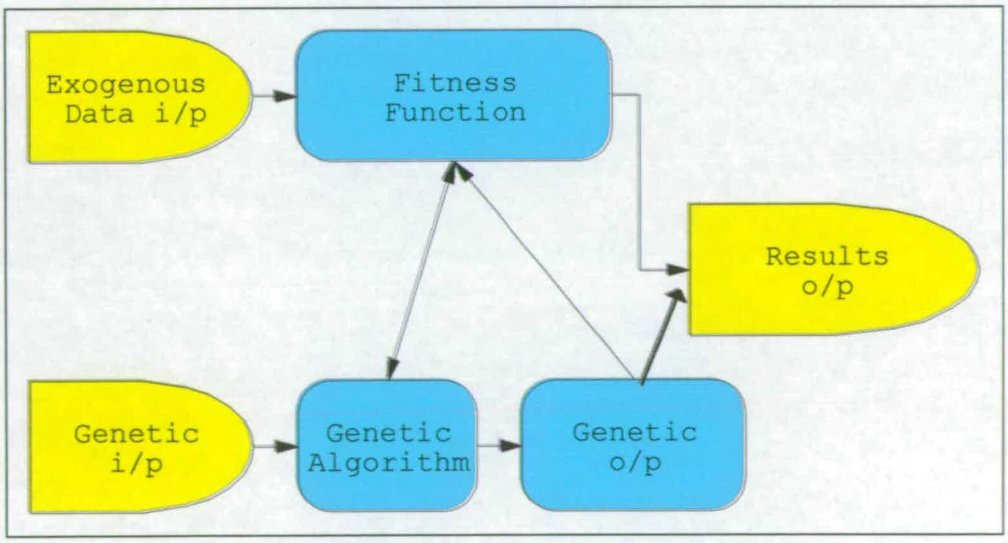


Figure 5.1 GAMES program structure.

The GA and its operators manipulate these possible solutions in order to arrive at an optimum, or most likely solution. The genetic operators are adjusted through the genetic input fields. When the GA finds the optimum solution it is passed through the fitness (or evaluation) function so that relevant results can be calculated and then displayed graphically. In addition the current population can be viewed as chromosome data in the genetic output field. The genetic operators will run adequately on the default settings in the genetic input field. However the optimisation process can be made quicker and more reliable through the manipulation of certain operators at runtime by the GAMES user. These genetic operators are discussed fully in Sections 5.5 and 5.6.

5.3 GA Structure

A Genetic Algorithm is an optimisation method based on evolution. A simple model, based on a feasibility study for GAMES, is used to describe the general structure of a GA. In this early example the UK Electricity Supply Industry (ESI) is assumed to consist of only coal fired and gas fired generating plant. The algorithm consists of a population of chromosomes. In this example each chromosome represents a possible fuel-mix between gas and coal generation over a selected time period (6 years are shown in Figure 5.2.). Chromosomes are made up of strings of genes, each representing a possible single years proportion of gas to coal usage.

The algorithm passes through a number of phases:

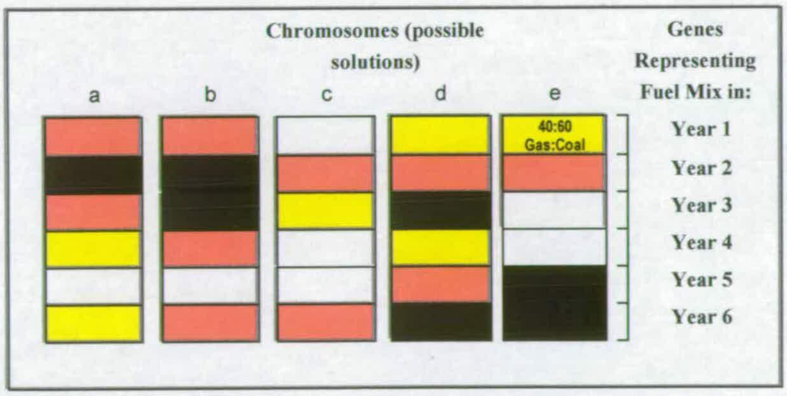


Figure 5.2 Population of 5 chromosomes made up of 6 genes. Each gene represents the proportions of gas and coal based generation needed to meet the yearly demand. Darker colours represent more coal whereas lighter colours represent more gas plant.

1. Initialisation where a number of chromosomes (possible solutions) are randomly generated. These form the initial population which could also be seeded with deliberately good or bad possible solutions to push the GA towards or away from certain optima. The process and effect of seeding is detailed in Section 5.6.1.

2. The evaluation (or fitness) function, which contains the technical, economic and environmental functions that describe primary energy choices in the ESI, assigns each new chromosome a fitness which affects its probability of selection. There is a higher chance of selection for the fitter chromosomes, or better possible solutions to the fuel mix.

3. An elitist function is used to mark the fittest chromosome in the population so that it can be carried forward if it is fitter than the fittest chromosome in the next generation.

4. Each chromosome is given a chance of selection for a new population based on its fitness. Fitter chromosomes have a greater chance of being selected for the new population.

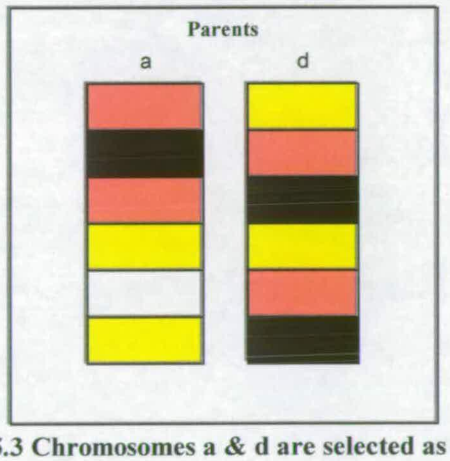


Figure 5.3 Chromosomes a & d are selected as parents

5. Chromosomes from this new population are selected in pairs to become parents for the new generation. In this case a and have been selected. Each pair of parents breeds subject to a user defined crossover rate to create new fuel-mix solutions based upon the constraints of the evaluation function.

6. The first step in breeding involves splitting strings of genes off two chromosomes and swapping them. This is known as crossover. Figure 5.4 shows the two point crossover used in both the feasibility study, which only contained gas and coal generation and in GAMES, which was a full working model of the UK ESI. This breeding technique randomly selects two points along the parent chromosomes and swaps the genes within the two crossover points to form the genetic structure of two children. The two children then

replace their parents in the next generation.

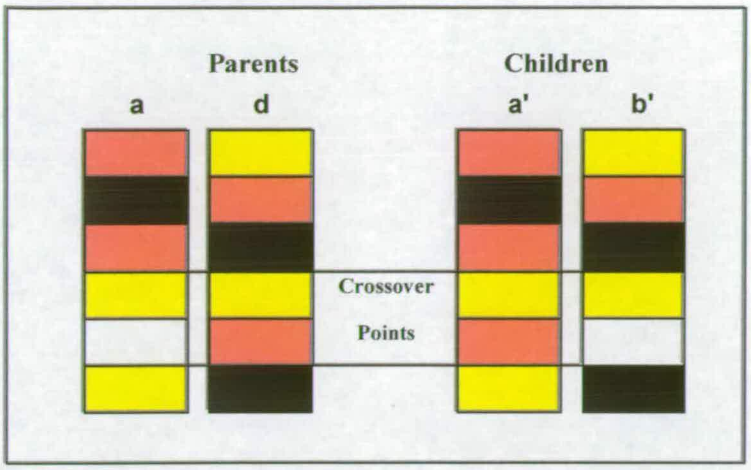


Figure 5.4 Breeding of parents (two point crossover)

7. A number of the child chromosomes have a random number of genes, or strings of genes, randomly mutated. This aids diversity in the population which prevents the GA becoming stuck in local optima. The amount of mutations depends on a user defined mutation rate and the size of each mutation can be set to reduce as the GA converges (the population becomes similar and stops changing). This allows a more refined search in the latter stages of the optimisation.

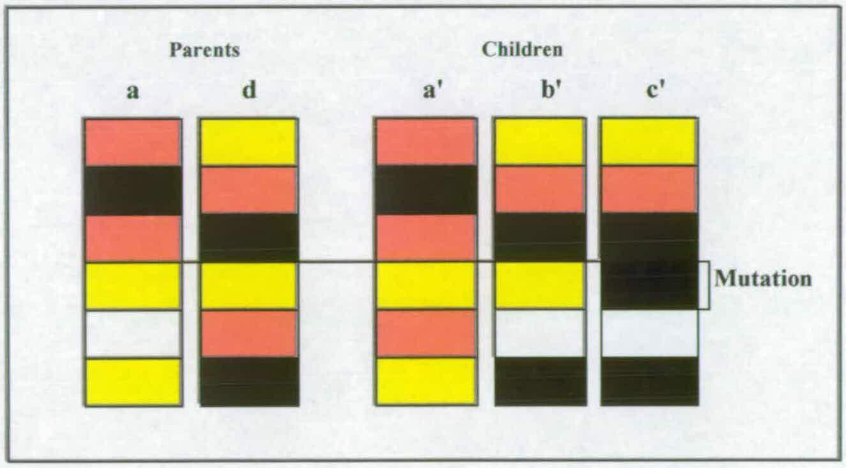


Figure 5.5 Mutation (c' is a mutation of b')

8. The flatten operator, an advanced function designed specifically for this study, is described fully in Section 5.6.3. It is attached to the mutation operator and investigates the possibility of using linear variations where non-linear changes in generation procedure are suggested by the GA. This serves to reduce the chance of stop-start (or construct-decommission) polices which are unlikely in real ESI forward planning strategies.

9. Recall also forms part of the mutation process. It is a new, advanced, genetic operator and is discussed in Section 5.6.5. Segments of chromosome from previous generations are placed within the current population's chromosomes. Although this function is rarely called it gives the GA a memory of where it has come from and allows it to backtrack if necessary. This operator is based upon living organisms which carry long strings of inactive DNA which can become operative through mutation.

10. The GA returns to the evaluation function (phase 2) and assesses the fitness of each chromosome in the new population. This process, of evaluation, selection, crossover and mutation, continues until the fittest, or most likely, set of possible fuel-mix solutions that satisfy the requirements of the fitness function have been found.

11. To ensure that the global optimum has been reached a temporarily high mutation rate can be used at this stage to push the population away from where it has converged in the search space. If it consistently returns to the same point a global optimisation can be assumed. The advanced operator that performs this task is called radiate and is discussed in Section 5.6.4.

All the operators described above have been specially written for long-term primary energy forecasting in the ESI. This was to accommodate the large and complex genetic representation of such a large model. The majority of these are based on standard genetic operators and their implementation is described in Section 5.5. The flatten and recall operators were designed and implemented for this study and represent an extension to existing GA theory. The radiate operator uses a novel approach to apply an existing process of increasing mutation to test for global optimisation. These three advanced operators are discussed in Section 5.6 along with seeding and gene holding.

5.4 Genetic representation

The representation of a problem is critical in the design and use of a genetic algorithm. Representation is problem specific and an ideal set-up is often only found after some experimentation. GAMES uses a similar representation method to that of the feasibility study which assumed a UK ESI based on gas and coal generation only. The representation strategy is:

1. Establishment of variables that are to be represented as genes.

2. Combination of the genes into chromosomes.
3. Definition of the population.

Sections 5.4.1, 5.4.2 and 5.4.3 explain how this representation process takes place in GAMES.

5.4.1 Representing Genes

Since electricity cannot be stored and this study assumes that demand will always be met, available capacity must exceed expected generation. To ensure that this is the case there must be sufficient resource and plant. As yearly electricity demand is an exogenous data field that is set before the optimisation, each gene (G_n) can represent the yearly proportions of generation methods that are to be used to meet that yearly demand. This has been implemented through splitting each gene into smaller segments called DNA (D_n). Each DNA segment represents the proportion of demand met by each individual generating method in a single gene. The sum of all the DNA segments in a single gene must always equal 100 to ensure that the sum of yearly generation by all types of plant meets yearly demand. Therefore each gene consists of a string of numbers that must always add to the sum of decimal one hundred.

$$G_n = (D_1, D_2, D_3, D_4, D_5, D_6, \ldots\ldots.. D_n) \qquad \textbf{Equation 5.1}$$

where:

$$\sum_{x=1}^{n} D_x \equiv 100 \qquad \textbf{Equation 5.2}$$

and: n = no. of generation types

Early GAs operated on a binary system which would involve the conversion of decimal D_n to its binary equivalent. If this was applied to GAMES, each gene would then consist of a string of these binary numbers and each chromosome a string of genes. The reasoning behind binary conversion originated from early problems which arose during the optimisation of a single binary number. Chromosomes represented this single binary number and each gene represented an individual binary digit from that same number. Subjecting every bit of the binary number to the genetic operators achieved the maximum number of genetic options that binary encoding allowed[64]. Due to the varying significance of each gene (or bit) other single bit codes, such as gray code, also proved popular. Both binary and gray coded GAs offered both elegance and flexibility and thus far have dominated GA research. However GAMES uses a GA to solve a particular problem, the future generation mix of the ESI, and its results depend on the relative accuracy of exogenous data. Using decimal integers for each of the proportions of generations dramatically reduces the size of the search space whilst still enabling results to remain within the expected errors due to exogenous data discontinuity. In fact such a large problem needs to be constrained in this manner to limit unnecessary computational expense caused by an over-sized search space. This method, of using real floating point numbers, has proved successful in applied GA applications and has, in spite of reduced schema processing, benefited from the resulting reduction in search area[65].

5.4.2 Representing Chromosomes

As yearly aggregates can provide reliable trends in critical data sets, such as electricity price and mean climatic temperature, the full time horizon has been split into yearly time periods. Using monthly, or daily, time periods would also increase the size of the model which would be unnecessary as yearly trends are sufficient for long-term planning decisions. Each gene (G_n) represents one year of generation within the forecast period. However the ESI is a non-linear system that follows dynamic responses to changes in environment. Events that occur today have an effect on future events and predicted future events have an effect on what is done today. For example no new plant will be constructed if the depletion of its fuel is imminent; whilst conversely if no new plant is constructed the resource will last longer. To eliminate errors due to this loop any forecast over a time horizon must solve for the whole time horizon simultaneously. A GA can evolve an optimum set of variables based on a function that describes the problem over the whole time horizon. This is achieved through the evolution of possible solutions for each year within the full time horizon. Each possible solution is independent, created from previous generations and represents a single chromosome (C).

$$C = (G_1, G_2, G_3, G_4, G_5, G_6, \ldots\ldots G_m) \qquad \textbf{Equation 5.3}$$

where: m = no. genes in a chromosome (number of forecast years)

Inserting the gene representation into the above equation gives the following matrix:

$$C_{nm} = \begin{bmatrix} D_{11} & D_{12} & D_{13} & D_{14} & \cdots & \cdots & D_{1m} \\ D_{21} & D_{22} & D_{23} & D_{24} & \cdots & \cdots & D_{2m} \\ D_{31} & D_{32} & D_{33} & D_{34} & \cdots & \cdots & D_{3m} \\ \vdots & \vdots & \vdots & \vdots & & & \vdots \\ \vdots & \vdots & \vdots & \vdots & & & \vdots \\ D_{n1} & D_{n2} & D_{n3} & D_{n4} & \cdots & \cdots & D_{nm} \end{bmatrix} \qquad \textbf{Equation 5.4}$$

where: m = no. genes in a chromosome (number of forecast years).

and : n = no. of DNA segments in a gene (methods of electricity generation).

This chromosome matrix represents a single possible solution to the yearly mixture of generation methods (D_{1m}, $D_{2m}...D_{nm}$) over the length of the forecast period (D_{n1}, $D_{n2}...D_{nm}$). By default GAMES forecasts the mixture of 8 primary energy sources used in electricity generation over a 40 year forecast period. This chromosome representation would be given by an 8 × 40 matrix. If these default settings were changed to a 20 year forecast period, the chromosome representation would be changed to an 8 × 20 matrix.

5.4.3 Defining the Population

A population (P) is a collection of chromosomes where:

$$P = (C_1, C_2, C_3, C_4, C_5, C_6, \ldots\ldots C_p) \qquad \textbf{Equation 5.5}$$

where: p = population size.

And: C_1, C_2, ...C_p= are separate chromosomes (possible solutions)

Each member, or chromosome, within the population, (C_1, $C_2...C_p$), represents a possible solution to the primary energy mix in generation over the whole forecast period. The population represents the group of evolving possible solutions within the GA. As the optimisation process continues the GA breeds new, fitter, populations of possible solutions.

The size of the population is important to the operation of the GA. If the population is too small it will converge on a sub-optimum solution too quickly. Conversely if the population is too large the GA will waste computational resource and therefore slow the optimisation process[66]. The population size in GAMES has been set to 100 as this has been shown to allow adequate diversity without excess computational expense. Some GAs use varying population sizes[67] but this approach dramatically increases the complexity of the GA and has proved unfeasible for GAMES running on standard PCs.

5.5 Standard GAMES genetic operators

The GAMES GA uses six core operators, which are standard GA functions, and five non-standard operators. The standard operators have been tested on a multitude of standardised test problems from the prisoners dilemma to the travelling salesman problem[68]. The basis of each standard function comes from Z. Michalewicz[69] but most have been altered considerably or totally re-written. Changes were necessary to convert the original code from C to C++ and to suit the ESI problem which is larger in scope and more complicated than the test problems used by Michalewicz.

5.5.1 Initialisation

Before the GA can be run a stable environment must be established. All input variables must be verified, output file space created and sufficient memory allocated for the population data. In addition the starting point for generating a series of pseudo-random integers must be seeded using the time, day and month at runtime. This is necessary as standard calls to generate a random number in C++ follow an algorithm that, unless seeded, will always start at the same point. Once an environment has been established the initial population is initialised. GAMES stores each chromosome in a population structure which allows simple reference to single segments of DNA within each gene from any chromosome in the current population. The initialisation function also sets the upper and lower bounds for DNA data to 0 and 100 respectively and sets the constraint that the sum of all values (or individual generating proportions) within a single gene (or yearly outcome) always equals 100. This ensures that the sum of generation in a given year (represented by a gene) is always 100% of yearly demand. Once the data boundaries have been set, each gene that has not been seeded (set to a known or previous value), is filled with random values within these bounds.

5.5.2 Fitness Evaluation

The fitness evaluation function assigns a fitness to each chromosome; where a chromosome represents the possible yearly proportions of electricity generation by each generating method over the whole 40 year forecast period. The fitness calculation uses a general utility function that describes the major, and some of the minor, factors that influence the choice of generation mix in a privatised ESI. The general utility function relies on exogenous variables that are created by relevant forecasts. Details of the functions that describe how electricity is generated within a privatised ESI can be found in Chapter 6. The fitness of each chromosome in the population is stored in the penultimate segment of the chromosome structure where it can be called by both the elitist and selection operators. The evaluation function is first called after initialisation then it is called to evaluate the fitness of every following generation.

5.5.3 Elitist

The elitist function first finds the fittest chromosome in the population and stores it as the last member in the population structure. It also identifies the least fit chromosome in that population. Then, if the fittest member of the current generation is worse than the fittest of the previous generation, the latter replaces the least fit member of the current generation. There is much debate about the advantage of elitist operators. Elitism is often incorrectly viewed as a method of filling the current population with the fittest members of previous generations. This would impair diversity which is critical for the success of all GAs. Correct usage of elitism ensures that the fittest individual is never lost so the population can be kept more diverse which aids the breeding of relatively unfit chromosomes. The breeding of relatively unfit individuals allows the propagation of, often vital, segments of chromosome that might otherwise be lost. Along with mutation this process ensures that the whole search space is considered and reduces the risks of confusing local and global optima.

5.5.4 Selection

There are numerous evolutionary strategies which vary greatly in structure. There are many variations on the mechanisms used to achieve each strategy. However all evolutionary processes can be described in terms of selective pressure and diversity[70]. Selective pressure concerns the fitness level needed for survival and breeding; high selective pressure implies that only the fittest survive. Diversity concerns the range of individuals (chromosomes) within the population and how they represent the whole search space; high diversity implies that the population consists of individuals which originate from a variety of different areas in the search space. Mechanisms that increase selective pressure decrease diversity and reducing selective pressure increases diversity. The reverse is not always true; some mechanisms, such as heuristic mutation, that increase diversity do not always reduce the selection pressure. The importance of maintaining diversity cannot be underestimated. In biological terms diversity forms the essence of survival from disease: An example is the South African Cheetah whose present population is so reduced that it has lost the majority of genetic variation that controls the enzymes responsible for immune response. The result is that most fatal diseases now effect the whole Cheetah population, rather than fractions of the population which was the case when population levels, and immune diversity, were high[71]. In computational terms a lack of diversity causes the omission of high proportions of possible solutions from the search. In this case the algorithm would provide a local optimum in place of the global optimum and give incorrect solutions to the optimisation problem considered.

5.5.4.1 Elitist & Expected Value Selection

The most basic selection methods are based on the elitist selection method where the fittest half of the chromosomes are preserved and the less fit half are removed. The remaining half then breed twice to refill the population. Such methods have high selection pressure and therefore need large populations and high mutation rates to provide diversity. Large populations are computationally intensive and even increasing the mutation rate does not eliminate the tendency for the offspring of very fit, or super-chromosomes, to drown out other individuals that might otherwise contribute valuable genetic material. Another variation, the expected value model, aims to remove the continuous re-selection of the fittest by counting the selection, crossover and mutation operations applied to individual chromosomes and removing them from the population when the count reaches a pre-defined number. The removal of fit chromosomes once their child or mutated forms exist reduces selective pressure and thus aids diversity. The elitist expected value model, a combination of these two methods, gives an efficient compromise[72].

5.5.4.2 Ranking Selection

A second method of reducing premature convergence, due to super-chromosomes, uses a system where the number of offspring from an individual increases with the order of fitness but not proportionally. The chromosomes are ranked in order of fitness then the expected offspring are assigned in a manner that the highest ranked obtains less than twice the offspring of the mid-ranked chromosome[73].

Figure 5.6 shows, along its x axis, a population of ten chromosomes ranked in ascending order of fitness. The graph shows the expected numbers of offspring (over a number of generations) that would keep the population at a constant size. The line that passes through the origin indicates a proportional relationship between rank and breeding. The lines that start at 0.4 and 0.8 show reducing advantage given to fitness in the selection process. The gradient of the line can be used to control the balance between selective pressure and diversity in the population. This balance can be influence to a greater extent by using a non-linear relationship between ranking and selection.

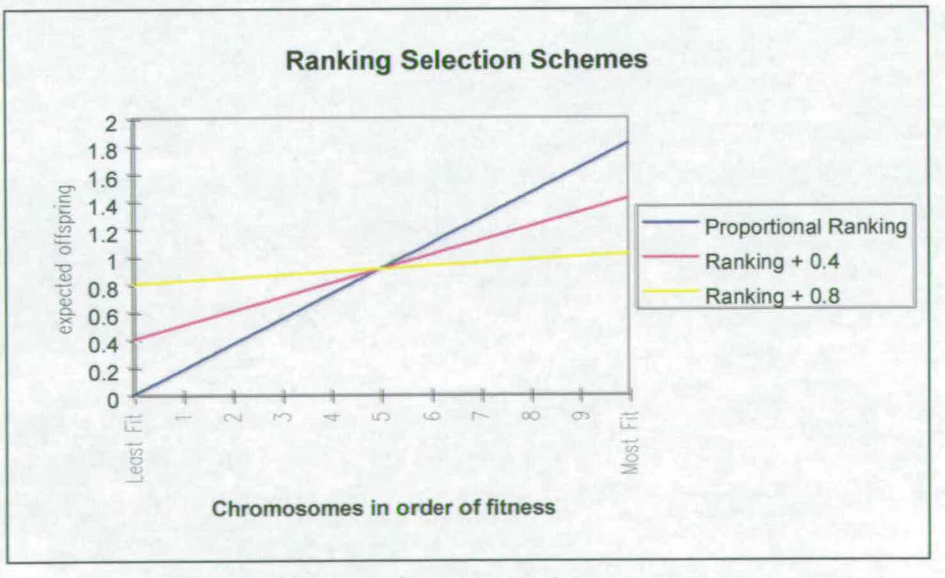


Figure 5.6 Selection based on ranking chromosomes.

5.5.4.3 Tournament Selection

A further method of selection based on ranking is tournament selection[74]. This method randomly selects a number (k) of individuals from the population and keeps the fittest for breeding and mutation. This process repeats until the number of selected chromosomes is equal to the population size. The selected chromosomes undergo breeding and mutation to create the next generation. Larger values of k increase the selective pressure but diversity is maintained until k approaches the size of the population. The drawback of both ranking and tournament methods is that relative fitness of individuals is ignored. For example no account is taken of a chromosome that is twenty percent better than the one ranked immediately below but only two percent worse than the member above it.

5.5.4.4 Roulette Wheel Selection

Including the relative fitness of different chromosomes in selection can prove computationally expensive as the difference in fitness value between each adjacent chromosome must be calculated. This is especially important in the case of the very large problem of modelling generation methods in the ESI. The solution is found in a method of selection known as roulette selection which avoids ranking altogether. Roulette selection assigns a probability of selection based on the fitness of each chromosome relative to the fitness of the whole population. A roulette wheel is constructed with slots sized according to the proportional fitness of each chromosome. GAMES uses this method in the following manner:

1. The fitness value (f_n) of each chromosome (C_n) (where n = 1,2,3,.....Pop Size) is calculated.

2. The sum of f_n in the population is calculated giving the total population fitness (F).

where $$\boldsymbol{F} = \sum_{n=1}^{PopSize} f_n$$ **Equation 5.6**

3. Each individual's proportion of total population fitness, or relative fitness (r_n) is calculated.

where $$\boldsymbol{r_n} = f_n \,/\, F$$ **Equation 5.7**

4. The cumulative fitness (u_n) is calculated for each chromosome.

where $$u_n = \sum_{i=1}^{n} r_i$$ **Equation 5.8**

5. As all values of u_n lie between 0 and 1 and their spacing is relative to their proportional fitness, a random number between 0 and 1 will have a chance of finding each space between chromosomes c_{n-1} and c_n that reflects the proportional fitness of the upper chromosome c_n. This process of spinning a roulette wheel is repeated over a number of times that equals the population size. Each spin selects a chromosome and copies it into a new selected population that is the same in size as the previous population.

6. The new selected population reflects the proportional fitness of each chromosome and is used in the selection of parents for breeding (cross over) and mutations which will finally create the next generation. Each member of the selected population has an equal opportunity for breeding and mutation although the selected population will contain multiple copies of the fitter chromosomes.

This is the most efficient method of including proportional fitness differences whilst maintaining a balance between selective pressure and diversity. The random element keeps the selection process true to the Schema Theorem[75]; that all members of a population must have a chance, however small, of breeding. The random element also reduces the premature convergence that can be caused by over breeding of super-chromosomes. This problem can be further reduced by adjusting the relationship between proportional fitness and selection rate so that a twenty percent fitter chromosome may only produce fifteen percent more offspring. GAMES uses roulette selection along with a simple elitist function that ensures that the single fittest chromosome in the population always has an opportunity to breed. This combination along with an equal opportunity for breeding and mutation across the selected population provides a stable basis for the evolution of optimum solutions whilst allowing enough control, through mutation and crossover rates, for the adaptation of the GA to different ESI scenarios.

5.5.5 Crossover

Breeding is achieved through the process of crossover. Crossover involves the creation of offspring chromosomes through the combination of parent chromosomes. There are many ways by which parents can be combined to create child chromosomes, each with their own advantages. These methods of crossover can be grouped into three classes of operator:

1. Arithmetic combination that concerns the value of each gene and uses a combination of each parent's genes.

2. Heuristic crossover will always create children which are fitter than their parents. In depth knowledge of the problem is necessary to be able to apply this method successfully.

3. Segment crossover techniques involve the exchange of genes between parents to create child chromosomes.

It has become standard practice for the control of GAs to include a crossover adjustment. This is normally in the form of a control over the probability of crossover. The standard term for this control is the crossover rate.

5.5.5.1 Crossover Rate

Crossover operators act on the selected population which consists of chromosomes whose frequency within the population reflects their relative fitness. The probability of crossover is dependent on a crossover rate. The crossover rate is simply the probability, between zero and one, of a single chromosome within the selected population being chosen for crossover. High crossover rates reduce the diversity of the population and can cause premature convergence. Crossover rates that are too low restrict the exchange of genetic data between individuals and slow down the evolutionary process. An ideal crossover rate balances premature convergence with evolutionary progress. Crossover rates are problem specific and should be adjusted through experimentation. GAMES uses a figure of 0.8 as a default value as this has proved to be a successful figure. The evaluation of this 0.8 crossover rate involved monitoring the standard deviation of chromosome fitness' within consecutive populations over numerous optimisations. If this deviation was found to drop before an optimum was found a lower crossover rate was used. Conversely if the GA did not converge, or if convergence took longer than expected, the crossover rate had to be increased.

5.5.5.2 Arithmetic Crossover

This class of crossover operator creates child chromosomes through an arithmetic combination of the parent's genes[76]. It is often defined as a vector operator although this would not apply to the GAMES GA as each chromosome represents more than a single binary number. If the standard arithmetic crossover is applied to two parent chromosomes (P_1 and P_2), each parallel pair of genes (x_1& y_1, x_2& y_2,....... x_n& y_n) is operated upon:

$$P_1 = (x_1, x_2, x_3, \ldots\ldots x_n) \qquad \textbf{Equation 5.9}$$

and

$$P_2 = (y_1, y_2, y_3, \ldots\ldots y_n) \qquad \textbf{Equation 5.10}$$

where: n = chromosome size (or number of forecast years in GAMES)

Standard Arithmetic crossover would give two child chromosomes (C_1 and C_2):

$$C_1 = (x'_1, x'_2, x'_3, \ldots\ldots x'_n) \qquad \textbf{Equation 5.11}$$

and

$$C_2 = (y'_1, y'_2, y'_3, \ldots\ldots y'_n) \qquad \textbf{Equation 5.12}$$

That are created subject to the operators:

$$x'_n = \mathrm{r}x_n + (1-r)y_n \qquad \textbf{Equation 5.13}$$

and

$$y'_n = \mathrm{r}y_n + (1-r)x_n \qquad \textbf{Equation 5.14}$$

where: r = random value
and: $= 0 \le r \le 1$.

This method is also known as intermediate crossover, linear crossover or guaranteed average crossover when r is set to a constant value of 0.5. Arithmetic crossover cannot be applied to the GAMES GA as each gene is not a simple arithmetic value that can be manipulated, but a complex string of DNA representing a years proportions of electricity generation by different methods.

5.5.5.3 Heuristic Crossover

Heuristic methods use the fitness of each parent to try to produce child chromosomes that are fitter than their parents. Simple hill climbers, which are iterative procedures that find peaks in graphs, use heuristic methods where some random fraction of the difference between two attempted solutions is added to the greater of the two in the search of a maximisation. As there is a high probability that the new solution will fall out with the search space this method can prove computationally expensive. In problems with complex GA representation, such as with GAMES, the evaluation of individual genes that will provide fitter child chromosomes is very difficult. Other Heuristic crossover techniques simply evaluate the offspring and remove children that are less-fit than their parents. This method dramatically increases selection pressure and reduces the diversity of the population. Heuristic crossover is therefore only used in the fine-tuning of solutions or in cases where the best direction for the search has previously been determined by a different GA.

5.5.5.4 Segment Crossover

Segment crossover techniques involve the movement but not the changing of gene's values. Taking our two parent chromosomes (P_1 and P_2):

$$P_1 = (x_1, x_2, x_3, \ldots\ldots x_n) \qquad \textbf{Equation 5.15}$$

and

$$P_2 = (y_1, y_2, y_3, \ldots\ldots y_n) \qquad \textbf{Equation 5.16}$$

where n = chromosome size (or number of forecast years in GAMES)

The simplest version of this method of breeding is the single point crossover. A single point (k) is randomly chosen along the chromosome and all the following genes are swapped between parents to create two children (C_1 and C_2):

$$C_1 = (x_1, x_2, x_3, x_k, y_{k+1}, y_{k+2}, y_{k+3}, \ldots\ldots y_n) \qquad \textbf{Equation 5.17}$$

and

$$C_2 = (y_1, y_2, y_3, y_k, x_{k+1}, x_{k+2}, x_{k+3}, \ldots\ldots x_n) \qquad \textbf{Equation 5.18}$$

This method is not suited to binary chromosomes, that represent a single number where each gene represents a single bit, as the offspring may be out with the bounds set for chromosome values. Segment crossover is more suited to larger problems, such as GAMES, that use complex representation of chromosomes and need to keep gene integrity. Representation strategies that use each gene as a value, or group of values, can use segment crossover to provide model stability by ensuring that each gene is kept whole. As GAMES fits into this representation category it is a perfect candidate for segment crossover and initially used a single point crossover. In this case, where each gene represented the yearly primary energy mix in generation, the crossover took the first years from one parent and the final years from the other parent to make a new solution, or child chromosome.

The disadvantage of single point crossover is that the offspring always inherit a chromosome end from each parent which limits the number of possible children. The simplest solution to these limitations is found through the use of two point crossover. This uses the same rules as the single point method, but uses two randomly selected points (k and m) along the chromosome, between which genes are swapped to create two children. Using this method on two parents P_1 and P_2 (defined above) would give two offspring:

$$C_1 = (x_1, x_2, x_3, x_k, y_{k+1}, y_{k+2}, y_{k+3}, y_m, x_{m+1}, x_{m+2}, x_{m+3}, \ldots . x_n) \qquad \textbf{Equation 5.19}$$

and

$$C_2 = (y_1, y_2, y_3, y_k, x_{k+1}, x_{k+2}, x_{k+3}, x_m, y_{m+1}, y_{m+2}, y_{m+3}, \ldots . y_n) \qquad \textbf{Equation 5.20}$$

This method allows the crossover of any single gene, single group of genes or chromosome end in the creation of child chromosomes. This method is simple, efficient and provides a good compromise between effectiveness and computational expense[77]. It has proved to be the best breeding method for the GAMES GA although forthcoming increases in CPU speeds may allow more complex methods of crossover. Two point crossover allows groups of yearly primary energy mixes to be passed between parents. The groups can vary in size from a single year to chunks as large as the chromosomes themselves.

A progression that could be implemented would be to use multiple crossover points (even numbers only) which, although too computationally expensive at present, might allow the GA to explore more possibilities at each generation. A further possibility is the use of uniform crossover. This method randomly chooses a probability of crossover which is applied to each gene in the parent chromosomes. Individual genes rather than segments are swapped. Although sometimes efficient this will, when applied to GAMES, reduce the transfer of small trends in generating method.

5.5.6 Mutation

Mutation involves the random change of one or more genes in a selected chromosome. The probability of a mutation occurring is governed by the mutation rate. Mutations introduce extra variability into the chromosomes which increases diversity. It is through this process that the whole search space is investigated during a GA search or optimisation. There are many forms of mutation with the standard operator being uniform mutation which are defined in Section 5.5.6.2. There is a case for a mutation strategy that changes as the optimisation process progresses; allowing for a coarse start and a refined end to the search. Non-uniform mutation, highlighted in Section 5.5.6.3, allows this in a controllable manner. Other operators include problem specific operators such as Flatten and Recall which are discussed in Sections 5.6.3 and 5.6.5 respectively.

5.5.6.1 Mutation Rate

The mutation rate defines the chance of a single gene, within the whole population of chromosomes, undergoing a mutation. Typical values of mutation rate (m) when using a uniform mutation strategy are:

$$\boldsymbol{m} < 1 \,/\, (\text{no. of genes in a chromosome}) \qquad \textbf{Equation 5.21}$$

Higher values of m will result in a mutation in every chromosome which will increase diversity to such an extent that convergence on an optimum will become matter of random chance rather than by evolution. Within the above constraint higher rates will give a better view of the whole search area due to an increased diversity. Lower mutation rates are useful for refined searches to finalise the optimum point, as at such times diversity can be reduced to bring about a more precise search. A period of forced high mutation rate after the GA has converged on an optimum will move it away from local optima but not a global one. This is an effective test for premature convergence

5.5.6.2 Uniform Mutation

Uniform Mutation is the standard GA mutation operator. Each gene of the new population has an equal probability of selection for mutation. This probability is controlled by varying the mutation rate. The selected gene (g) then undergoes some random change that will not destabilise the model. Normally each gene represents a single number that lies between an upper bound (UB) and a lower bound (LB). This must be kept valid through the use of a mutation function. The mutated gene (g') is kept within these bounds by applying a 50% chance of:

$$g' = g + r(UB - g) \qquad \textbf{Equation 5.22}$$

or a 50% chance of

$$g' = g - r(g - LB) \qquad \textbf{Equation 5.23}$$

where r = random number that satisfies $0 \le r \le 1$

However each gene in GAMES represents the proportion of demand met by each of the included generating methods (DNA) and the sum of these values must always equal 100. This complicates the mutation process as a gene that is selected for mutation must always consist of DNA members (D) that satisfies:

$$0 \leq D \leq 100 \qquad \textbf{Equation 5.24}$$

and

$$\sum_{1}^{n} D_n = 100 \qquad \textbf{Equation 5.25}$$

where n = number of DNA members (or generation methods) included in each gene.

This is achieved by mutating the DNA members (D_1,..... D_n), from the selected GAMES gene (G), in randomly chosen pairs (*j and k*), one negatively and one positively. The mutated gene (G') can be found if:

$$G = (D_1, D_2, D_3, D_4, D_5, D_6, \ldots\ldots D_n) \qquad \textbf{Equation 5.26}$$

$$G' = (D_1, D_2, \{D_j+((100 - D_3)r)\}, D_4, D_5, \{D_k-((100 - D_3)r)\}, D_7, \ldots D_n) \qquad \textbf{Equation 5.27}$$

where r = random number that satisfies $0 \leq r \leq 1$

However if the value of the second chosen DNA is not able to compensate for the alteration of the first chosen member and:

$$D_k-((100 - D_j)r) < 0 \qquad \textbf{Equation 5.28}$$

Then D_k is set to zero and the remaining value (which will be negative) of $\{D_k-((100 - D_j)r)\}$ is added to another gene. If this DNA goes negative the remainder is, once again, passed on. This continues until the whole gene satisfies all constraints. If, after a number of tries, it is still not possible to satisfy the DNA constraints the mutation is declared void.

5.5.6.3 Non-Uniform Mutation

As large mutations increase diversity it is efficient to include a function that will reduce the effect of mutations as the optimisation process progresses. This helps to include the whole search space at the start of the optimisation and to allow for a more refined search around the optimum when it has been found. This can be achieved by reducing the magnitude of individual random mutations (r) near the end of the process. GAMES uses a non-uniform mutation operator[78] on each DNA member (D) within the gene that has been selected for mutation. As with the uniform mutation method DNA members are chosen in random pairs (*j and k) and adjusted inversely* so that the sum of DNA members always equals 100. The operator is dependent on the ratio of generations that have been completed (t) to the number of generations expected (T) and uses this ratio with a mutation factor (F) in the form of a 50% chance of the mutated DNA member *(D')*:

$$D'_j = D_j + \left(100 - D_j\right)\left(1 - r^{\left(1 - t/T\right)^F}\right) \qquad \textbf{Equation 5.29}$$

And the corresponding randomly chosen DNA member pair will undergo:

$$D'_k = D_k - \left(D_k\right)\left(1 - r^{\left(1 - t/T\right)^F}\right) \qquad \textbf{Equation 5.30}$$

where r = random number that satisfies $0 \leq r \leq 1$

F is inserted as the exponent of $(1-t/T)$ so that it can alter the rate by which mutations are reduced as the optimisation nears its end and t/T tends to 1. As the mutation factor tends to 0, $(1-t/T)$ tends to 1 and the operator tends to a uniform mutation. Higher mutation factor values exponentially reduce the magnitude of individual mutations as the process nears its end.

GAMES uses a non-uniform mutation that initially offers a default mutation factor setting of four. This default value has proved efficient but can be altered by the user if necessary. This is a simple method of improving the mutation operator as it is computationally inexpensive and robust. Other mutation strategies use heuristic methods which involve the evaluation of mutations before the mutated chromosomes are re-released into the current population. These methods waste computational resource whilst also reducing overall diversity: By killing off mutated chromosomes that would otherwise have a chance of breeding, and passing on possibly vital genetic material, heuristic methods of mutation have not yet proved themselves worth their costs[79]. However these methods can be employed towards the end of the optimisation process when diversity is not so important. Games contains one heuristic mutation operator called flatten. This function is outlined in Section 5.6.3.

5.6 Advanced GAMES genetic operators

The inclusion of non-standard operators has caused a discrepancy between the terms Genetic Algorithm (GA), Evolutionary Algorithm (EA) and Modified (or hybrid) Genetic Algorithm (MGA). Traditionally all GAs were only binary representations of problems and, due to their relative simplicity and standard form, they have been well researched and understood. The introduction of non-standard operators has resulted in the re-evaluation of much of that part of the previous understanding which is still relevant, but subject to the operators being used within the algorithm. GAMES fits into the category of MGAs but efforts have been made to keep the GAMES GA within the known theoretical bounds of traditional GAs. The use of non-uniform mutation, seeding and fruit machine operators, as discussed in their respective Sections 5.5.6.3, 5.6.1, and 5.6.2, does not deviate from this theoretical basis. The exceptions to this are the inclusions in GAMES of two new operators, outlined in Section 5.6.3 and 5.6.5, called Flatten and Recall respectively. The first of these new operators is the flatten operator that utilises a component of robotic control which smoothes a robot's path around obstacles. It looks at the yearly generation from a particular primary energy and removes the peaks and troughs. As excessive peaks and troughs in yearly generation are rare, this operator simply pushes the algorithm along its natural path. The recall operator is also novel and has not been used in GA applications. It is fundamentally different to previous GA operators as it allows a limited amount of genetic data transfer across generations. This gives the GA a memory of where it has been thus allowing it to make multiple backward steps if necessary.

5.6.1 Seeding

During the initialisation of a GA the starting population must be set. The simplest way to fill this initial population is with random possible solutions. Hopefully this should give a representative cross-section of the whole search space. Better diversity could be achieved through repeated random selections ensuring that the whole search space is considered. Another option is to run the GA with a very large, randomly created, initial population to find the region of the optimum within the search space. A high mutation rate would further increase the diversity of this large search. Then the GA could be re-run, seeded with a smaller population, from within the region of search space known to contain the optimum. This second level of optimisation should be set up for a more refined search; low levels of mutation and high selective pressure. An old population can also be used as a seed when exogenous variables have been slightly changed. This can vastly reduce convergence time as the old population should be in the correct region of the search area. To allow this it must be possible to store old populations and use them as initial populations. GAMES allows for this whilst also allowing the user to edit the initial population. Creating a known population that is far from a known optimum is a valid method of searching other areas of the search space. As the population moves towards the known optimum its progress can be logged and viewed graphically. This is an effective method of assessing the performance of the GA and benefits of new operators.

5.6.2 Fruit-Machine

Previous models of the ESI used a yearly iterative process which has to approximate the effects of a future event on the present, whilst the present always has an effect on the future. For example the more gas used today the less there would be in the future; but if planners knew that gas would soon become scarce, and more possibly expensive in the near future, less long term gas based generation strategies would be implemented. The GAMES model is dynamic and able to solve such inter-dependencies over time. This has been achieved by solving across the whole forecast period simultaneously, a task made feasible through the use of a dedicated GA. An unavoidable result of this is that the system cannot be shocked by a previously unknown events. Energy system planners need to investigate the effects of unknown events to test for the stability of their strategies.

The Fruit-Machine operator, so called because of its user interface in GAMES, allows the user to *hold* individual years by fixing all the genes in the population that represent years that are not to be changed. This allows the user to re-run a scenario, with an unexpected event added, and hold the preceding years to investigate the outcome of the event. To achieve this the user must first run the GA without including the unforeseen event. Each chromosome (C) is represented by:

$$C = (y_1, y_2, y_3, y_4, y_5, y_6, y_7, y_8, y_9, \ldots\ldots y_p) \qquad \textbf{Equation 5.31}$$

where p = population size.
and y_n = an individual gene representing a years generation strategy.

Once optimised, the population must be saved. The unforeseen event, such as an oil price shock, can then be added by altering the exogenous variables. The GA must be seeded with the previous population but holding all the years preceding the shock; gene (or year) six in this example. All the seeded chromosomes (C^{held}) will now have a number of held genes which can not be altered by the genetic operators.

$$C^{held} = (y_1^{held}, y_2^{held}, y_3^{held}, y_4^{held}, y_5^{held}, y_6^{price\ shock}, y_7, y_8, y_9, \ldots\ldots y_p) \qquad \textbf{Equation 5.32}$$

Then the GA can be re-run to investigate the outcome of the shock. As the second forecast will contain less genes (years) the length of each chromosome is shortened. Shorter chromosomes reduce the size of the search space which increases the speed of the optimisation.

5.6.3 Flatten

GAMES is an electricity generation led model; it forecasts the generation by different methods then calculates whether there is enough capacity and builds extra plant if necessary. Although there is considerable volatility in all privatised electricity markets sudden changes from one generating method to another are, without external or resource influence, uncommon[80]. To help the optimisation process include this a function called Flatten has been included in the GAMES GA.

The Flatten operator is similar to smoothing operators used in GA based robotic path finding[81] which smoothes the robots path around obstacles. The Flatten operator, used in GAMES, is a heuristic mutation function as described in Section 5.5.6.3. It is called with a probability set by the mutation rate, which is a user defined figure for the probability of mutation in an individual gene within the population, as defined in Section 5.5.6.1. It works by taking a random string of genes adjacent to the selected gene and replacing an individual DNA with the average values across the chosen genes. In energy terms it randomly selects a section of the forecast period, from two years upwards, then it averages out sudden changes in generation method. As it is a heuristic method, which can cause a reduction in diversity, it is not used until the final stages of an optimisation by using the inverse of the mutation factor described in Section 5.5.6.3.

5.6.4 Radiate

Radiate is a simple operator that involves pushing the population away from an optimum. If the population consistently returns to that same optimum result it can be concluded that the global optimum has been found. The operator is called by the operator through the *Radiate* button. It works by temporarily increasing the mutation rate whilst continuing the evolutionary process. The high mutation rate increases diversity allowing the GA a better view of the whole search space. To ensure that this is effective the mutation factor, defined in Section 5.5.6.3, is reduced to zero, providing uniform mutation. Uniform mutation is necessary as Radiate is used near the end of an optimisation where mutation factors other than zero would reduce the possible size of mutations and therefore limit the ability of the algorithm to examine the whole search space.

5.6.5 Recall

GAs are based on evolution. Evolution evokes thoughts of Darwin, apes and humans. A better analogy is the simplest bacterium, containing a single chromosome that can undergo the simplest mutations and reproductive methods. Using a bacterium as a rough guide GAs have proved efficient in utilising computational power to solve difficult optimisation problems.

However the drive to improve on existing GAs continues as the problems attempted to be solved by this method, and their solutions, become more complex. It is therefore necessary to try and adopt some of the evolutionary mechanisms that differentiate between the simplest bacterium and more complex systems.

It is now widely believed that animals and plants contain more than one set of genetic code. Complex life-forms contain both duplicate and old, disused, genetic code although this extra information often serves little or no purpose in the life, growth or reproduction of the individual. In fact only 4% of human genetic material is used in protein construction, the remainder has no apparent use other than genetic storage[82]. The mechanisms by which this came about are complex and out-with the scope of this study but the effects are relevant. As the unused genetic material is subject to mutation rates similar to those of the used genetic material many mutations can occur without causing an immediate effect on the individual. This allows the carrying or storing of mutated (sometimes severely) and old information without causing deaths and therefore the loss of the mutated information. The result is that the population can adapt more quickly to environmental changes; as small mutations (or irregularities during breeding) can bring out hidden characteristics within the population.

It is possible to give a GA extra storage chromosomes to emulate the copies of chromosomes that exist in animal and plant life. This has been applied to the GAMES GA through storing random chromosomes, that are neither the best or worst in the population, and breeding them with the current, visible, population as a rare mutation in the current population. Not only does this process aid diversification but also reduces the negative impacts of mapping. By allowing the survival of solutions, if only for relatively few generations, that would either die or be mapped elsewhere in the search-space the possibility of passing through an improbable set of solutions to arrive at a possible optimum is not eliminated. This should become one of the steps necessary to help the evolution of GAs from bacterium equivalents into more advanced forms. The only disadvantage in the inclusion of this process is the increase in computational resource.

5.7 Summary

Genetic algorithms are powerful optimisation tools which use the speed of modern computers to actively evolve solutions to problems. They are vastly quicker than random searches and enhance the examination of more complex search areas than is possible using simple hill climbing techniques. The principle behind hill climbing algorithms, or all gradient sensitive iterative techniques, is that the optimum solution will be found at the highest peak. GAs also optimise to the highest peak, or lowest trough, but in addition can operate with multiple hills in the search space. This is achieved by the inclusion of the random element in mutation, without which GAs are simply inefficient hill climbers. The most effective mutation operators are problem specific as they can serve to omit unnecessary areas of search space. This chapter has discussed the application and theory behind two new mutation operators. Although both of these operators are problem specific the application of flatten and the structure of recall should prove useful in this and a multitude of different GA optimisation problems.

6. FITNESS FUNCTION COMPONENTS

6.1 Overview

The functions that describe the ESI have been chosen to satisfy the following requirements:

- Sufficient complexity has been included to describe the ESI with enough detail to base a study into its future.

- A limit has been imposed on the amount and size of endogenous functions to reduce computational expenditure and the time needed to find an optimum solution.

- Flexibility has been built into the compiled software to allow the user to change the state of many of the functions via the exogenous variables at run-time, rather than only by the programmer during the building of the model.

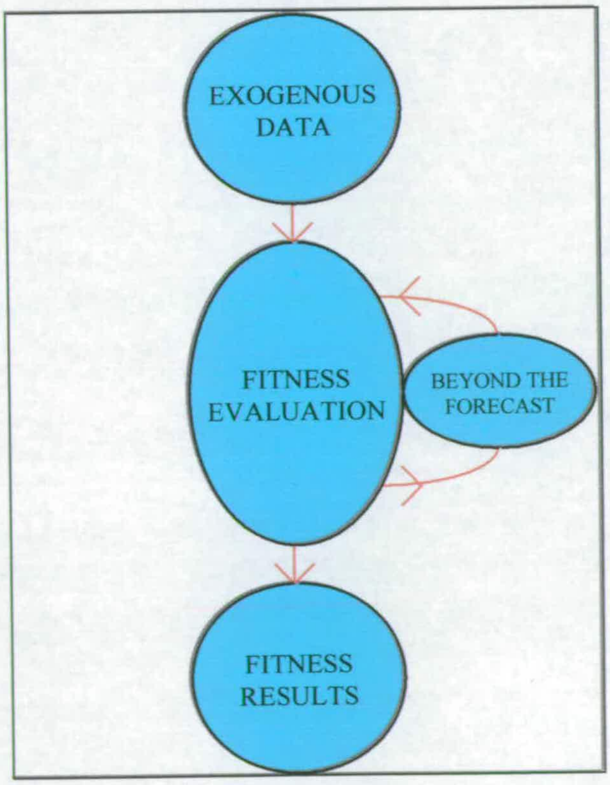


Figure 6.1 The ESI Model Within the GA Fitness Function of GAMES.

As the ESI forecasting model is solved using a Genetic Algorithm (GA) all the endogenous functions that describe the ESI lie within the GA's fitness function. The design of the GA itself allows the fitness function to be changed without having consequential effects on the optimisation of the model. Conversely the user of GAMES can make large changes to the model itself, through the manipulation of exogenous variables, or even by editing the code within the fitness function, without having to change the GA that solves the model.

This chapter takes the GAMES GA, which provides possible solutions and then optimises them to find the most likely solution, and separates from it, the fitness function, which describes the ESI. The GAMES fitness function contains the model of the ESI. Each of the critical constituent parts of the fitness function are explained and their relevance to the model as a whole is discussed. The constituent parts of the ESI fitness function, or evaluation functions, are illustrated in Figure 6.1. Exogenous data concerns the variables that will have an effect on the model itself. These can be historical, for validation of the model or predicted based on possible future scenarios. The evaluation functions are described fully in Sections 6.2 to 6.22 and are as follows:

6.2 Fitness evaluation
6.3 Demand for electricity in both peak and yearly values.
6.4 Non renewable resource changes due to consumption or scenario changes.
6.5 Renewable resources and their relative costs.
6.6 Capacity based on plant, resource, and possible emissions constraints.
6.7 Generation of electricity within existing capacity to meet a present demand
6.8 Plant lifetime load factor calculation and use.
6.9 Heat rate and calorific values.
6.10 Plant construction needed to meet both peak and yearly generation needs.
6.11 Operating & maintenance costs
6.12 Contractual arrangements and their effects on the ESI.
6.13 Externalities and their associated costs.
6.14 Fossil fuel combustion for emissions calculations.
6.15 Emissions reduction and associated costs.
6.16 Environmental taxes as fixed and variable costs for each generation method.
6.17 Risk strategy and costs.
6.18 Fixed costs of new or upgraded plant.
6.19 Variable costs of generation.
6.20 Returns from generation, per unit or contractual.
6.21 Beyond the forecast, which allows calculations beyond the forecast period.
6.22 Fitness result calculations.

These functions are valid within the forecast's time period. In order to eliminate errors due to unrealistic outcomes beyond the forecast's time period an additional set of functions are needed to continue solving beyond the forecast's time period. These functions, that consider events beyond the forecast, operate by recalling selected fitness function parts and applying them forwards beyond the forecast. Section 6.21 discusses this process in detail. The fitness function's results are used by the GA to evaluate the chances of survival for each attempted solution to the generation spread problem.

6.2 Fitness Evaluation

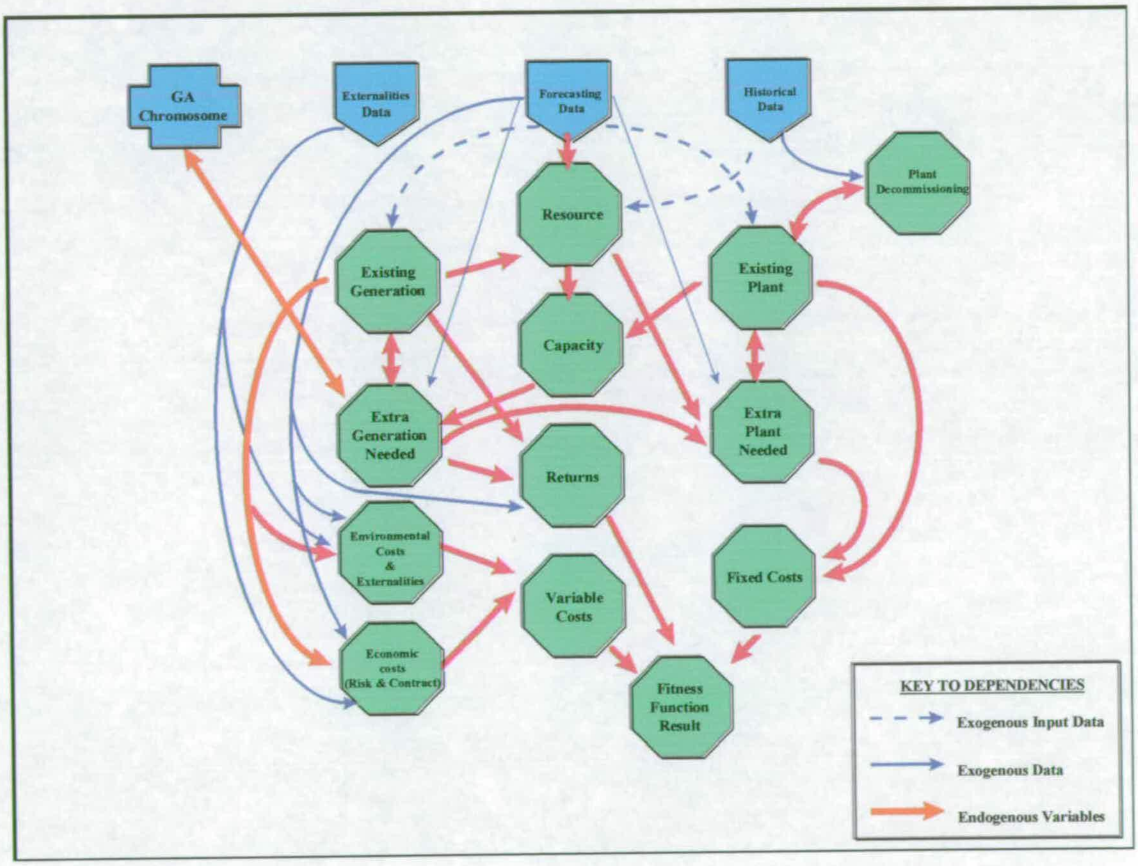


Figure 6.2 Schematic of ESI Fitness Function.

The fitness, or evaluation, function forms the most critical part of any GA. The structure of the GA itself (the selection breeding and mutation strategies) depends on the structure of the fitness function. This section details the functions within the GAMES fitness function. Figure 6.2 shows the complexity of the function's outline and how the graphical representation of large-scale models can be difficult to comprehend. Its task is simply to give a grade, for the purpose of comparison, to possible solutions of the forecasting problem.

6.3 Demand

The demand for electricity is rapidly increasing world-wide. In developing countries the rate of increase is far greater than that of more developed nations. The demand in developing countries is being pushed by the increase of energy consuming products that are replacing traditional methods of agriculture, production and transport. The supply and distribution of electricity in these countries is often not able to meet the increased demand. The planning of new generating facilities is regularly based on a *maximum output* basis. Figure 1.1 shows predictions made in 1991 for the demand for electricity until the year 2010.

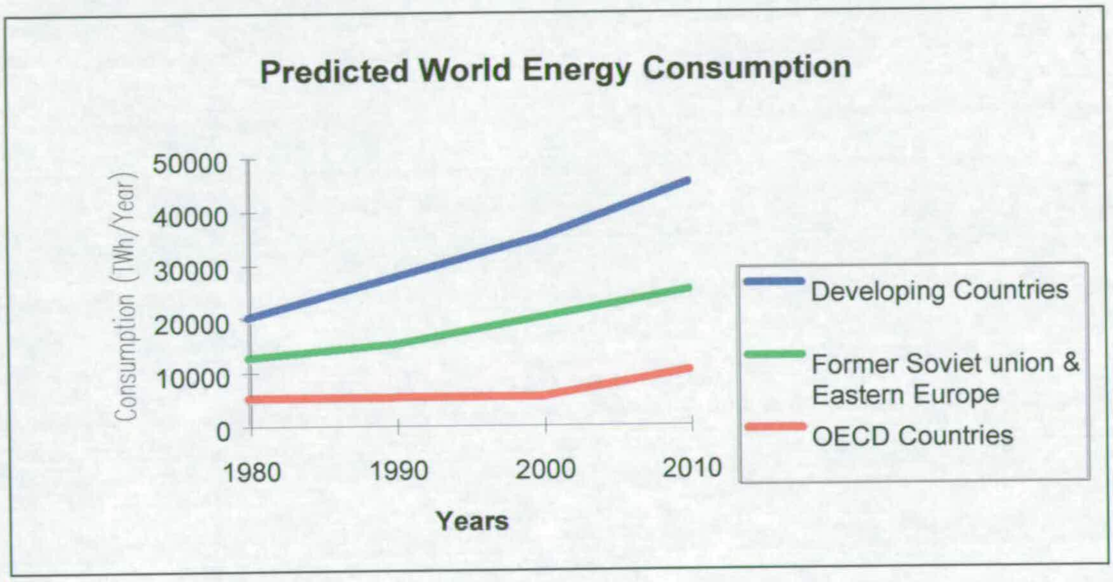


Figure 6.3 Predicted Energy consumption until the year 2010.[83]

In the UK future energy requirements are predicted using models based on past energy usage. This is often performed using data from industrial and domestic meter readings. Factors such as Gross Domestic Product (GDP), population and consumer goods trends are also used in demand modelling. In Britain the demand for electricity varies greatly with climatic conditions. In winter the peak load is almost twice that of the summertime peak load. The demand for electricity also varies considerably on an hourly basis as industrial and domestic sectors use more or less energy. Predicting the demand is therefore very complicated. To allow for such a complicated demand curve the scheduling and despatch of plant must be flexible to allow for errors in demand forecasts. As electricity cannot be stored some generators must be able to synchronise and accept load with little warning to cope with peak loads. This generally involves a different type of technology to that of base load generation. Therefore plans for constructing new generating plant rely greatly on long term demand forecasts.

Long term forecasts of electricity demand in GWh (yearly energy usage) can be used to plan for the generation needed to satisfy the demand. Yearly generation forecasts can give an indication of the minimum plant needed to provide the load however to create an accurate model of plant the yearly peak demand (GW) is needed. Peak demand can be predicted using similar methods to the yearly demand. However to create a comparison between peak demands over a number of years, a correction for the possibility of bad weather coinciding with a peak demand period must be made. This is accomplished by using a common weather base which includes an average cold spell (ACS) correction. The ACS is defined as "..that combination of weather elements which give rise to a level of peak demand within a financial year which has a 50% chance of being exceeded by weather variations alone"[84]. The methodology by which peak demand is corrected for ACS conditions can be considered as two separate functions:

- Firstly the demand/weather coefficients are estimated based on historical demand and weather data for the hours 17:00 to 19:30 (high probability hours for UK peak demand) during the period from late October to late March (high probability months for ACS conditions).

- Secondly the actual demand is corrected for the ACS using 30 years of standard weather conditions obtained from regional weather stations across the UK. This correction is derived from the deviation between the demand/weather coefficient and the actual days weather conditions.

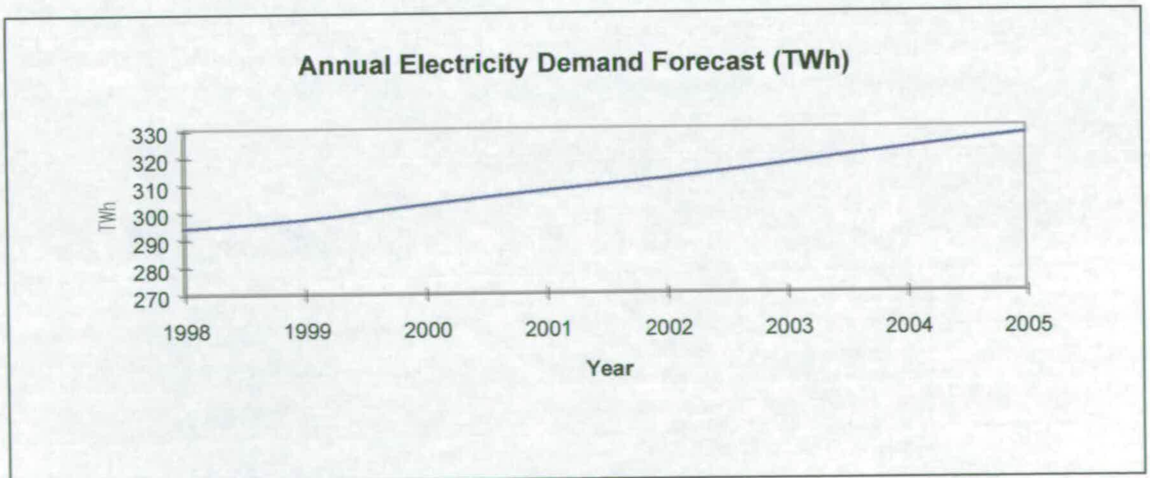


Figure 6.4 Annual Electricity Requirements Forecast from 1998 to 2005[85]

The National Grid Company's seven year statement provides figures for both annual energy requirement (TWh) and the ACS adjusted peak demand (GW) until the year 2005[84]. Longer term forecasts of these variables can be obtained on a percentile variation basis although the latter also requires predicted ACS conditions. These are applied to GAMES as exogenous data sets, within the exogenous forecasting data field, which can easily be manipulated to create different possible future scenarios upon which sensitivity analysis can be performed.

6.4 Non Renewable Resource

Non renewable methods of electricity generation include the use of fossil and nuclear fuels. The former includes the combustion of natural gas, coal or oil to convert the energy into heat which is used in a steam cycle to drive turbines. Both natural gas and *gassified* coal can be used in a combined cycle using the expansion of the gasses along with the steam cycle for a more efficient method of generation. The benefits of this process are detailed in Chapter 2. Combined cycle generation overcomes the maximum steam engine efficiency limit due to the Second law of Thermodynamics[86] and allows efficiencies of over 50% . Electricity generated through nuclear fission also involves a steam cycle that is subject to the same thermodynamic maximum efficiencies.

When calculating non renewable resource the possibility of importing the fuel must be included with the indigenous reserve. The resource limit is therefore a fiscal one as indigenous production costs must be less than the import value to make them viable. Once the indigenous reserves near depletion, and become more expensive to obtain, the cost of the fuel can no longer be held down by the internal market. The result on electricity generation is a higher uncertainty for the continued supply of that particular fuel. As higher risks mean higher unit costs, the ability of that method of generation to compete against another is reduced. The known domestic and world fossil fuel reserves are as follows:

	OIL (million barrels)	**GAS (cubic metres)**	**COAL (million tonnes)**
UK	4,600	0.6×10^{12}	3,800
WORLD	136,700	142×10^{12}	1,039,182

Table 6.1 World and UK fossil fuel Resource[87].

	OIL (Btu)	GAS (Btu)	COAL (Btu)
UK	2.88×10^{16}	2.16×10^{16}	1.01×10^{17}
WORLD	5.468×10^{18}	5.11×10^{18}	2.77×10^{19}

Table 6.2 World and UK fossil fuel Resource in Btu (Converted through million tonnes of oil equivalent $\cong 40\times10^{12}$ Btu $\cong 10^3$ teracalories $\cong 397\times10^6$ therms).

Fossil fuels are not used solely for electricity generation. As much as 70% of the UKs crude oil goes into the petroleum refineries, 27% is exported and only 0.8% goes to electricity generation. Only 20% of natural gas is used in CCGT whilst over 80% of the UKs indigenous and imported coal is used in generation. Nuclear fuel is all imported and, except for a tiny contribution to research institutions, this fuel goes into the UK's nuclear reactors. Much of the spent fuel can be reprocessed and some of this reactive material is converted for reuse which increases the overall efficiency of the fuel.

GAMES includes non renewable resources within the exogenous forecasting data field. The existing available resource (a_n) in year 1 ($n = 1$) for each non renewable method of generation is included, in TWh, before the first year of the forecast period. Each consecutive year calculates the energy used in generation (e_n) and subtracts this from the existing available resource. In addition the available resource is reduced by an exogenous value of resource usage by industries other than the ESI (i_n) converted into TWh. The result gives the resource available for generation in the following year (a_{n+1}) i.e.:

$$a_{n+1} = a_n - e_n - i_n \text{ (TWh)} \qquad \textbf{Equation 6.1}$$

where: n = year of forecast

There is also a facility to force an increase, or decrease in the known available resource in any year. This is achieved by altering i_n, the yearly exogenous value of resource usage by industries other than the ESI.

6.5 Renewable Resources

There is enough renewable energy potential within the UK to easily satisfy the present demand for electricity. Figure 2.2 shows how the largest resource lies in offshore wind energy. Unfortunately having a windy coast line does not, in itself, provide electricity. In fact the costs involved in building and maintaining an offshore wind farm are presently so high that large scale generation using this resource is not competitive. The location of a renewable resource is also critical. For example the transmission costs involved in transporting electricity from the Highlands of Scotland are sufficient to make many possible hydro projects unfeasible.

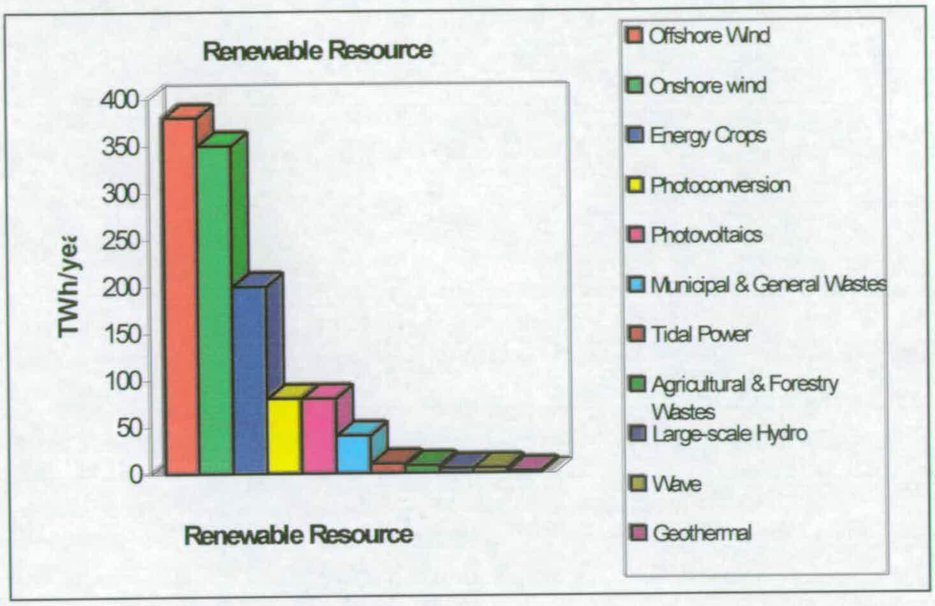


Figure 6.5 Accessible renewable resource at a cost of less than 10p/KWh or less using 8% discount in 1992[88] (note that the current market price for electricity ≈ 2.7p/kWh).

Improvements in technology will increase the availability of many resources in the near future. However there will always be a difference between the gross theoretical resources and the net exploitable potential. Obtaining a practicable value for renewable resources in the UK includes many factors that are difficult to quantify such as:

- The cost of covering our landscape with wind turbines beyond simple calculations for land values.
- Unpredictable shoreline erosion patterns due to tidal or wave schemes.
- Irrigation issues resulting from hydro schemes
- Reduction of stability problems in the National Grid and connected generators resulting from the numerous embedded plant, specifically the use of induction machines in wind turbines.

There have been many studies that include these issues in a qualitative manner. Quantitative analysis has proved more difficult and the results are therefore varied. A study by the Energy Technology Support Unit (ETSU), part of the Department of Trade and Industry (DTI) shows possible renewable resource figures for the year 2005, based on an 8% discount rate (Figure 6.6)[88]. The results show a marked difference between the accessible and practicable renewable resource. It must be noted that the inclusion of 90 TWh/Year of energy producing crops could only occur if there was a major change in the UK and European agricultural policies.

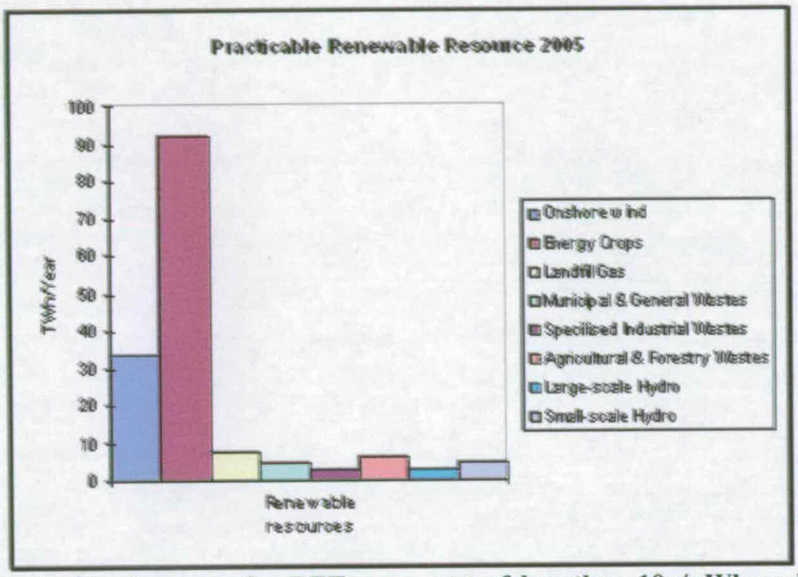


Figure 6.6 Practicable Resource for RETs at a cost of less than 10p/KWh or less using 8% discount in 2005[89].

Unlike fossil fuel resources the long term depletion of available renewable resource (a_n) is, with the exception of waste combustion, linked to the capacity of the generation method that utilises that resource. It is worth noting that in the short-term hydro resource can be linked to the water stored in the reservoirs although the long-term resource figures include sites with sufficient yearly, or seasonal, water run-off to sustain a hydro plant. In addition hydro plant must be connected to the electricity grid system without unrealistic transmission costs

As with non renewable primary energy resource GAMES includes renewable resources within the exogenous forecasting data field. The existing available resource for each renewable method of generation is included, in TWh, before each year in the forecast period. These values can easily be altered during or between optimisations. The resource constraint on wind power, hydro power and non-proven technologies concerns the maximum amount of renewable power resource (p_n) that could be constructed in GW. This is also included within the GAMES exogenous forecasting data field. This value is calculated on a yearly basis starting with an initial exogenous value at year 1. Each year the exploited power resource is calculated by subtracting the plant constructed (c_n) during the previous year and adding any exogenous increases in this resource (i_n) due to increases in the efficiencies of these technologies:

$$p_{n+1} = p_n - c_n + i_n \text{ (GW)} \qquad \textbf{Equation 6.2}$$

where: n = year of forecast

6.6 Capacity

Capacity sets the limits for generation and is used to calculate the extra plant needed so that generation will meet demand. It is calculated based on available plant, expected outages and resource limitations. The GAMES model sets two capacity limits. The first is peak capacity which is measured in GW, which limits generation by an individual method at any instance. The second is yearly capacity which limits the yearly TWh of generation by any method. Both maximum and yearly capacities are described in detail below:

6.6.1 Peak Capacity

The GAMES model is generation led; in that it allocates generation to the most efficient generation methods. To allow for increases in generation, and the decommissioning of old power stations, new plant can be added to the system if necessary. The generation limit for any instant is set by the peak capacity (p_n) at that time. Peak capacity for each generation method is the sum, in GW, of existing plant and any new plant (w_n) of the same type working at a maximum plant lifetime power factor (including outage time). This figure is subject to the resource limitations outlined in Sections 6.4 and 6.5.

$$p_{n+1} = p_n + w_n \quad \text{(GW)} \qquad \textbf{Equation 6.3}$$

constrained by:

$$p_{n+1} < \text{Resource} \quad \text{(GW)} \qquad \textbf{Equation 6.4}$$

where: n = year of forecast

6.6.2 Yearly Capacity

The Yearly capacity (y_n) is defined as the maximum possible yearly generation (in TWh) for a particular type of plant using all available plant at maximum lifetime plant power factor, compensating for planned outages, that does not exceed resource limitations. Yearly capacity differs from peak capacity in that it gives a yearly limit to generation rather than setting a maximum for a particular instant within that year. Yearly capacity is calculated as the sum of existing capacity and capacity installed in the previous year (i_n).

$$y_{n+1} = y_n + i_n \quad \text{(TWh)} \qquad \textbf{Equation 6.5}$$

constrained by:

$$y_{n+1} < \text{Resource} \quad \text{(TWh)} \qquad \textbf{Equation 6.6}$$

where: n = year of forecast

6.7 Generation

The primary assumption in GAMES is that electricity demand will always be met by generation. The proportion of each different type of generation scheduled to meet this demand is set by the GAMES GA. The proportion of each generating method is therefore, as a result of the primary assumption, the same proportion of the demand. Thus the actual generation figures for each generation method can be calculated.

Electricity Demand is given as the ACS (Average Cold Spell) demand and the yearly demand which is described in Section 6.3. The ACS demand represents the peak, cold spell adjusted, demand and is given in GW. Peak generation (p_n) must meet this peak demand without exceeding the peak capacity constraints for each generation method i.e.:

$$p_n = \text{ACS}_n \quad \text{(GW)} \qquad \textbf{Equation 6.7}$$

constrained by:

$$P_n < \text{Resource} \quad \text{(GW)} \qquad \textbf{Equation 6.8}$$

where: n = year of forecast

The yearly demand (y_n) , which represents the electricity demanded on a yearly basis, must be met by yearly generation (g_n) without exceeding the yearly capacity constraints for each generation method i.e.:

$$g_n = y_n \text{ (TWh)} \qquad \textbf{Equation 6.9}$$

constrained by:

$$g_n < \text{Resource} \quad \text{(TWh)} \qquad \textbf{Equation 6.10}$$

where: n = year of forecast

If, due to resource constraints, a particular generation method exceeds its capacity (either peak or yearly capacity) the allocated generation values given by the GA are declared void. If a void result was passed from the fitness function to the GA operators every time a generation method with depleted resource was called to generate the program would spend much of its time passing void messages. In order to speed up the optimisation process a technique called Mapping has been adopted. Mapping involves eliminating void solutions by mapping them into feasible areas of search space. GAMES achieves this by taking the shortfall in generation that was caused by a resource limit and spreading it evenly across the remaining valid generation methods. As such a solution is unlikely to be a global optimum the GA will continue to evolve fitter solutions from the new "mapped" point in the search space[90].

6.8 Plant Lifetime Load Factor

The Plant Lifetime Load Factor (PLLF) gives an indication of the usage of a particular plant. It is defined as the proportion of electricity generated, in TWh, by the plant (g_n), in a specific time period, against the total amount of electricity, in TWh, that could have been produced if the plant had been running at maximum output for the same time period (m_n). (Note: PLLFs are often expressed as a percentage).

$$PLLF = {}^{g}\!/_{m} \qquad \textbf{Equation 6.11}$$

where: n = time period

A yearly PLLF of 0.85 - 0.95 (85% - 95%) indicates base load plant running flat out. The missing 5% - 15% is due to scheduled maintenance and forced outages. In the case of a base load station, such as nuclear plant generation into the present UK electricity pool, the PLLF can give an indication of the reliability. In GAMES the load factor is used in variable cost, resource and plant lifetime calculations. Plant lifetimes are based on both expected and actual PLLFs for all the plant in the ESI model.

As the PLLF is based on plant usage, the type of plant and how it is used in the electricity market influences the PLLF. Most plant has an optimum PLLF that includes forced and scheduled outages. At this PLLF the financial returns from generation are at a maximum. Demanding more than optimal load from a particular plant increases the unit cost of generation and reduces the competitiveness, within the market, of that plant. Market forces imply that a less competitive type of plant will be scheduled less often which will force the PLLF back to optimum. However demanding less than optimum load from that same plant will also increase unit costs and reduce competitiveness. In this case the PLLF will be further reduced forcing it away from its optimum. Therefore maximum economic efficiency for a plant is achieved by keeping it at or above, but never below, its optimum PLLF.

6.9 Heat Rate

An indication of the efficiency of generation by combustion is the heat rate. The heat rate is given by the ratio of input to output energy in a plant using a particular fuel. Because generation is measured as electrical power, in kWh, heat rate is given by the energy needed to generate a unit of electrical power, or Btu/kWh. The actual value of heat rate depends on the fuel, plant size and the load factor. The following three tables show heat rates for coal, oil and gas combustion generating plants[91].

Plant Rating (MW)	Heat Rate at 100% Load Factor	Heat Rate at 80% Load Factor	Heat Rate at 60% Load Factor	Heat Rate at 40% Load Factor	Heat Rate at 25% Load Factor
50	11000 Btu/kWh	11088 Btu/kWh	11429 Btu/kWh	12166 Btu/kWh	13409 Btu/kWh
200	9500 Btu/kWh	9576 Btu/kWh	9871 Btu/kWh	10507 Btu/kWh	11581 Btu/kWh
400	9000 Btu/kWh	9045 Btu/kWh	9252 Btu/kWh	9783 Btu/kWh	10674 Btu/kWh
600	8900 Btu/kWh	8989 Btu/kWh	9265 Btu/kWh	9843 Btu/kWh	10814 Btu/kWh
800-1200	8750 Btu/kWh	8803 Btu/kWh	9048 Btu/kWh	9625 Btu/kWh	N/A

Table 6.1 Typical coal plant heat rates.

Plant Rating (MW)	Heat Rate at 100% Load Factor	Heat Rate at 80% Load Factor	Heat Rate at 60% Load Factor	Heat Rate at 40% Load Factor	Heat Rate at 25% Load Factor
50	11500 Btu/kWh	11592 Btu/kWh	11949 Btu/kWh	12719Btu/kWh	14019 Btu/kWh
200	9900 Btu/kWh	9979 Btu/kWh	10282 Btu/kWh	10949 Btu/kWh	12068 Btu/kWh
400	9400 Btu/kWh	9447 Btu/kWh	9663 Btu/kWh	10218 Btu/kWh	11148 Btu/kWh
600	9300 Btu/kWh	9393 Btu/kWh	9681 Btu/kWh	10286 Btu/kWh	11300 Btu/kWh
800-1200	9100 Btu/kWh	9155 Btu/kWh	9409 Btu/kWh	10010 Btu/kWh	N/A

Table 6.2 Typical oil plant heat rates.

Plant Rating (MW)	Heat Rate at 100% Load Factor	Heat Rate at 80% Load Factor	Heat Rate at 60% Load Factor	Heat Rate at 40% Load Factor	Heat Rate at 25% Load Factor
50	11000 Btu/kWh	11794 Btu/kWh	12156 Btu/kWh	12940 Btu/kWh	14262 Btu/kWh
200	10050 Btu/kWh	10130 Btu/kWh	10442 Btu/kWh	11115 Btu/kWh	12251 Btu/kWh
400	9500 Btu/kWh	9548 Btu/kWh	9766 Btu/kWh	10327 Btu/kWh	11267 Btu/kWh
600	9400 Btu/kWh	9494 Btu/kWh	9785 Btu/kWh	10396 Btu/kWh	11421 Btu/kWh
800-1200	9200 Btu/kWh	9255 Btu/kWh	9513 Btu/kWh	10120 Btu/kWh	N/A

Table 6.3 Typical gas plant heat rates.

Heat rate is used to calculate the fuel needed to ensure that yearly demand is met by yearly generation. This is necessary for the yearly resource calculations, described in Section 6.4, and in order to calculate fuel costs.

6.10 Plant

This study assumes that plant is constructed to meet or exceed the forecast peak and yearly electricity that will be generated by each of the 8 plant types. This value includes outage time due to maintenance and the excess, or spinning reserve needed to account for unexpected deviations from forecasts. This follows from the primary assumption in GAMES, that demand will always be met by generation.

The model does allow for excess plant to remain off-line. This minimises the variable costs and, in some cases, the only outgoing payments are interest payments on the initial capital. In this way plant can also be decommissioned before the natural plant life is exceeded. This would only happen if technology, in the form of more successful competing generating methods, overtakes the older plant or if the political risk becomes too high for a particular type of plant to be allowed to continue operating.

Expected plant life is technology specific and is subject to change throughout the lifetime of any particular plant. This is often caused by legislation penalising older, or ageing, plant in order to reduce pollution or risks of accidents. The result is that the expected plant life is usually calculated to be shorter than the expected physical life of the machinery, usually 25-30 years for combustion based generation, 15-50 for the mechanical parts of hydro power plant (although the civil engineering normally lasts much longer) and 15 - 25 years for most wind turbines.

The extra peak plant needed (p_n) to provide a yearly generation that meets peak demand is calculated by subtracting the value of existing plant (p_{n-1}), in GW, from the peak generation (k_n), in GW. In addition the average outage (o_n), the spinning reserve (s_n) and the expected plant decommissioning (d_n) are added to the extra plant needed to meet peak generation. The final result is also subject to the Plant Lifetime Load factor (PLLF).

$$p_n = (k_n - p_{n-1} + s_n + o_n + d_n) \div \text{PLLF (GW)} \qquad \textbf{Equation 6.12}$$

where: n = year of forecast

The extra plant generating capacity needed (c_n), in TWh, to insure that yearly generation (g_n) is met is calculated in a similar manner. This is to ensure that there is enough plant capacity to meet average outage (t_n), the spinning reserve (r_n) and the expected plant decommissioning (s_n). The existing plant generating capacity (c_{n-1}) is subtracted from the yearly generation in TWh which is constrained by the available resource.

$$c_n = (g_n - c_{n-1} + r_n + t_n + s_n) \div \text{PLLF (TWh)} \qquad \textbf{Equation 6.13}$$

where: n = year of forecast.

This value of plant generating capacity is then converted from yearly TWhs into the GW of plant that would be needed to provide this amount of energy. This value is then compared with the peak plant needed and the extra plant that is to be constructed in year n is taken from the larger of these values.

When the expected plant life is reached there are the options of keeping the plant operating for peak load times only, upgrading the plant to extend its life or decommissioning the plant. The choice involves an analysis of the costs of adopting each strategy. Demolition and rebuilding new plant on, or close to, the same site offers the advantage of lower capital costs for infrastructure (roads etc.), lower repairs and maintenance costs and the salvage value of old plant is deducted from the capital costs of the new plant.

6.11 Operating & Maintenance costs

Operating and maintenance costs are included as exogenous inputs in GAMES. As defined in the Factories Act 1961 an acceptable standard of maintenance is "one that sustains the utility and value of the facility"[92]. However in the UK ESI, the regulation of such a vague statement is separated into health and safety issues and emissions controls. Both of these can be incorporated, with the operating costs, into the variable costs through the inclusion of planned outages and planned renovation or upgrading of generating plant. Some added capital costs may also be incurred for necessary safety and environmental control equipment. The actual expenditure on operation and maintenance (O&M) must both meet the regulatory requirements and satisfy a cost-benefit analysis for the plant. The regulatory requirements serve to apply an absolute minimum, with possible penalties for non-compliance. The cost-benefit analysis balances the reduction of forced outages, equipment damage and loss of revenue with the high costs of O&M. As the GAMES model is based on a GA this cost benefit analysis is achieved by the assessment of different solutions. The GA passes a number of possible solutions, of the primary energy mix in generation over a 40 year period, to the fitness function. Those possible solutions that achieve an ideal cost-benefit relationship are deemed fitter, survive and are chosen for the next generation of optimisation. The actual costs involved, and resulting fitness of the possible solution, vary depending on the type of plant and its usage which is discussed in Section 6.6. Typically O&M costs are around 3%-7% of the capital costs for fossil fuel plant, 0.5%-3.5% of the capital costs for wind and hydroelectric plants. These figures do increase with the age of the plant so the expected life of a plant is critical in calculating the extent of regular maintenance.

6.12 Contractual arrangements

The new electricity market structure in the UK will include a large scope for individual contractual arrangements between players in the market, typically between the generators and the suppliers who provide electricity for the consumers. GAMES includes the facility to add extra contractual arrangements as they arise in the electricity market. They are split into long-term, medium-term and market-price contracts in accordance to the new pool rules described in Chapter 2.

6.12.1 Long-Term Contracts

Long-Term contracts cover periods longer than one year. They can offer the supplier a maximum price limit (or price cap) for electricity whilst providing a guaranteed demand for energy produced by that generator. In the near future contracts will include *price sharing* strategies that will divide the risk of the demand falling below predicted values between the suppliers and generators. A typical cause of an over estimated demand is a mild winter, or early spring. In this case the risk share could even include an industry that consumes electricity but benefits from warmer than average weather. Ice cream manufacturers are an example. Contracts of this type are included in the model within the calculation of returns from generation. A maximum market price is set for electricity generated within price cap contracts. Risk sharing contracts are implemented through the inclusion of a minimum yearly revenue from plant included within these arraignments for the contract period.

In the UK renewable energy incentives such as the Non Fossil Fuel Obligation (NFFO) for England and Wales and the Scottish Renewables Order (SRO) in Scotland have created the must-take contracts. Successful applicants to the NFFO and SRO are provided with must-take contracts which guarantees that all the electricity generated by these stations must be purchased, by the electricity pool, at a price scale agreed for 15 years. This price is set as an exogenous input and can include a sliding scale when the contract period has ended. The majority of renewable generation and all of nuclear generation is under must-take obligations.

6.12.2 Medium-Term Contracts

Medium-term contracts extend from one day to a couple of years. They guarantee a supply at a defined price, or price structure, for a short period. Their advantage over long-term contracts is that they allow both parties to *play* the market and benefit from either seasonal or simply market led fluctuations in electricity price. The disadvantage is that this form of speculation can increase the volatility in the market.

6.12.3 Market-Price Contracts

Presently market-price contracts are the contractual obligations of all the players in the market. Regulatory bodies will limit the cost of electricity for the consumer and maintain the obligation to provide electricity to remote areas. Within this scope the suppliers and generators will operate a half-hourly spot market for electricity. The yearly average market price is supplied to GAMES as an exogenous variable although if capacity greatly exceeds demand this price is reduced.

6.13 Externalities

The drive to include environmental costs in decision making and the cost-benefit analysis involved in plant mix choices has led to an increased awareness of the impact of environmental issues. As the scope of environmental issues in electricity generation is large a full quantitative analysis is not possible. However it is possible to identify the key issues and assess their impacts on energy usage in generation. It is important to note that the preservation of the environment has become an exceedingly political issue and that the UK policy towards environmental issues in electricity generation, specifically towards renewable technologies, is no exception [93].

The understanding of environmental economics has increased over the past decade as governments have acknowledged the costs, in financial terms, of environmental damage. The use of energy can be linked to the damage of natural ecosystems, human health, livestock and man-made structures. The associated costs of this damage is referred to as the external costs, or externalities of energy, as it is not reflected in the market price for the energy that caused the damage. In the case of electricity generation a regulatory policy of emissions control, with the power to penalise or even shut down plant, has been adopted. The amount and type of regulation is based on external costs along with market and political concerns. Through regulation electricity generators are becoming more accountable for their external costs, it is highly probable that this trend will increase[94]. As accountability does increase it will also become more direct through taxation structures that penalise by the exact external costs incurred by each generator. Although this in itself will help with the liberalisation of the electricity market some control over the trading of externalities might be necessary.

A comprehensive study of the external costs in electricity generation in was started by the European Commission in 1991. The project was called *ExternE Externalities of Energy*[95] and contains the following:

- The integration of environmental concerns in the choosing of fuels and energy technologies.
- The evaluation of the costs and benefits of strict environmental standards.
- The development of indicators of environmental standards of different technologies to enable direct comparisons.
- The investigation of policy initiatives to encourage competition and market mechanism in the energy sector.

All of the above factors include the "*quantification of the environmental and health impacts of energy use...*" Which is one of the study's primary objectives.

The inclusion of externalities into the GAMES model was centred around the findings of the ExternE project. Using the quantitative analysis provided by the study on the external costs of generation using different fuels, sets of functions were derived and included in the GAMES forecasting model. The externalities included can be split into two categories:

1. Quantifiable Damage

- Public health (including disease).
- Occupational health (including disease).
- Crops as a result of atmospheric pollution.
- Forests
- Terrestrial ecosystems
- Fisheries due to acidic deposition

2. Quantifiable impact to Environments

- Water quality
- Air Quality
- Global warming
- Noise Pollution
- The destruction of sites of historical or cultural importance

The external functions in GAMES that solve the externalities are split into $f_n(E_{fixed})$ and $f_n(E_{variable})$ where $f_{(1....n)}(E_{fixed})$ and $f_{(1....n)}(E_{variable})$ represent the external functions for each method of electricity generation (1...n) providing indices for both the fixed and variable costs for each generation. This accommodates the proportional link between some of the externalities and generation increases along with the proportional link between other externalities and the construction of new plant. The total external ($f_n(E)$) cost of each generation method, in standardised financial units, is given by:

$$f_n(E) = f_n(E_{fixed}) + f_n(E_{variable})$$ **Equation 6.14**

The total external costs can therefore be given by:

$$\sum_{1}^{n} f_n(E)$$ **Equation 6.15**

where: n is the number of generation methods under analysis in the model.

The external costs provide a vital addition to the model as they are a reality. Their inclusion can dramatically change the outcome of a scenario and therefore great care is needed when deriving their values. This is primarily as many external costs, such as the impact on the National Health Service caused by air pollution, are not currently accounted for by direct regulation or taxation of the generators but are included within the government's treasury budget. Some externalities, such as the depletion of natural gas, are presently not accounted for and are simply taken from the country's assets.

6.14 Fossil Fuel Combustion

The determination of emissions from a particular power station can be monitored directly. As GAMES is a fuel based model emissions calculations can be made using the amount of fuel that is used and the method of its combustion. This is achieved through the calculation of the mass of pollutant that is created through the combustion of a single tonne of fuel, or emissions factor. The model contains these values, which are derived in Sections 6.14.1, 6.14.2 and 6.14.3, and uses them to calculate the yearly emissions from each method of fossil fuel combustion. This is achieved by multiplying the emissions factor by the amount of fuel needed to achieve the required generation, which is itself derived from heat rate in Section 6.9. As the issue of combustion is very complex and a full analysis is beyond the scope of this study the following assumptions are used:

- Aggregate values for the constituents of each fuel can be used to give the combustion equations for each typical UK fuel. These figures are subject to change as the domestic resources are used and as economic factors change.

- Fuels can be defined on an elemental basis and the constituent parts that are not included within the elements of carbon, sulphur and nitrogen can be considered of negligible effect and are not taxable. The exception being that of particulates which are included as ash and taxed for their landfill value. Although this is a large simplification of very complex paths of combustion the relatively large percentage of CO_2 SO_2 and NO_x emissions makes this assumption valid.

- All combustible elements of the fuel will be fully oxidised to form gaseous emissions and all the oxygen necessary to fully burn the fuel will be available for this process. This assumption is valid for carbon and sulphur as their uptake ranges from 85%-90%[96] however nitrogen has a lower uptake of oxygen and nitrogen from the atmosphere often reacts to form NO_x at high temperatures.

- Combustion of a given mass of fuel releases the fuel's full calorific value within the plant's combustion area. This assumption is ensured by the long time periods that fuel spends in the combustion area, typically ten times the combustion time for coal with an adequate supply of air.

6.14.1 Gas Combustion

The percentage masses of the main constituents of the gas used in the UK's gas fired power stations, their molecular masses and their reaction formulae when combusted in air are as follows:

Constituent of Gas	%Mass of Gas	Molecular Mass	Combustion Equations
methane	91.98	19	$CH_4 + 2O_2 \rightarrow CO_2 + 2H_20$
ethane	4.50	30	$2C_2H_6 + 7O_2 \rightarrow 4CO_2 + 6H_20$
propane	1.38	44	$C_3H_8 + 5O_2 \rightarrow 3CO_2 + 4H_20$
butane	0.25	58	$2C_4H_{10} + 13O_2 \rightarrow 8CO_2 + 10H_20$
pentane	0.03	72	$C_5H_{12} + 8O_2 \rightarrow 5CO_2 + 6H_20$
hexane	0.01	86	$2C_6H_{14} + 19O_2 \rightarrow 12CO_2 + 14H_20$

Table 6.4 Molecular, Percentage masses & combustion equations for constituents of natural gas.

Table 6.4 shows how we can approximate that the alkanes are totally oxidised giving only carbon dioxide (CO_2) and water vapour (H_2O) if total combustion is assumed. Assuming total combustion implies that there is an excess of air throughout the fuel mixture so levels of carbon monoxide (CO) are negligible. In addition the effects of increased temperature within the reaction are ignored as this results in the formation of small quantities of nitric oxides (NO_X) from the atmosphere[97].

Table 6.4 gives the Molecular masses and the combustion equations for over 98% of the constituent parts of natural gas. It is assumed that the 2% are impurities that are either inert or have a negligible effect. As the molecular mass of CO_2 is 44 and the molar proportions can be taken from the combustion equations it follows that:

$$\begin{array}{llcl} & 1 \text{ mole } CO_2 & : & 1 \text{ mole methane} \\ \Rightarrow & 44 \text{ kg } CO_2 & : & 16 \text{ kg } CH_4 \end{array}$$

As methane forms 91.98% of natural gas
1 kg of natural gas will give:

$$\left(\frac{44 \times 0.9198}{16}\right) = \mathbf{2.5295\ kg} \qquad \textbf{Equation 6.16}$$

of CO_2 due to the constituent methane when fully combusted. Table 6.5 completes this process for the remaining constituents.

Constituent of Gas	CO_2 Emission from the Combustion of One Tonne of Natural Gas
methane	2.5295 tonnes
ethane	0.1173 tonnes
propane	0.0414 tonnes
butane	0.0075 tonnes
pentane	0.0092 tonnes
hexane	0.0003 tonnes
TOTAL	2.7052 tonnes

Table 6.5 Constituent CO_2 Emission from the Combustion of 1 Tonne of Natural Gas.

Table 6.5 uses the above method to give the constituent contribution to CO_2 emissions for the combustion of natural gas in the production of electricity. The average efficiency of CCGT plant is 45%. If the calorific value of natural gas is 50MJ/kg and in 1997 99,080 GWh of electricity were produced by the combustion of gas then:

$$\frac{99080 \times 10^9}{50000 \times 0.45} = \mathbf{4.4 \times 10^9} \text{ tonnes of gas were burnt in 1997} \qquad \textbf{Equation 6.17}$$

as the combustion of one tonne of natural gas gives 2.7052 tonnes of CO_2 the total amount of CO_2 emissions due to the combustion of natural gas in 1997 was:

$$4.4 \times 10^9 \times 2.7052 = \mathbf{1.19 \times 10^{10}} \text{ tonnes of } CO_2 \qquad \textbf{Equation 6.18}$$

6.14.2 Coal Combustion

The percentage masses of the main constituents of the coal used in the UK's coal fired power stations, their molecular masses and their reaction formulae when combusted in air are as follows:

Constituent of Coal	%Mass of Coal	Molecular Mass	Combustion Equations
carbon	79.7	12	$C + O_2 \rightarrow CO_2$
sulphur	0.8	32	$S + O_2 \rightarrow SO_2$
nitrogen	0.9	14	$2N + O_2 \rightarrow 2NO$
ash	9.6	-	-

Table 6.6 Molecular, percentage masses and combustion equations for constituents of UK coal.

Assuming total combustion as with natural gas:

- Assuming excess air during combustion carbon is completely oxidised to carbon dioxide and levels of carbon monoxide (CO) are negligible.

- Sulphur is completely oxidised to sulphur dioxide and the air levels are not so high as they aid the formation of sulphur trioxide (SO_3).

- Nitrogen is completely oxidised to nitric oxide (NO) and the effects of increased temperature within the reaction are ignored, although this results in the formation of small quantities of nitric oxides (NO_X) from the atmosphere.

Table 6.6 gives the Molecular masses and the combustion equations for 91% of the constituent parts of the UK's coal resource. The shortfall represents the moisture content. It is assumed that impurities other than nitrogen and sulphur are either inert or have a negligible effect.

It is accepted that there are variations in the purity of coals. Calorific values range from 21.28MJ/kg in Westfield mined coal to 26.9MJ/kg in Rashiehill & Backshot mined coal. In addition the sulphur content from these two mines is 1.8% and 0.9% respectively. The ash nitrogen and moisture levels also vary between mines. GAMES uses an average figure for these values which can be varied depending on the quantity of the UK's coal resource.

As the molecular mass of CO_2 is 44 and the molar proportions can be taken from the combustion equations it follows that:

1 mole CO_2 : 1 mole carbon

$\Rightarrow$ 44 kg CO_2 : 12 kg C

As carbon forms 79.7% of UK coal

1 kg of coal will give:

$$\left(\frac{44 \times 0.797}{12}\right) = \mathbf{2.92\ kg} \qquad \textbf{Equation 6.19}$$

of CO_2 when combusted.

Table 6.7 completes this process for the remaining constituents.

Constituent of Coal	Emission from the Combustion of One Tonne of Coal
carbon	2.92 tonnes CO_2
sulphur	0.016 tonnes SO_2
nitrogen	0.019tonnes NO
ash	0.0096 tonnes ash*

Table 6.7 Constituent CO_2 Emission from the Combustion of One Tonne of UK coal.

Table 6.7 uses the above method to give the constituent contribution to emissions for the combustion of coal in the production of electricity. The average efficiency of coal plant is 30%. If the calorific value of this sample of coal is 26MJ/kg and in 1997 110,151 GWh of electricity were produced by the combustion of coal then:

$$\frac{110151 \times 10^9}{26000 \times 0.30} = \mathbf{1.412 \times 10^{10}} \text{ tonnes of coal combusted} \qquad \textbf{Equation 6.20}$$

as the combustion of one tonne of coal creates the emissions given in Table 6.7 it follows that the emissions due to coal combustion in 1997 were approximately:

$$1.412 \times 10^{10} \times 2.92 = \mathbf{3.23 \times 10^{10}} \text{ tonnes of } CO_2 \qquad \textbf{Equation 6.21}$$

$$1.412 \times 10^{10} \times 0.016 = \mathbf{2.26 \times 10^{8}} \text{ tonnes of } SO_2 \qquad \textbf{Equation 6.22}$$

$$1.412 \times 10^{10} \times 0.019 = \mathbf{2.68 \times 10^{8}} \text{ tonnes of NO} \qquad \textbf{Equation 6.23}$$

$$1.412 \times 10^{10} \times 0.0096 = \mathbf{1.36 \times 10^{8}} \text{ tonnes of ash} \qquad \textbf{Equation 6.24}$$

6.14.3 Oil Combustion

The calculations for oil emissions, when being burnt for electricity generation, are similar to those of coal. The major difference is that the ash and nitrogen content of oil is assumed to be negligible, therefore only CO_2 and SO_2 calculations are performed for oil emissions.

* Ash is given as a percentage of combusted weight of material.

Constituent of Oil	%Mass of Oil	Molecular Mass	Combustion Equations
carbon	84.6	12	$C + O_2 \rightarrow CO_2$
sulphur	4	32	$S + O_2 \rightarrow SO_2$

Table 6.8 Percentages, molecular masses and combustion equations for the constituents of oil.

As with coal the following assumptions have been made:

- Assuming total combustion as with coal, carbon is completely oxidised to carbon dioxide and levels of carbon monoxide (CO) are negligible.
- Sulphur is completely oxidised to sulphur dioxide and the air levels are not so high as they aid the formation of sulphur trioxide (SO_3).
- The differences between the oils used in electricity generation can be aggregated so that the UK's total emissions from this fuel can be calculated. The percentages of the constituents in oil are subject to change with economic and resource changes.

Table 6.8 gives the Molecular masses and the combustion equations for 88.6% of the constituent parts of the UK's oil resource. It is assumed that impurities other than nitrogen and sulphur are have a negligible effect on the environment or will not be subject to taxation in the foreseeable future.

As the molecular mass of CO_2 is 44 and the molar proportions can be taken from the combustion equations it follows that:

$$\begin{array}{lccc} & 1 \text{ mole } CO_2 & : & 1 \text{ mole carbon} \\ \Rightarrow & 44 \text{ kg } CO_2 & : & 12 \text{ kg C} \end{array}$$

As carbon forms 84.6% of combustible oil
1 kg of oil will give:

$$\left(\frac{44 \times 0.846}{12}\right) = \mathbf{3.102\ kg} \qquad \textbf{Equation 6.25}$$

of CO_2 when combusted.

Table 6.7 completes this process for the remaining constituents.

Constituent of Oil	Emission from the Combustion of One Tonne of Oil
carbon	2.92 tonnes CO_2
sulphur	0.08 tonnes SO_2

Table 6.9 Constituent CO_2 Emission from the Combustion of One Tonne of oil.

Table 6.9 uses the above method to give the constituent contribution to emissions for the combustion of oil in the production of electricity. The average efficiency of oil plant is 38%. If the calorific value of this sample of oil is 39MJ/kg and in 1997 4,889 GWh of electricity were produced by the combustion of oil then:

$$\frac{4889\times10^{9}}{39000\times0.38} = \mathbf{3.299\times10^{9}}\text{ tonnes of oil combusted} \qquad \textbf{Equation 6.26}$$

as the combustion of one tonne of oil creates the emissions given in Table 6.8 it follows that the emissions due to oil combustion in 1997 were approximately:

$$3.299\times10^{9}\times3.102 = \mathbf{1.02\times10^{10}}\text{ tonnes of } CO_2 \qquad \textbf{Equation 6.27}$$

and

$$3.299\times10^{9}\times0.08 = \mathbf{2.64\times10^{8}}\text{ tonnes of } SO_2 \qquad \textbf{Equation 6.28}$$

6.15 Emissions Reduction

The reduction of emissions involves an increase in both capital and operation costs. An example of this is the £400,000,000 that Drax, Europe's largest coal-fired power station, invested to install sulphur dioxide scrubbers. In addition the unit cost of electricity increased by 0.6 pence when the scrubbers were operational. In order to remain competitive it was often necessary to generate without the use of the scrubbers[98].

The costs of reducing emissions can be included into capital costs and as a function of the running costs. These costs are called Ambient Costs (AC) and can be calculated for any particular plant by:

$$AC_{Total} = G(\,AC_{CO_2} + AC_{SO_2} + AC_{NO_2} + AC_{ash}\,) \qquad \textbf{Equation 6.29}$$

where: G = Generation in kWh

Ambient control costs must be balanced against any incentives to reduce emissions or penalties for pollutants. The final expenditure on ambient control is proportional to the present, and predicted future, taxation of emissions. GAMES assumes that in regards to the extent of its emissions control strategy, privatised generating utilities will maximise their profits through the cost-benefit analysis of emissions control against emissions taxation. This is implemented through the inclusion of emissions taxes or emissions control costs. As The GAMES GA assesses the fitness of each possible solution of generation mix over a 40 year period, the fittest solution will contain the most profitable combination of emissions control costs and the costs incurred through emissions taxation.

6.16 Environmental Taxes

Taxation of fossil fuels can be incorporated into the overall fuel costs for each kWh generated by its combustion. However the taxation of the emissions from combustion based generation is plant specific. Past trends can give an indication of these levels and an approximation based on real and theoretical values can give the average percentage of each taxable pollutant for each generation method. An adjustment is included within GAMES that allows for an increase in the pollutants within the fossil fuel as the UK's resources are depleted. Once the domestic resource is depleted the pollutant levels can be set to a European average. Emissions taxation from domestic fuels are calculated as follows:

$$\text{Tax Cost} = \text{mass of pollutant} \times \text{tax rate} \times \text{pollutant factor} \qquad \textbf{Equation 6.30}$$

where:

$$\textbf{pollutant factor} \propto \{f(\text{domestic resource})^{-1} + F(\text{fuel price})\} \times \{\text{proportion of pollutant}\}$$

Equation 6.31

GAMES groups emissions taxes into five separate fields. Each field can be adjusted independently and are outlined in Sections 6.16.1 through to 6.16.4. The five Taxation fields include:

6.16.1 Fossil fuel levy.
6.16.2 Carbon Tax.
6.16.3 $N0_x$ Tax.
6.16.3 $S0_x$ Tax.
6.16.4 Ash Tax.

6.16.1 Fossil Fuel Levy

The fossil fuel levy was introduced to provide support for renewable technologies at the cost of the larger fossil fuel combusting plant. The intention was to allow the smaller, *less polluting* schemes compete against the larger established generating methods. The tax was originally set at 10% of revenue from fossil fuel combustion but was reduced in 1998 to 1% after criticism by the European Commission that the levy was subsidising the nuclear industry. Of the funds raised by the levy 96% went to the Nuclear industry and the remainder went to the renewable technologies[99]. The new rate of 1% pays for the present and future NFFO and SRO projects although nuclear subsidies still continue through the allocation of must take contracts which are described in Section 6.12.

6.16.2 Carbon Tax

The idea of carbon taxation was introduced to encourage utilities to move away from high carbon content fuels and thus reduce CO_2 emissions. Although the unilateral introduction of this tax has as yet been rejected by the UK, it is highly likely that it will be introduced Europe wide in the near future as a measure to achieve the 1997 Kyoto summit targets. The calculation of this tax involves the multiplication of the carbon content of combusted fuel by the taxation level. This is done on a yearly basis and the user of GAMES can alter the yearly taxation levels applied on a year by year basis.

6.16.3 Nitrogen & Sulphur Taxes

Sulphur and Nitrogen emissions are also not yet taxable, although penalties for excess emissions do exist. As with carbon taxation (Section 6.16.2) this is set to change and the facility to directly tax for SO_x and NO_x emissions is built into GAMES as a direct yearly tax on these emissions.

6.16.4 Ash Tax

Ash is taxed by its landfill costs. The present cost in the UK is £3 per tonne of ash and this figure is set to rise to over £10 per tonne within the next decade. The amount of ash produced by coal combustion depends on the quality, or ash content, of the coal. A yearly aggregate value is used in GAMES which can be altered to investigate the impact of using different types of coal. Variations in ash content and yearly ash tax rate can be entered as exogenous data on a year by year basis. The yearly taxation costs involve the multiplication of these figures with the mass of coal used in generation in that same year.

6.17 Risk

All electricity generation has associated with it elements of risk. Risks can be associated with human life, the environment or technological aspects. Each of these risks is often forecasted and given a monetary value. The costs of reducing each risk is then compared to this value to prove its viability. In addition these values are added to the investment risk to give a final total risk. The total risk gives an indication of the project's worst case profit margin (be it negative or positive). There are many methods by which this worst case scenario can be avoided.

GAMES assumes that risk management strategies are utilised to limit worst case scenarios to acceptable levels. This is achieved through a structure of penalties which penalise possible solutions to the long-term primary energy mix in generation that do not follow risk avoidance strategies. The level of these penalties can be altered on a year by year basis using the exogenous externalities data field. When investigating the feasibility or the sustainability of a technology the risks and methods of dealing with them must be known. This is so that a realistic worst case, adjusted by risk management strategies, can be used[100]. The risks that have a primary affect on generation choices can be divided into three main groups: Market risk, technological risk and political risk. Sections 6.17.1, 6.17.2 and 6.17.3 describe these risks and the method by which GAMES includes them into the ESI model.

6.17.1 Market Risk

A free market in electricity will allow speculation. Speculation causes market volatility which increases the risks involved in playing the market. Presently the UK pool also experiences volatility as a result of having to meet an uncertain short-term (hourly, daily and weekly) demand. GAMES makes the assumption that generators use contractual arrangements to reduce the impact of excess volatility. Most contracts involve agreements that span a time-scale that will not be affected by short term market fluctuations. GAMES allows for long term Must Take contracts that ensure that all the electricity generated by the particular power station is purchased by the grid. The result is that plant that has a must take contract can generate at capacity based on the knowledge that there is a fixed unit price. This has a similar effect on the market as the base load generators had under the former nationalised generation network.

A second method of reducing market risk is vertical integration. This involves investments along the supply chain. The result is that the risks of unexpected fuel price rises are eliminated and can even be exploited by vertically integrated generators. As this strategy does not directly affect the decision to build a particular type of plant it is not included within games. However vertical integration along the fuel supply chain does affect fuel price which is one of the exogenous variables included in the GAMES forecasting model.

6.17.2 Technology risk

The reliability of plant continues to be a major handicap against investment in new renewable generation schemes. The only notable example is the exploitation of large and medium-scale hydro power. A simple function is included in GAMES to reduce the returns from unreliable, or non-proven, plant in order to assimilate the extra costs of unscheduled outages and maintenance. The technology risk function simply adds a user defined sum to the cost of every kWh generated by unreliable plant.

The risks associated with technology are not limited to non-proven methods of generation. Even established generation methods are liable to be superseded by advances in technology. The modular design of most CCGT power plant should enable such advances to be adopted quickly. In reality the expense of going off-line and modernising plant is so great it only happens when the existing plant has already reached the end of its expected life. The larger generating utilities are able to adopt strategies to reduce the impact of plant becoming redundant or even failing. The most common responses to technological risk are horizontal integration, risk sharing and diversification described in Sections 6.17.2.1, 6.17.2.2 and 6.17.2.3 respectively.

6.17.2.1 Horizontal Integration

This method aims to increase market share by absorbing the competition and utilising their technologies. Horizontal integration relies upon the assumption that if one operation is doing badly the other will be doing well. This provides a buffer by which poorly performing generating plant, that is temporarily returning low profits, can be sustained until the market returns to its favour. Therefore a result of horizontal integration is an increase in diversification. To account for this effect GAMES includes a function that sets a minimum amount of diversity in generation. Possible solutions that contain less diversity than this minimum level incur a user defined penalty.

6.17.2.2 Risk sharing

Typically this occurs by sharing the risk through joint ventures. Often expensive and risky ventures are shared by competing companies which would be unable to accept the risk individually. This strategy has not yet been adopted in the generation side of the electricity market. At present risk sharing has been limited to oil exploration but extensive research into weather associated risks, due to both global warming and local effects, may result in risk sharing between utilities that benefit from periods of abnormally high temperatures and utilities that benefit from low temperatures.

6.17.2.3 Diversification

This involves swapping a specific risk for a general market risk. Most generating utilities own generating plants that rely on different fuels to reduce the effect of a failure of an individual fuel supply. In addition diversity is kept because each method of generation has its place in the market. The GAMES diversity function assumes that at any one time there is a limit to the proportion of any one generation method. This figure can be adjusted by the user but is typically around 70% based on historical data. The penalties for lack of diversification follow a linear increase with percentage value over the set maximum.

6.17.3 Political Risk

Political risk is closely related to environmental and technological hazards. Although often media led public opinion affects political policy decisions. Even if the information that forms public opinion is of a low quality politicians will often act to satisfy the voters demands. Accurate forecasting of such an indirect and inefficient process is not feasible, however to allow for political trends GAMES includes a weighting that can be used to handicap a generation method on a yearly basis. This tool is likely to be misused subjectively and is therefore normally set to zero unless the effects of political risk are being assessed. Valid examples of its use include the modelling of the 1996 Labour election manifesto promises of ending the "dash for gas"[101] and to cease the construction of new nuclear power generating plant. The implications of this are the application of a heavy weighting against the construction of new nuclear plant and a lesser weight applied against CCGT plant. The resulting costs increases in a linear fashion with every GW of new plant commissioned. The size of the weight is user defined for each generating method.

6.18 Capital Costs

The initial, capital, costs of building a new electricity generating plant are made up from a variety of sources. Different plant types have different costs associated with them. The installed costs of wind power are very site specific due to terrain, road access and distances from national distribution and transmission grid. Wind power technology itself is relatively new which causes up to a 20% variation in manufacturing costs[102]. High head mini hydro plants have capital costs associated with civil engineering and installation along with manufacturing and connection costs applied to all embedded generation schemes.

Wind power capital costs are mostly based on *blade swept area.* This does not allow for comparisons between different energy producing technologies. To compare different technologies the capital cost *per installed kW* is needed. An example of different costs per installed kW is shown in Table 3.1. The payment procedure for capital costs is quite complex. Normally yearly payments are made that include the interest for the capital and capital sum based on a prearranged repayment formulae.

EXAMPLES OF APPROXIMATE CAPITAL COSTS

Energy Producing Technology	£/kW
Wind Farm (400kW turbines)	**800 - 1200**
High Head Mini Hydro (200m, 200kW)	**950**
Large Gas Power Station (with 600MW Generators)	**750**
Large Oil Power Station (with 600MW Generators)	**800**
Large Coal Power Station (with 600MW Generators)	**900**

Table 6.10 Examples of capital costs involved in different types of electricity generation[103].

During the forecast period payment calculations are made on a yearly basis with each plant type being subject to the same repayment conditions that are set by the user. At the end of the forecast period any plant that has not exceeded its pay-back period, in that it has outstanding debt, is charged for the borrowed capital. In order to make comparisons between competing plant types a net-present value (NPV) calculation is made. All suggested plant construction capital costs are discounted equally to make a fair playing field. This is done using a single payment present worth function shown in below.

$$\text{Payment Due} = \text{Remaining debt} \times \left[\frac{1}{(1+d)^n}\right] \qquad \textbf{Equation 6.32}$$

The yearly capital and interest payments along with the remaining NPV end payment are added to the yearly fixed costs.

6.19 Yearly Costs

The yearly cost of generating electricity varies between differing electricity generating technologies. These costs can be separated into fixed costs and variable costs. Fixed costs are not dependant on generation and include loan repayments, local rates, land rental, connection charges, insurance and general site maintenance.

The total yearly fixed costs (*F*), in pounds sterling, depend on plant capacity (*p*), in GW ie:

$$F = p\sum_{x=1}^{x=n} f_x(fixed)$$ **Equation 6.33**

where: $f_x(Fixed)$ = an explanatory function, in £/MW, that describe a particular fixed costs.
and: n = number of explanatory fixed cost functions

Variable costs are those that are directly influenced by plant output and include fuel costs, reactive power charges, a proportion of maintenance costs and emissions taxes. The total yearly variable costs (*V*), in pounds sterling, depend on yearly generation output (*g*), in MWh ie:

$$F = g\sum_{x=1}^{x=n} f_x(Variable)$$ **Equation 6.34**

where: $f_x(Variable)$ = an explanatory function, in £/MWh, that describe a particular variable costs.
and: n = number of explanatory fixed cost functions

Non renewables have high proportion of variable costs due to the cost of fuel and emissions. Conversely renewables have a high proportion of fixed costs as their major costs include loan repayments, general maintenance, local rates, land rental and insurance, which all electricity generators must pay for. For example a wind farm will have variable costs of around 2.5% of the total fixed costs per annum or alternatively 0.5p/kWh with an additional reactive charge of

0.3p/kWh (where, in the case of induction generators, reactive power demand is assumed to be approximately 30% of the energy produced by each turbine)[104].

The model uses the sum of yearly fixed and variable costs give the overall yearly costs. In addition the interest payments on the money used for the capital costs must be accounted for. Although these interest payments vary due to interest rate changes during the plants life they are not considered to be variable costs. Low renewable variable costs means that these payments, discounted at a user defined interest rate, form a major part of the overall yearly costs for the technology.

6.20 Returns

The returns from electricity generation depend on the amount of electricity sold to the electricity pool and the pool price during that period. The UK pool rules, in force at the time of writing this thesis, allow each generator to offer a half hour selling price for electricity 24 hours in advance[105]. The pool takes as many generation bids as it needs to satisfy the expected half hourly demand starting from the cheapest bids. The final price paid by the pool to the generators is the highest bid price reached as they accept bids to meet the expected demand. The pool price, is highly volatile but yearly averages are more predictable. GAMES uses a yearly aggregate value of pool price (p) in p/kWh. The return from generation (r) is therefore given by the product of this value and the yearly generation by each method of generation (g).

$$\mathbf{r} = p \times g \qquad \textbf{Equation 6.35}$$

The UK electricity market is set to be changed by the year 2000 to a system that is more contractual and less volatile. This will enable generators to sell electricity at a lower unit price under long and medium-term contracts. This will reduce their market risk which will, over the contract period, compensate for the lower returns. Although generators selling on the short term market will obtain higher prices for electricity their market risk price will increase accordingly. This has been incorporated into the model by allowing fixed, reduced or capped prices for electricity.

6.21 Beyond the Forecast

If the model were to stop optimising at the end of the forecast period and ignore what happens after that time it would suggest diminishing our fossil fuel reserves regardless of the costs of having redundant plant the year after the forecast period has ended. To account for this GAMES continues its optimisation for twice the forecast period. The exogenous data needed to continue the forecast is extrapolated from the final years of the forecast period. The costs and revenues are calculated for this extra time period and added to the fitness result as described in Section 6.22. Although this is a large approximation the cost of maintaining or decommissioning redundant plant is high which makes the continuation of the model beyond the set forecast period necessary.

6.22 Fitness Result

The value returned from the fitness function is given by the sum of all the revenues from electricity generation minus the sum of all the costs. This also applies to the revenues and costs generated after the forecast period as described in Section 6.21. The return value also includes the sum of all externalities political functions and risks and penalties for exceeding technical and market constraints. This figure is therefore not representative of the actual profits within the ESI as many of these functions within this macroeconomic model represent weights, penalties and cost conversions. These weights and penalties are used to keep the optimisation within a realistic search space. They are not to adjust the importance of internal functions in order to influence the final results.

The fitness result gives a grade to the chromosome, or possible solution that has been evaluated. The fitness value affects the chances of this chromosome surviving to breed and have an influence over the next generation of chromosomes. In this manner those possible solutions which have high fitness results survive and those with low results are lost. The functions outlined in this chapter operate by contributing to the overall fitness result of each chromosome. Although the combination of these functions is non-linear and discontinuous, due to imposed constraints, they do not pose a problem to the optimisation process. This is because the GA only needs to assess the fitness of each possible solution, rather than create a mathematical solution to the simultaneous combination of these functions.

6.23 Summary

The functions, constraints and weighting mechanisms described within this chapter are included within the GAMES fitness function and represents the overall utility function which forms the core of the forecasting model. This function is used to assess the fitness of possible solutions passed from the GA selection operators. High fitness results imply that the possible solution is nearer to the optimum than low fitness results. However because the GA selection is based on the relative fitness of possible solutions, the actual values are not relevant.

7. THE G.A.M.E.S. PROGRAM

7.1 Overview

GAMES has been created using Microsoft Visual C++™ version 4. It has been compiled for use with Microsoft® Windows NT™. This takes advantage of dedicated 32 bit technology, pre-emptive multitasking and overall platform stability which is not fully available in Windows 95™ and Windows 98™.

GAMES has been designed to look like and run like standard Windows software and is easy to operate. Section 7.2 outlines the basic operational skills needed to run GAMES. Data manipulation is similar to that of common spreadsheets and is divided into Historical, Forecasting and External data sheets outlined in Section 7.3. Before running the genetic algorithm (GA) the user is given access to critical genetic operator functions. The manipulation of each of these operators is described in Section 7.4. The user can view the progress of the GA both during and after the optimisation process. The GA's progress can be assessed by analysis of the population or by viewing the model's output results. Section 7.5 concerns the results which can be displayed graphically or sent to a text file that can be viewed using Microsoft Excel or any text editor or spreadsheet. Viewing by spreadsheet has been simplified by a Microsoft Excel Macro that has been created to automatically read, and graphically represent these text files.

7.2 Starting GAMES

GAMES has been created with a Windows user in mind. Any Windows user who can operate the most basic functions in Windows Excel can easily master all the GAMES controls. GAMES can be operated without any knowledge of GAs as the default settings are set for optimum overall performance. For advanced use and manipulation of the genetic algorithm itself an understanding of GAs and their operators is needed. Altering the genetic operators can improve the quality of results and the time taken to generate them. It must be noted that the misuse of these options may compromise results.

7.2.1 Opening GAMES

To start GAMES the user needs to double click the GAMES icon on their desktop. The icon is shown below:

Figure 7.1 GAMES icon.

This brings the initial screen:

Figure 7.2 The initial GAMES option screen

The initial screen offers four choices:

1. *Edit Variables*; which starts the exogenous data editing wizard.
2. *Look*; which opens previous results and displays them as text or graphically.
3. *Go GA Go*; which is only enabled after the Edit Variables wizard is complete and allows the user to start the model immediately or manipulate the GA before starting the model.
4. *Quit*; which ends GAMES.

7.2.2 Priority Setting

GAMES does not interfere with any other applications whilst open and running. However the evolutionary process of the GA has been given a high processor priority to reduce the time needed for the model to achieve its goals.

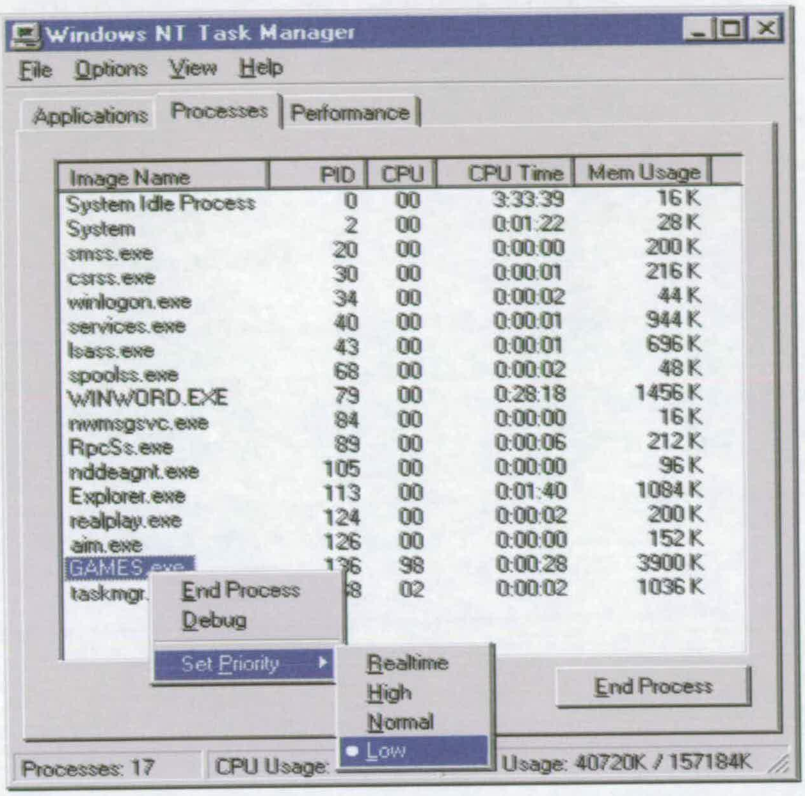


Figure 7.3 Using Windows NT Task Manager to set GAMES priority to low.

It is advisable to use the Windows NT Task manager to set the GAMES priority to low if the computer GAMES is running on will be needed for other processor intensive tasks. The Task Manager is opened by pressing *Ctrl + Alt + Del*. Once Task Manager has been opened use the right mouse button to click on *GAMES.exe* then choose *Set Priority* then left mouse button click on *Low*. GAMES will now run in the background with a low priority status.

7.3 Data Input

Data that is made available to the model is called exogenous data; in that it is derived externally to the model. The format by which this data is accessed and physically entered into the model designed to be intuitive as GAMES is intended for use by specialists in energy planning, not information technology. Exogenous data is split into three data sets, each with a separate data form. Each form represents separate exogenous data sources, or reference material. The three groups are:

1. Historical Data
2. Forecasting Data
3. Externalities

Historical data, discussed in Section 7.3.1, concerns occurrences before the time period of the model. Forecasting data includes the initial configuration of the model along with the exogenous data that describes possible future changes in the economy or technical experience in the energy sector. The majority of ESI sensitivity analysis performed using GAMES depends on changes to this data set which is described in Section 7.3.2. Section 7.3.3 looks at the final form, Externalities that provides the data necessary for the inclusion of political, technical, economic and environmental functions that lie out-with present simplistic long term models of the ESI.

7.3.1 Historical Data

A user of GAMES might wish to make forecasts that start before the present date (ex-post) and extend into the future (ex-ante). Correlations can be made between real and forecast scenarios and the error in the scenario can be assessed. An example of an ex-post/ex-ante forecast would use past data until year five and then rely on exogenous variable projections from year five to the end of the time period.

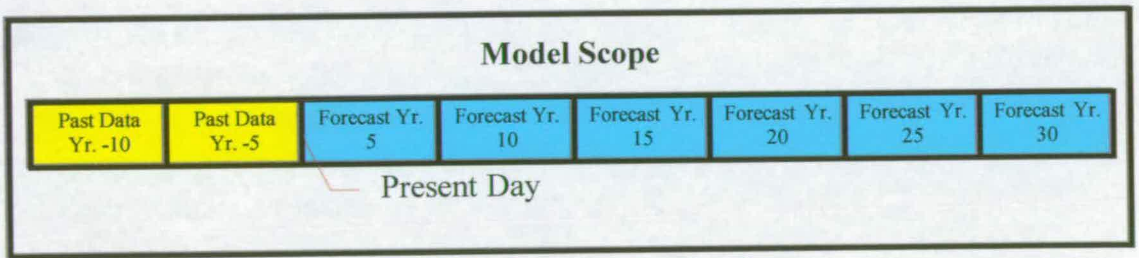


Figure 7.4 Using historical data in a forecast.

Due to the privatisation of the ESI, and its subsequent changes in structure, GAMES can not use past data to find probable trends in future events. However some historical data is necessary to create accurate scenarios. To reliably model electricity generation a starting point is needed. To achieve this the model must know the present generating capacity for each energy source. This includes generating plant that is not yet on-line but will be in the near future. In order to account for existing plant going off-line due to simply exceeding the its natural plant lifetime, the expected lifetime of all existing plant within the system is needed.

Historical data is placed into the model using the "Historical data" input sheet. The sheet is an integral part of the GAMES program but behaves in a similar manner to a spreadsheet. This includes the saving and loading of data along with cutting and pasting facilities. GAMES's familiar interface serves to minimise user training. The data is used in the fitness function to control the decommissioning, due to age, of plant along with providing a starting point for the plant forecast. The Historical Data Sheet is shown in Figure 7.5.

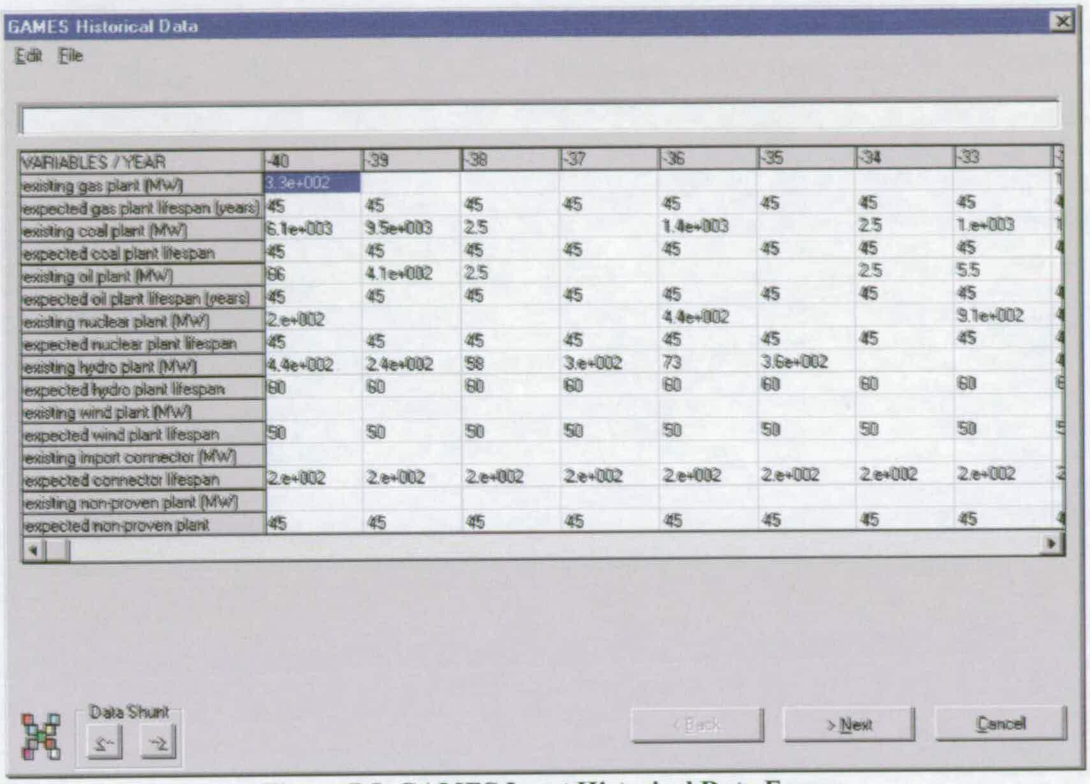


Figure 7.5 GAMES Input Historical Data Form.

The drop down menu bar can be used to open a new or existing sheet or save the displayed sheet.

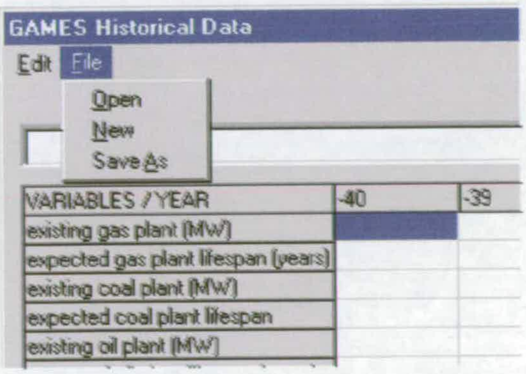


Figure 7.6 The GAMES Historical Data menu bar.

A standard Windows File Open or File Save window is called by clicking Open or Save As on the menu bar. All file access and saving in GAMES can be performed in this manner.

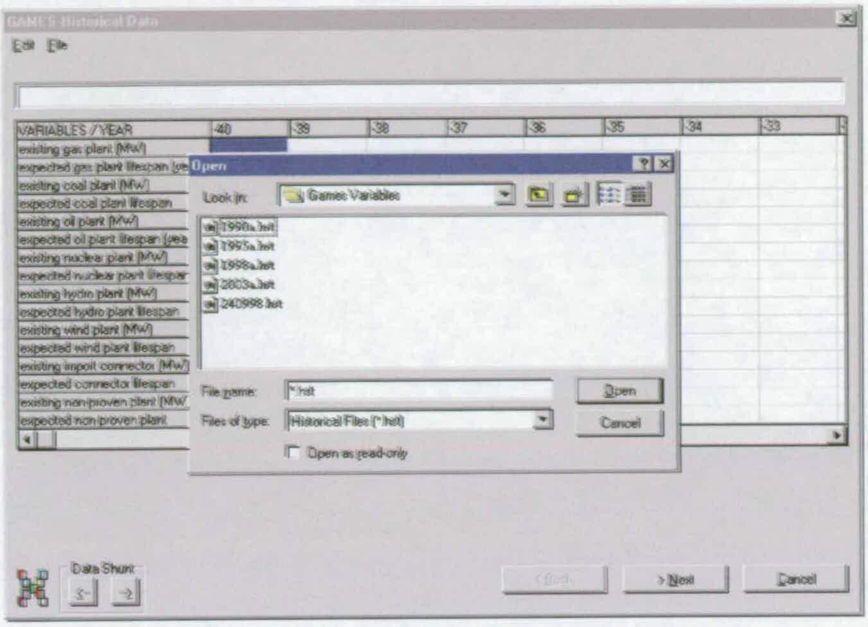


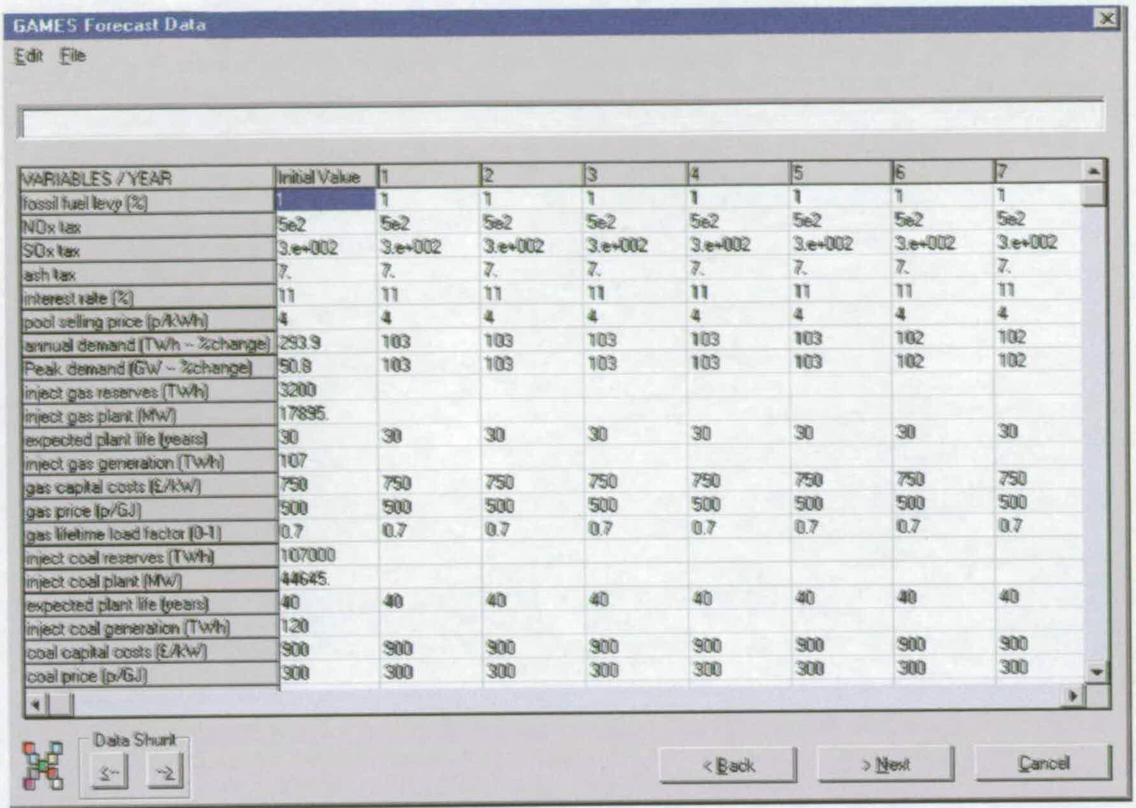
Figure 7.7 The GAMES File Open window.

7.3.2 Forecast Data

Forecast data uses a similar form to that of Historical data outlined in Section 7.3.1; in that it is based on a spreadsheet and is manipulated using the same tools. The form includes fields for all the data that the model needs to give the most likely generation spread for any possible scenario in the future. Data that results from historical events, such as the initial plant values, are displayed automatically; the remaining fields must be edited by hand or obtained from a file.

The data needed by GAMES to create the forecast model is varied and therefore not available from a single data source. This could result in a lack of continuity as all the data in this form has a direct effect on the scenario. To keep model integrity the continuity of data must be rigorously checked before it is used.

The Forecasting Variables include the annual and peak demands during the time period of the model, the energy resource available for each technology, technical information such as expected life and expected lifetime load factor for each generation method and the finance of generation. The Demand values are an initial value followed by a yearly percentile change whereas real values are taken for all other input fields.



VARIABLES / YEAR	Initial Value	1	2	3	4	5	6	7
fossil fuel levy (%)	1	1	1	1	1	1	1	1
NOx tax	5e2	5e2	5e2	5e2	5e2	5e2	5e2	5e2
SOx tax	3.e+002	3.e+002	3.e+002	3.e+002	3.e+002	3.e+002	3.e+002	3.e+002
ash tax	7.	7.	7.	7.	7.	7.	7.	7.
interest rate (%)	11	11	11	11	11	11	11	11
pool selling price (p/kWh)	4	4	4	4	4	4	4	4
annual demand (TWh ~ %change)	293.9	103	103	103	103	103	102	102
Peak demand (GW ~ %change)	50.8	103	103	103	103	103	102	102
inject gas reserves (TWh)	3200							
inject gas plant (MW)	17895.							
expected plant life (years)	30	30	30	30	30	30	30	30
inject gas generation (TWh)	107							
gas capital costs (£/kW)	750	750	750	750	750	750	750	750
gas price (p/GJ)	500	500	500	500	500	500	500	500
gas lifetime load factor (0-1)	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7
inject coal reserves (TWh)	107000							
inject coal plant (MW)	44645.							
expected plant life (years)	40	40	40	40	40	40	40	40
inject coal generation (TWh)	120							
coal capital costs (£/kW)	900	900	900	900	900	900	900	900
coal price (p/GJ)	300	300	300	300	300	300	300	300

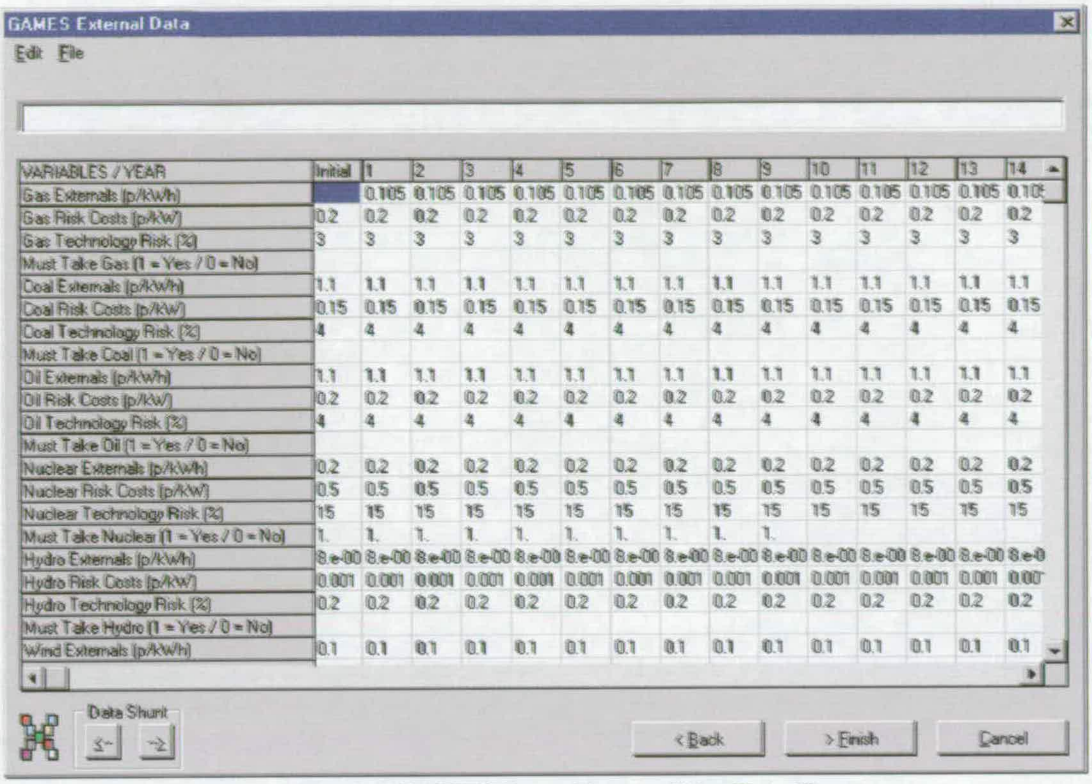
Figure 7.8 GAMES Input Forecasting Variables Data Form.

7.3.3 Externalities

The Externalities data form is manipulated in an identical manner to that of the Historical and Forecasting Data forms (Sections 7.3.1 and 7.3.2). It is constructed to perform like a spreadsheet that can be loaded from and saved to file, manipulated with the mouse or keyboard and scrolled to view and edit the data.

A general definition of Externalities is:

The costs and benefits that arise when the social or economic activities of one group of people have an impact on another, and when the first group fail to fully account for their impacts[106]. When applied to the ESI, externalities concern the associated costs of electricity generation that are not directly reflected in the market price for the energy.



GAMES External Data

Edit File

VARIABLES / YEAR	Initial	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Gas Externals (p/kWh)		0.105	0.105	0.105	0.105	0.105	0.105	0.105	0.105	0.105	0.105	0.105	0.105	0.105	0.10
Gas Risk Costs (p/kW)	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
Gas Technology Risk (%)	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
Must Take Gas (1 = Yes / 0 = No)															
Coal Externals (p/kWh)	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1
Coal Risk Costs (p/kW)	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15
Coal Technology Risk (%)	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4
Must Take Coal (1 = Yes / 0 = No)															
Oil Externals (p/kWh)	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1
Oil Risk Costs (p/kW)	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
Oil Technology Risk (%)	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4
Must Take Oil (1 = Yes / 0 = No)															
Nuclear Externals (p/kWh)	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
Nuclear Risk Costs (p/kW)	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
Nuclear Technology Risk (%)	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
Must Take Nuclear (1 = Yes / 0 = No)	1.	1.	1.	1.	1.	1.	1.	1.	1.	1.					
Hydro Externals (p/kWh)	8.e-00	8.e-00	8.e-00	8.e-00	8.e-00	8.e-00	8.e-00	8.e-00	8.e-00	8.e-00	8.e-00	8.e-00	8.e-00	8.e-00	8.e-0
Hydro Risk Costs (p/kW)	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.00
Hydro Technology Risk (%)	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
Must Take Hydro (1 = Yes / 0 = No)															
Wind Externals (p/kWh)	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1

Data Shunt

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< Back > Finish Cancel

Figure 7.9 GAMES Input Externalities Data Form.

In addition this form also includes some of the less direct economic influences in energy trading. The first is the deviation from normal market response due to the risk alleviating measures taken by the majority of players. The second influence concerns contractual obligations that have been, or could be at a later stage, entered into that restrict the workings of the electricity market. Both contractual and risk functions are included within the GAMES model.

7.4 Genetic Inputs

Before running the GA the genetic operators must be set. The user can set the number of generations, accept the default settings, and then click on *Go*. The default settings are:

- Population — Randomly generated
- Crossover Rate — 0.8
- Mutation Rate — 0.25 (High as the mutation is non-uniform)
- Mutation Factor — 4

Crossover rate, mutation rate and mutation factor can be edited on the GA operator form shown in Figure 7.10. Manipulating the population is performed using a separate form.

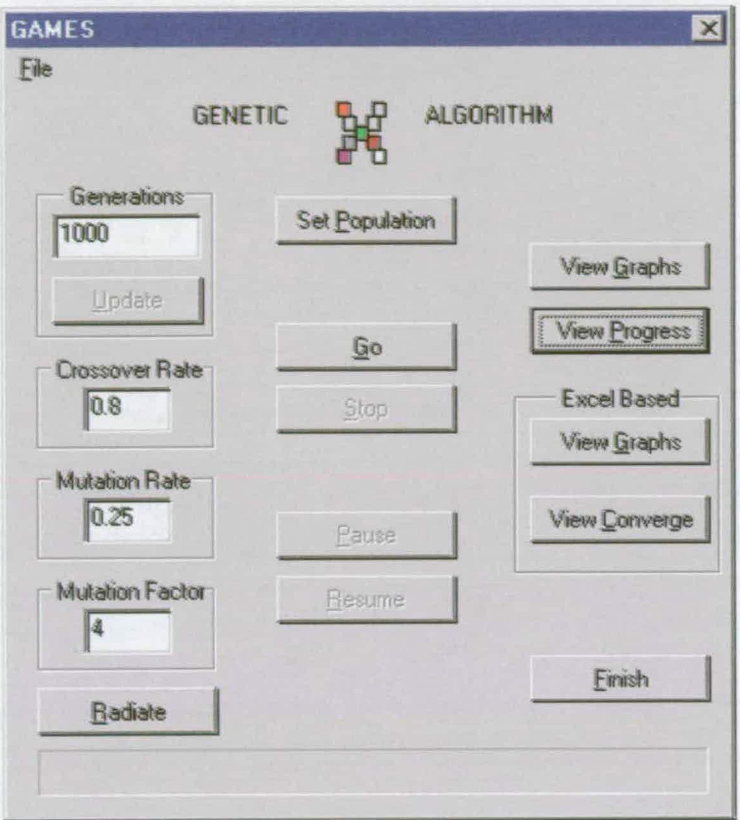

Figure 7.10 The GAMES GA operator adjustment and start form.

7.4.1 Population Manipulation

The GAMES GA uses a population of 100 chromosomes, or possible solutions. All, or a percentage, of these can be seeded before the optimisation is started. This allows the user to continue a previous optimisation based on a saved population. In addition the user can edit chromosomes from previous populations manually. Using an old population with a more refined set of genetic mutation and crossover operators can give a more focused view of a smaller search area resulting in a more accurate final optimum. An old population can also be used when exogenous variables have been slightly changed. This can vastly reduce convergence time as the old population should be in the correct region of the search area. However care must be taken to ensure that a local optimum from the previous set of exogenous data is not confused with the new global optimum. It is often advisable to start a new optimisation with a non-random population that is far from any optima. This will ensure that the whole search space is considered by the algorithm and any attempts by the GA to quickly converge on a sub-optimal peak will be clearly visible in the populations history.

To seed a population the Initial Population must be opened by clicking on *Set Population* in the Genetic Operator adjustment form. Clicking on *Seed* at the top of the page allows the selection of the percentage of the population that is to be seeded manually. The remaining population will be filled with data from an old population or a random population. Old or random populations are selected by clicking *Use Old Population* or *Use Random Population* respectively. The chromosome manipulation table will now be enabled and can be edited. Each box represents the proportion of yearly generation by each generating method. There is a maximum of 98% for an individual generating method as it is unreasonable to assume that the whole UK ESI will rely on over 98% generation by one fuel alone. Values greater than 98% would not comply with the risk strategies built into games and could result in model instability. The generation methods that have been edited must be fixed by clicking the relevant check boxes in the *HOLD* field. The seed is finally planted, and the remaining unfixed boxes in the chromosome automatically filled by clicking *Plant Seed*. Clicking *OK* returns the user to the Genetic Operator adjustment form.

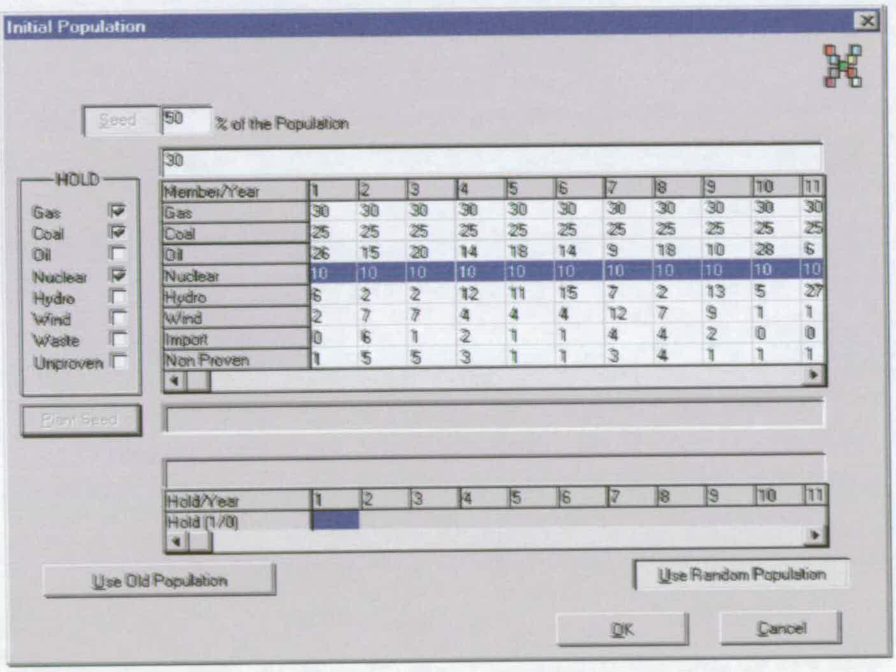

Figure 7.11 GAMES Population manipulation form used to seed a GA population.

GAMES is designed to optimise for the whole forecast period to allow for forwards and backwards dependencies in the model. This implies that, under normal operation, the model can never be shocked by an unexpected event, such as the 1991 Gulf War. To overcome this the user can run the scenario without the unexpected event, then add the unexpected event data and hold all the results from the time periods before the changed data. The GA is then set to optimise the effects of the unexpected event. This is achieved using the *Hold/Year* field in the

Population Manipulation form. Figure 7.12 shows how this field uses a binary code where a "1" tells the GA not to optimise that years genes. Normal use would involve a string of holds until the date of the unexpected event in the scenario. Holding individual independent groups of years is also possible.

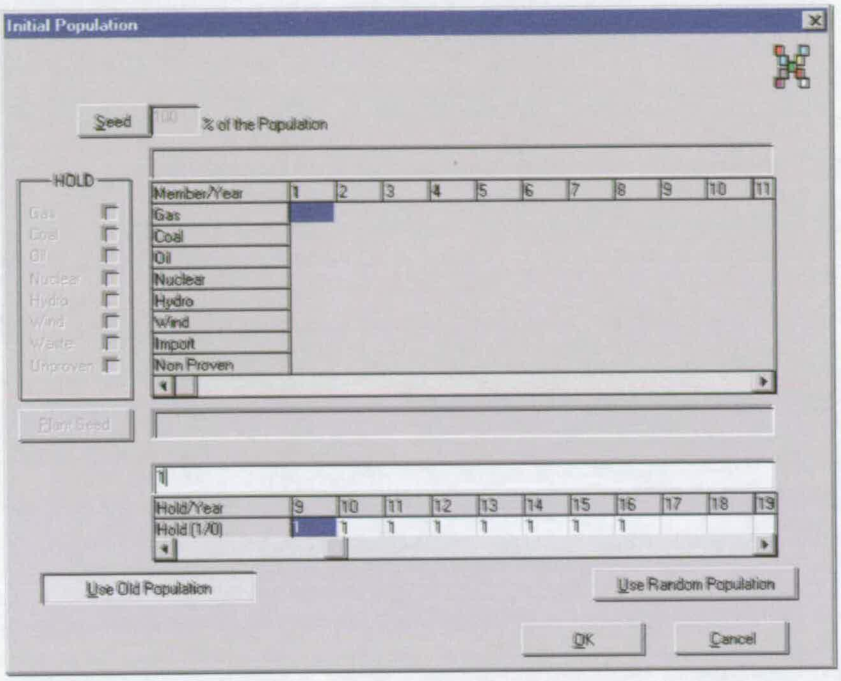

Figure 7.12 GAMES Population manipulation form used HOLD years to investigate the affect of an unexpected event.

7.4.2 Crossover Manipulation

Crossover involves the creation of child chromosomes through the cross-combination of parent's genes. There are many types of crossover, each with different benefits and shortfalls. GAMES uses a two point crossover. A two point crossover selects two crossing sites in the chromosome and swaps the genetic material between them. If P_1 and P_2 are the selected parents that represent the binary chromosomes

$$P_1 = (0_1\ 1_1\ 0_1\ 1_1\ 0_1\ 0_1\ 0_1\ 1_1\ 1_1\ 0_1\ 1_1) \qquad \textbf{Equation 7.1}$$

$$P_2 = (0_2\ 0_2\ 0_2\ 1_2\ 1_2\ 0_2\ 1_2\ 0_2\ 1_2\ 0_2\ 0_2) \qquad \textbf{Equation 7.2}$$

and the two randomly selected points are after the 3rd and 6th genes (or bits in the string) i.e.

$$P_1 = (0_1\ 1_1\ 0_1 \mid 1_1\ 0_1\ 0_1 \mid 0_1\ 1_1\ 1_1\ 0_1\ 1_1) \qquad \textbf{Equation 7.3}$$

$$P_2 = (0_2\, 0_2\, 0_2 \mid 1_2\, 1_2\, 0_2 \mid 1_2\, 0_2\, 1_2\, 0_2\, 0_2) \qquad \textbf{Equation 7.4}$$

then the two children C_1 and C_2 that result from the two point crossover are given by:

$$C_1 = (0_1\, 1_1\, 0_1\, 1_2\, 1_2\, 0_2\, 0_1\, 1_1\, 1_1\, 0_1\, 1_1) \qquad \textbf{Equation 7.5}$$

$$C_2 = (0_2\, 0_2\, 0_2\, 1_1\, 0_1\, 0_1\, 1_2\, 0_2\, 1_2\, 0_2\, 0_2) \qquad \textbf{Equation 7.6}$$

Two point crossover offers the opportunity for any of the first parent's individual, or group of individual, genes to be exchanged with their respective genes in the second parent. It is a simple and quick method of crossover that will not destabilise the model as chromosome integrity is always kept.

The crossover rate is the probability (from 0 to 1) of each chromosome in the population undergoing crossover. A high crossover rate enables quicker hill climbing and population convergence. Ideally the population should only converge once the exact area of the global optimum is found. However if the crossover rate is too high the standard deviation of the population will reduce before a global optimum is found. This will reduce the efficiency of the GA and could dramatically degrade the optimisation.

7.4.3 Mutation Manipulation

Mutation involves the random alteration of individual genes in a chromosome to ensure that the whole search space is considered in the optimisation. A single gene in GAMES represents, as a percentage, a single years proportional usage of each of the generation methods. To satisfy the assumption that demand is always met by generation the total sum of generation method proportions must always equal 100% in every gene. GAMES achieves this by mutation in pairs; as one generation method is increased by a random value another, within the same gene, is reduced by an equal amount.

The mutation rate always lies between 0 and 1and represents the chance of an individual gene undergoing mutation. A standard value is given by:

$$\textbf{mutation rate} = {}^{1}\!/_{(\text{No. of genes in the chromosome})} \qquad \textbf{Equation 7.7}$$

A higher mutation rate gives a better view of the whole search area but does not help the final stages of the optimisation where a lower rate of mutation would give a more refined search.

Changing the mutation rate during the optimisation process can give good results: High mutation rates, that reduce with convergence are very efficient if local optima convergence is not confused with convergence on the global optimum. A period of high mutation rate after the GA has converged on an optimum will move it away from local optima but not a global one this can be achieved by pressing the *Radiate* button on the operator adjustment form.

7.4.4 Mutation Factor

Large mutations are efficient at the beginning of an optimisation as they increase the diversity of the population. A method of refining an optimisation is to reduce the size of random mutations near the end of the process. GAMES uses a non-uniform mutation operator on each generation method within the gene, or year, that is to be mutated. The operator is dependent on the ratio of generations that have been completed (*t*) to the number of generations expected (*T*). The higher the ratio of completed generations (*t/T*) the smaller the effect of each mutation. This is achieved by scaling the random mutation value (*r*) by:

$$1 - r^{\left(1 - t/T\right)} \qquad \textbf{Equation 7.8}$$

where: $0<r<1$

The user can alter the rate by which this scaling down occurs through the use of a mutation factor (*F*) which exponentially increases, or decreases, the scaling function. It is implemented as shown below:

$$1 - r^{\left(1 - t/T\right)^F} \qquad \textbf{Equation 7.9}$$

where: $F \geq 0$

A mutation factor of zero would follow a simple uniform mutation as described in Section 7.4.3. The default mutation factor of four has been chosen as it was proven to be efficient in most cases. Higher mutation factors quicken the rate of mutation down-scaling near the end of the optimisation.

The mutation factor is also used to define the probability of a chromosome undergoing the GAMES specific function flatten. Flatten is a heuristic mutation operator which only changes the chromosome if the resultant, mutant, is fitter. As this could result in a reduction in diversity it is only implemented towards the end of the evolutionary process. This is achieved by using the inverse of the non-uniform mutation described above to ensure that it only has a small impact until the end of a search.

7.5 Viewing Results

The optimisation is started by clicking *GO* and can be paused and restarted an any time by clicking either *Pause* and *Resume* respectively.

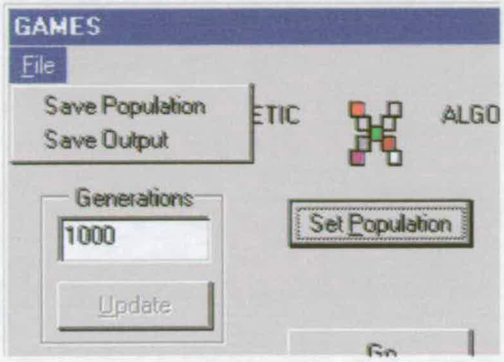

Figure 7.13 Saving Population or Output results.

The population and the output results can be saved whilst the GA is paused or stopped. Saving the population allows the user to return to that particular part of the optimisation process. Whilst paused the progress of the GA can be viewed. Clicking *View Progress* opens a text sheet that gives for each generation:

- Best value of fittest chromosome in the population.
- Average fitness of the population.
- Standard deviation of chromosomes in the population.
- The value of each gene in the fittest chromosome when the GA was paused.
- The value of the fittest chromosome when the GA was paused.

The results can also be seen at this stage. This can be done through Microsoft Excel by clicking the *Excel based* buttons *View Graphs* and *View Convergence*. These buttons open Microsoft Excel 7 macros which view the output results, population data or the convergence graphs for the GA. The ability to use a spreadsheet to view results allows further manipulation of that data. GAMES does include its own integral result viewing form. This can be accessed by clicking *View Graphs* in the GA operator adjustment form. Alternatively saved results can be seen by clicking *Look* on the GAMES title screen which opens the View Results form (Figure 7.14). Once the relevant files are opened the user is offered a choice of *View in Excel* or *View as Graphs.* By clicking the *View as Graphs* button the user opens the Output form. Figures 7.15 to 7.19 are examples of the results from GAMES scenario studies. They do not necessary represent a global optimum, and the most likely solution, but represent possible future outcomes to test scenarios.

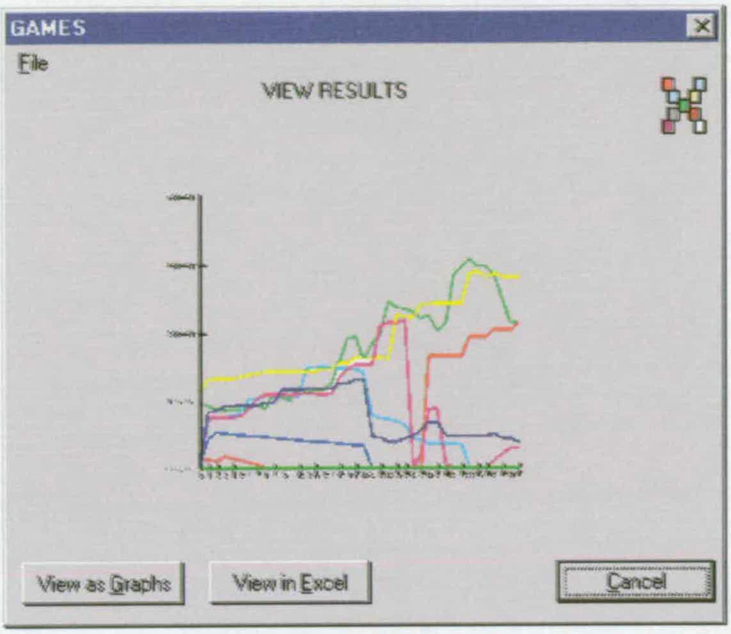

Figure 7.14 GAMES View Results Form.

The Output form has five tabs and three control buttons. The first control button allows the user to switch the graphs to *Black & White,* for black and white only printing. The remaining two control buttons allow the user to *Print to File* and *Print* the displayed graph.

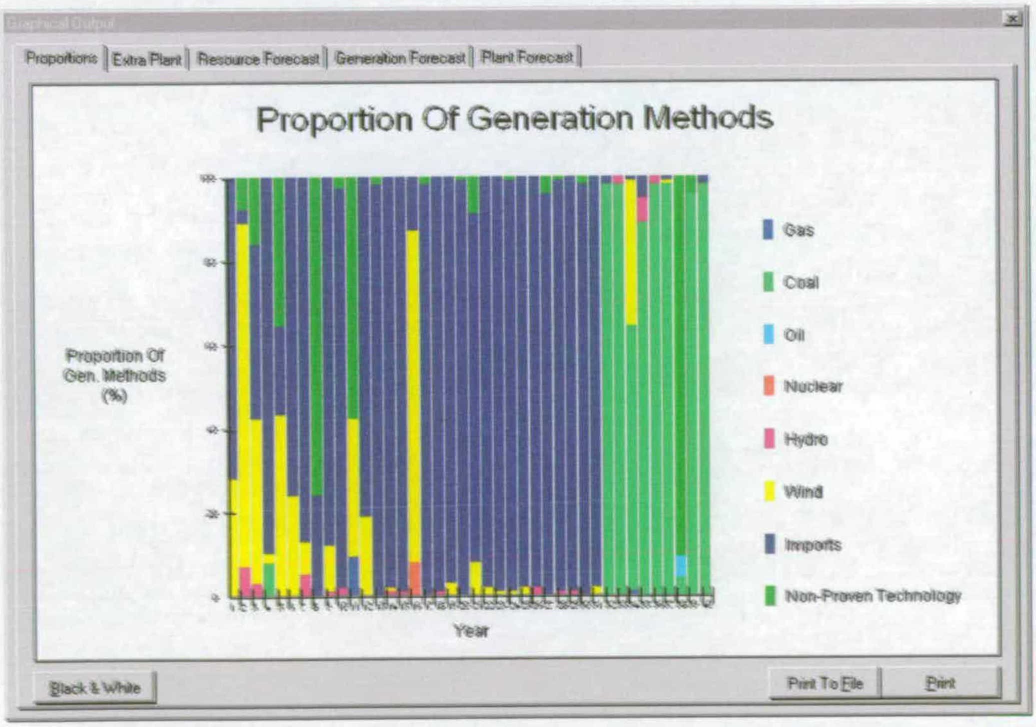

Figure 7.15 GAMES output graphic indicating yearly proportions of generation methods.

The First tab, *Proportions,* is a graphical representation of the fittest member of the population. Each generation method is given a colour and the yearly distribution of these colours represents the proportion of generation given, on a yearly basis, to each generation method. The Proportions graphic is useful in spotting trends in the results. It allows a quick estimation of where the optimisation is heading and clearly shows the change from unfeasible solutions to likely outcomes as the GA progresses. Figure 7.15 shows a possible solution to a scenario that includes external costs and clearly indicates the transitions, over time, between different generating methods. The results do not represent a crystal ball view into the future but give an indication of one of the most likely outcomes to a pre-defined future scenario.

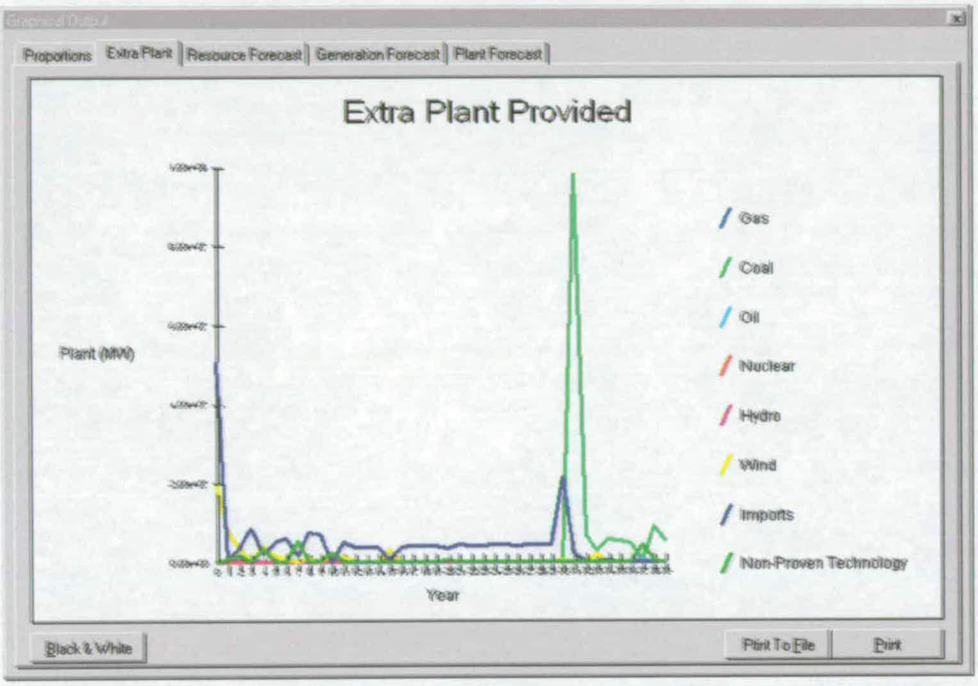

Figure 7.16 GAMES output graph of extra plant provided on a yearly basis.

The second tab, *Extra plant*, gives the extra plant built so that capacity will meet expected yearly generation demands. Each spike represents new plant that is due to come on-line that year. Figure 7.16 is a solution that sees an initial increase in wind powered generation and interconnector capacity due to high levels of environmental taxation. No new gas powered CCGT plant is constructed but gas reserves are depleted by year 30 due to generation by existing plant. At this point in time gas powered plant is replaced by coal plant, some wind turbines and even a small amount of non-proven generation schemes are used to make up for the shortfall.

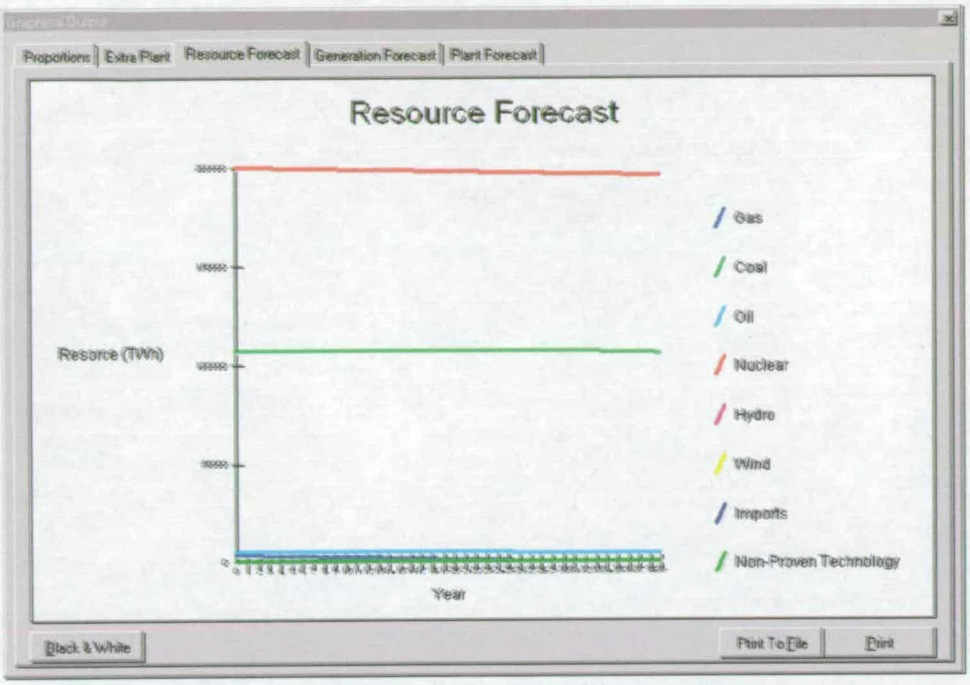

Figure 7.17 GAMES output graph of forecasted resource.

The third tab, *Resource Forecast*, shows the resource available to the UK ESI and clearly shows the depletion of gas reserves. This graph can be misleading if the UK resource and the world resource available to the UK are confused. As all the fissile material needed for nuclear fission is imported from a world market Figure 7.17 seems to show a disproportionately high nuclear resource. However these figures do account for world usage of these materials.

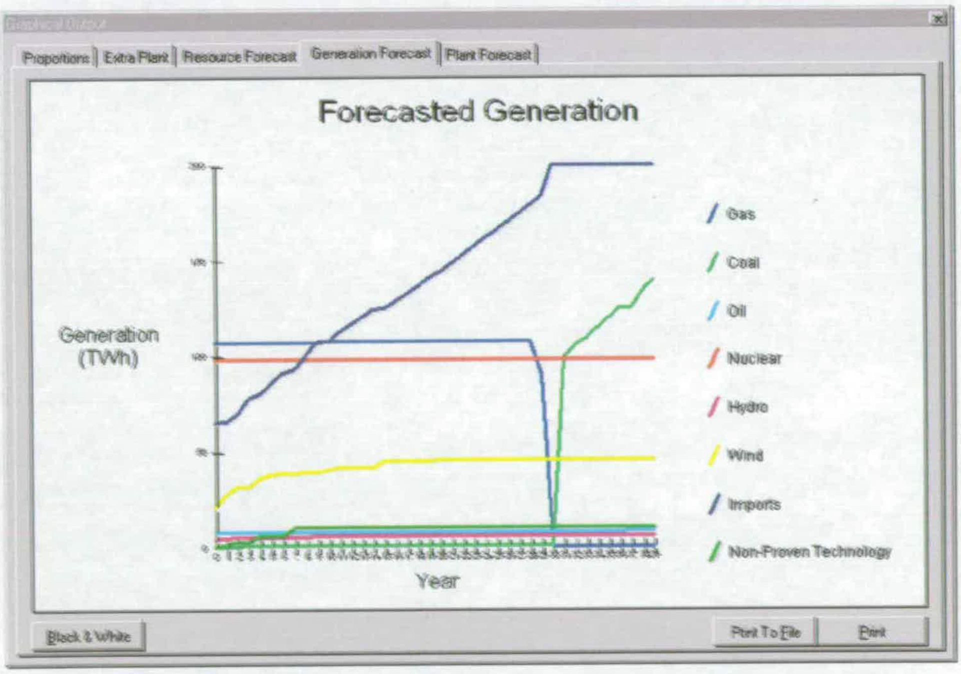

Figure 7.18 GAMES output graph of forecasted generation on a yearly basis.

The *Generation Forecast* tab shows the yearly forecasts for generation by each generation method. The depletion of UK gas supplies is clearly visible in Figure 7.18 and the resulting generation increases in coal, imported electricity, wind and non-proven technologies are shown. Due to its high external costs, coal generation is initially set to zero. Gas generation is used heavily as it has less external costs and is cheaper than coal until, in year 28, UK gas supplies start to run low. The model suggests that the generation shortfall, while the remaining gas power stations are being replaced by coal fired plant, is taken up by an increase in imported electricity from France. This would involve increasing the capacity of the interconnector between England and France. Because nuclear powered generation is under a *must-take* obligation the graph shows a straight line representing optimum yearly load factor.

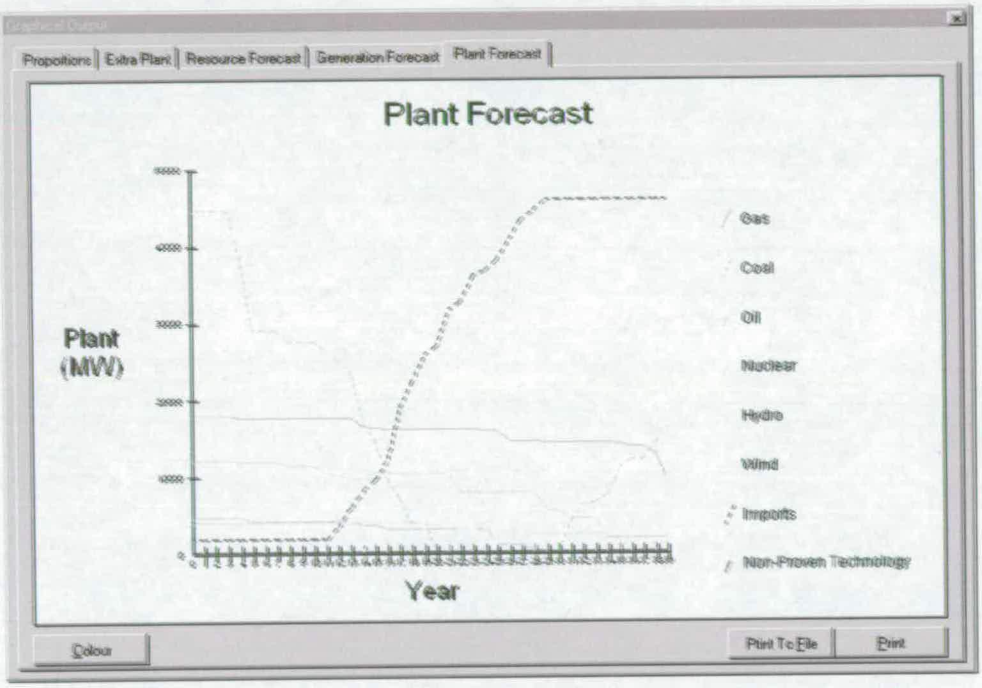

Figure 7.19 GAMES output graph of forecasted plant mix in black & white.

Figure 7.19 shows the final tab, *Plant Forecast*, in black and white mode. This mode is useful when printing without a colour or grey scale facility. The graph shows that no new gas plant is built during the forecast time period. The total gas capacity gradually reduces as old plant is decommissioned, and not replaced. However, it is clear that using the full extent of existing capacity is sufficient to cause the depletion of UK reserves within 30 years. Initially coal plant reduces quickly as it is not used until gas reserves become scarce and new coal plant is needed to meet the shortfall. The most prominent feature of all these graphs is the high usage of imported electricity. This is because French generation is not subject to the same environmental taxation as the UK in this scenario. This is interesting as it shows how future electricity trading within Europe might be affected by different taxation structures among the member states.

7.6 Summary

This chapter follows the operation of GAMES. Although it is has not been written as a user manual it gives an outline of the basic functions of the program. The data sets used as inputs and the results given are examples of possible scenario forecasts which are detailed in chapter 8. They show the application of the program to long-term energy planning in the UK ESI. The chapter also highlights the interface between the user and the GA. This is important because there are very few GA based programs that allow the user to change the nature of the genetic operators in an intuitive manner. For example the interface that controls the seeding and holding of genes was based on a fruit machine, with hold buttons under each relevant gene on the graphical display. This novel approach is an example of the effort to make GA applications accessible to users with a limited knowledge of GAs.

8. DISCUSSION OF RESULTS

8.1 Overview

This chapter discusses the results of a number of simulations completed by the Genetic Algorithm based Model of Electricity Supply (GAMES). The results validate GAMES as an ESI forecasting model. The first Section 8.2 looks at the results from the initial feasibility study. These results show how a simple GA was able to evolve solutions to a complex forecasting problem and are important as the foundations of GAMES were built upon this initial study. Section 8.3 discusses the GA's performance and shows how each genetic operator affects the overall optimisation process. Each operator has been designed and set up to aid the evolutionary process for the particular problem of forecasting electricity generation methods. Deviations from this optimum are also discussed. Section 8.4, on the model's performance, displays and discusses examples of forecasts made using GAMES. It gives the results of an ex-post validation forecast and five separate scenario studies. Each scenario investigates sensitivities in the model whilst also giving predictions as to the future of electricity generation in the UK. These particular scenarios were chosen because each represents a different aspect of the industry: The first extrapolates current political opinion concerning nuclear power and gas generation. The second forecast takes an environmentalists approach and charges the generators for the environmental costs of generation. The third investigates a change in expected resource constraints as an oil pipeline brings cheap oil into Europe. The fourth scenario looks at the possibility of a technical fault in the British-French interconnector and its effects on UK supply. The final scenario shows how the sensitive adjustment of taxation and regulation can result in a balanced long-term approach to generation in the UK.

8.2 Feasibility Study

A test model was initially created to investigate the feasibility of using a GA in ESI forecasting. This model assumed that all UK electricity was generated using either coal or gas. It incorporated forecasts such as emissions taxes, resource costs, technical advances and UK electricity demand; all of which could be altered for sensitivity analysis. The fitness function was constructed using functions based on economic theory and knowledge of the ESI. All functions were subject to environmental and technical constraints. The model's GA

(Evolver by Axcelis) was constructed using a fifty chromosomes population. Each chromosome represented an outcome of possible gas to coal mix over a forty year period. The chromosome itself consisted of forty genes, each representing a possible single years percentage of gas and coal generation. All, bar one, of the chromosomes started with random values assigned to each gene. The remaining chromosome could be seeded with a fit or unfit solution; the former to speed convergence and the latter to aid divergence.

Figure 8.1 shows the effect of a single chromosome seeded with 50% gas and 50% coal before the GA optimisation has started. This seed represents a possible, but highly unlikely, outcome that assumes all extra plant capacity will be met equally by gas and coal. The graph shows how this 50:50 fuel mix continues until year 21 when UK gas reserves are exceeded. At year 21 the model corrects the seed and replaces all of the, now redundant, gas fired plant with coal plant. This is represented by the peak in the extra output from coal plant. Although this solution is possible, and meets all the model's constraints, it is a highly improbable solution. An optimum solution was created through the evolution of a population of unlikely solutions into a population of optimised or highly likely solutions. The evolutionary process was controlled by a GA which used standard selection, breeding and mutation operators.

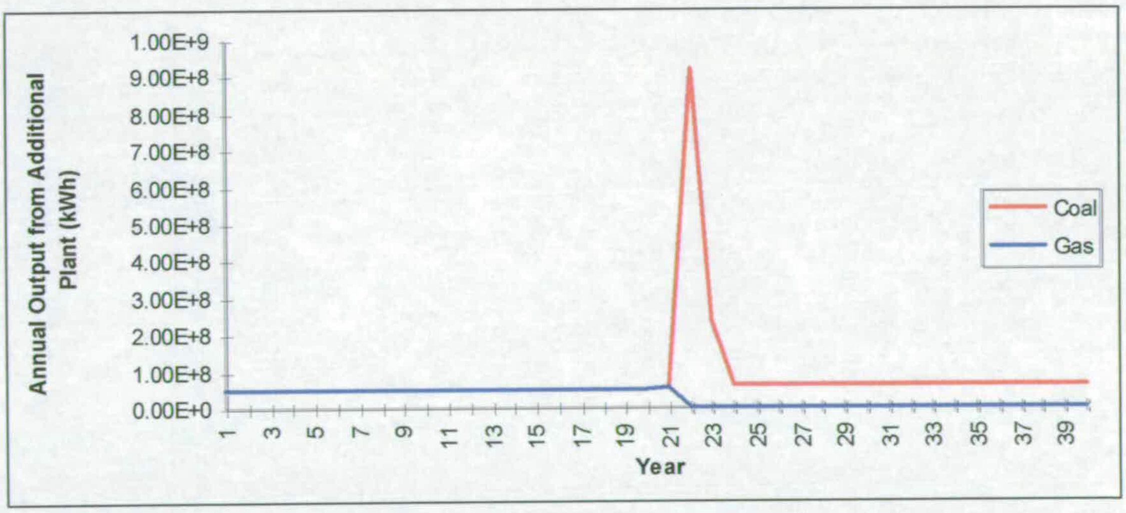

Figure 8.1 Starting (before optimisation at 0 Generations) 50% Coal 50% Gas Seed of a GA Based Forecast of Extra Output Needed from Additional Coal and Gas Plant.

Selection was based on a standard roulette wheel method which gives proportionally higher breeding rates to fitter chromosomes. Once selected, breeding was performed using a two point crossover to allow the passing down of market and technical trends through successive generations. This involved randomly selecting two points along the breeding chromosomes and swapping the sections within these points. Both parents and children were then re-inserted into the population replacing the two least fit solutions.

The mutation rate was manually altered during runs. It was increased after initial convergence to help ensure that a global, not local, optimum had been found. When an increased mutation rate had no further effect, it would be set to almost zero to aid final convergence. Figure 8.2 shows the GA's progression towards convergence on an effective energy resource utilisation plan. The sharp peak that represents the sudden replacement of gas plant with coal plant has been reduced and a trend towards building more gas than coal plant initially can be seen. This is consistent with what is expected from a gas and coal only ESI as the cheaper gas resource is there to be used so long as the financial lifetime of plant does not exceed the availability of resource.

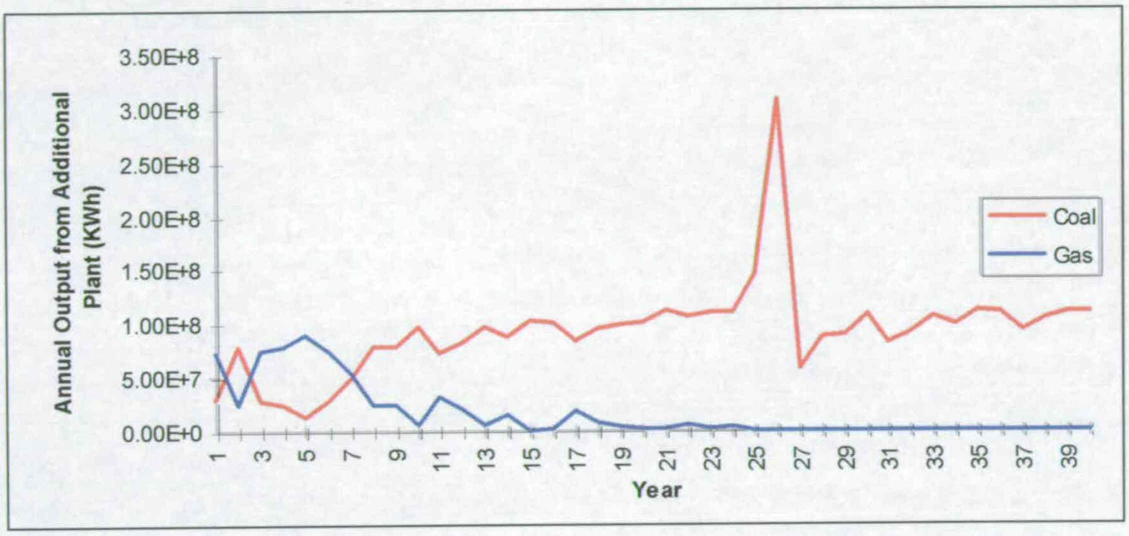

Figure 8.2 Mid point (2,000 Generations) GA Based Forecast of Extra Output Needed from Additional Coal and Gas Plant Needed

The model converged on an optimum solution after 200,000 generations. As the number of possible solutions was 10^{80} the GA was considered very effective. Figure 8.3 shows the optimum extra gas and coal plant needed to replace old plant whilst meeting a growing demand. The results indicate a change in strategy from gas to coal based on resource depletion. Initially gas plant construction is increased and then remains high over the next six years before dropping away between years six and thirteen. Gas plant construction beyond this period would be unlikely as the plant life would exceed present UK gas resources. To accommodate the resulting capacity shortfall extra coal plant construction is suggested to start in year five.

This scaled test model proved that by predicting the results of yearly generation mix decisions, a clear picture of the shape of a future ESI was possible. Using a GA based model allowed the inclusion of economic, technical and environmental constraints that otherwise proved insoluble using conventional mathematics due to their size and non-linear nature. The ability of GAs to solve large, non-linear, problems allowed rapid and comprehensive sensitivity analyses on the forecast model. The sensitivity studies showed stability in the model when fuel price, interest rate, taxation and electricity demand predictions were altered to examine their effect on future generation fuel-mix.

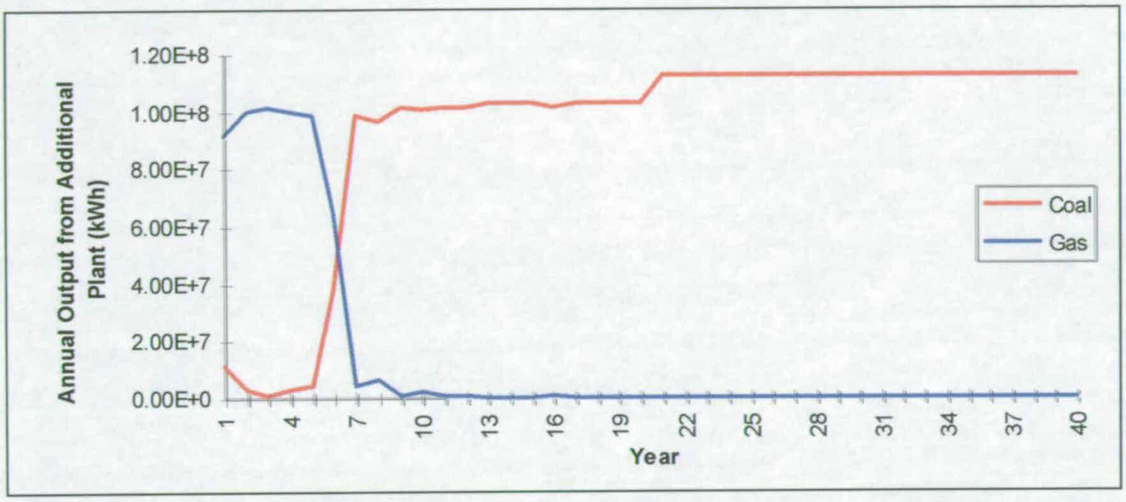

Figure 8.3 Convergence (200,000 Generations) GA Based Forecast of Extra Output Needed from Additional Coal and Gas Plant.

As a result of the success of the feasibility study a full size model was created. Unfortunately due to slow processor speeds and the memory intensive use of Microsoft Excel by Evolver it was not possible to expand the existing test model. To include extra generating methods and real data, a comprehensive model of the ESI was written from scratch on a new platform. Although the general structure of the GA used to solve this model was based on a standard GA by Z. Michalewicz[107] all of the genetic operators were re-written for this specific application. This Genetic Algorithm based Model of Electricity Supply (GAMES) was written in C++ using Microsoft Visual C++ 4. C++ was chosen as its object oriented structure facilitates rapid code alteration along with aiding intuitive GA design. GAMES was designed to run on Windows NT which is the most stable of the windows operating systems in common industrial use. Windows NT also offers pre-emptive multitasking and dedicated 32 bit technology which helped speed up the evolutionary process and give added stability to the GAMES GA.

8.3 GA Performance

A Standard GA uses selection, crossover and mutation to evolve solutions to the fitness function. Better solutions evolve with the passing of consecutive generations. The efficiency of the evolutionary process can be increased through the manipulation of these standard functions and the inclusion of further evolutionary operators. The benefit of any additions to the standard GA must be greater than their computational expense as changes to the standard GA often increase computation, and therefore also the time, needed to complete each generation. This section discusses the performance of the GAMES GA and how new functions work both independently and in combination with standard operators to improve the optimisation process.

The performance of any GA can be tested by monitoring the fitness of the best individual in the population, the average fitness of the population and the standard deviation of individuals within the population over a number of generations. The fitness of the best individual indicates the speed with which the GA can find an optimum. Steps in the best fitness indicate local optima found by the GA. Although a steeper slope indicates rapid convergence on an optimum, it can also indicate a lack of diversity due to excessive selective pressure. The average fitness of the population shows how the whole population's fitness compares to the best individual's fitness. It should increase along with the best value as the difference between the average and best gives an indication of where the population lies in the search space. The average should vary but should never converge on the best value as this would indicate a lack of diversity. If the selective pressure is too high the average will rise until it reaches the best value indicating that the whole population has become multiple copies of the same chromosome. The actual spread within the population is given by the standard deviation. This shows the diversity of the population and although it can vary from generation to generation it should not rise or fall over the course of a normal GA optimisation. Operators such as non-uniform mutation have can the effect of reducing the standard deviation within the population as they reduce the effect of individual mutations. For this reason the non-uniform mutation operator used in GAMES is adjusted to only have a dominant effect near the end of the optimisation.

The GA performance indicators, mentioned above, were used to test the performance of individual genetic operators. This was achieved by isolating the effects of each operator. GAMES was run eight times, with one operator changed each time. Because some operators rely on the existence of others, the test procedure started with a core GA and was built up operator by operator until the final GAMES GA structure was created. The test procedure was as follows:

1. Control with standard GA mutation and crossover rates.
2. Flatten operator test, which is a heuristic mutation operator
3. Non-Uniform Mutation Test which investigated the inclusion of non-uniform mutation.
4. Recall Test which investigated the addition of the Recall operator to test number three.
5. Mutation Rate Tests that investigated changes in mutation rate.
6. Crossover Rate Test which assessed the effects of crossover rate changes.
7. Radiate Test that looked into the use of the Radiate function.
8. Radiate Test with a destructive seed added to ensure global optimisation.

The results from each of these tests are shown and discussed in Sections 8.3.1 to 8.3.8 respectfully. The results show how each operator aided the optimisation process and how the model remained stable through out testing.

8.3.1 GA control

Settings

Flatten Mutation	=	Not Applied
Mutation Factor	=	0 (Uniform Mutation)
Recall	=	Not applied
Mutation Rate	=	0.025
Crossover Rate	=	0.8
Radiate	=	Not Applied
Seed	=	Not Applied

The control test was used to standardise the GA performance tests. It does not use the specially designed GAMES operators Radiate, Recall, Seed or Flatten. Figure 8.4 shows the first 3000 generations of a 5000 generation run as this is the most interesting phase of the optimisation process. Both the rate of initial optimisation and the final stages of the search can be seen within this number of generations.

Due to the elitist function the best chromosome is always kept. This causes the gradient of the best value graph to be positive or zero, but never negative. In this control the best value increased gradually which proves that the GA is operational. The crossover and mutation rates were set to achieve an average performance for the whole search, remaining constant throughout the search, and therefore the overall optimisation process was slow. An optimum result was found if the search was continued to around 20,000 generations. The average fitness went both up and down as the population travelled between local optima. This curve roughly followed the direction of the best value trace. The standard deviation remained constant which shows a good choice of mutation and crossover rates.

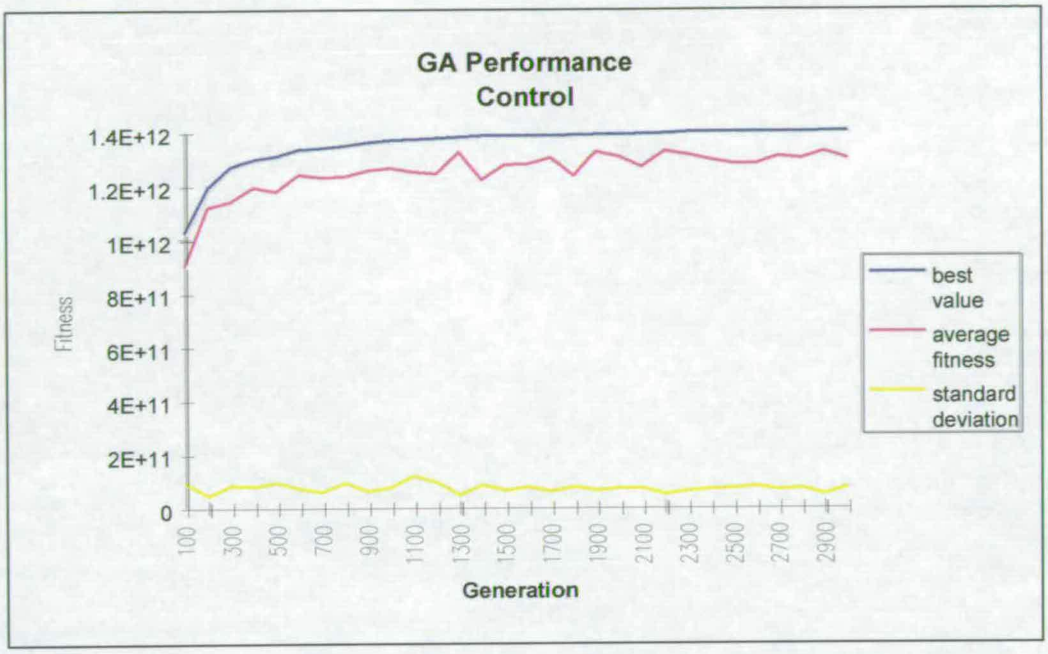

Figure 8.4 Graph of Standard GA Performance represented by the best fitness value, average fitness and standard deviation of chromosomes. This Graph is used as a control for the testing of other operators and only contains the vital components of the GAMES GA.

8.3.2 Flatten Operator Test

Settings

Flatten Mutation	=	Active
Mutation Factor	=	0 (Uniform Mutation)
Recall	=	Not applied
Mutation Rate	=	0.025
Crossover Rate	=	0.8
Radiate	=	Not Applied
Seed	=	Not Applied

The Flatten operator was specially created to speed up the GAMES optimisation process. It is a heuristic mutation operator, added to the existing mutation operator, that is subject to the same mutation rates. It mutates a chromosome by removing excessive peaks and troughs in consecutive gene fragments (DNA) or yearly generation procedures. Although this increased the total amount of mutation the heuristic part did not increase diversity to the same extent as random mutation. The increase in diversity within the population can be seen in Figure 8.5 as the standard deviation of chromosome values is higher than that of the control in Figure 8.4.

Because this operator was added to the existing uniform mutation operator the slightly slower final convergence was due to the total increase in mutations. Section 8.3.3 investigates the addition of a non-uniform mutation which eliminated this effect.

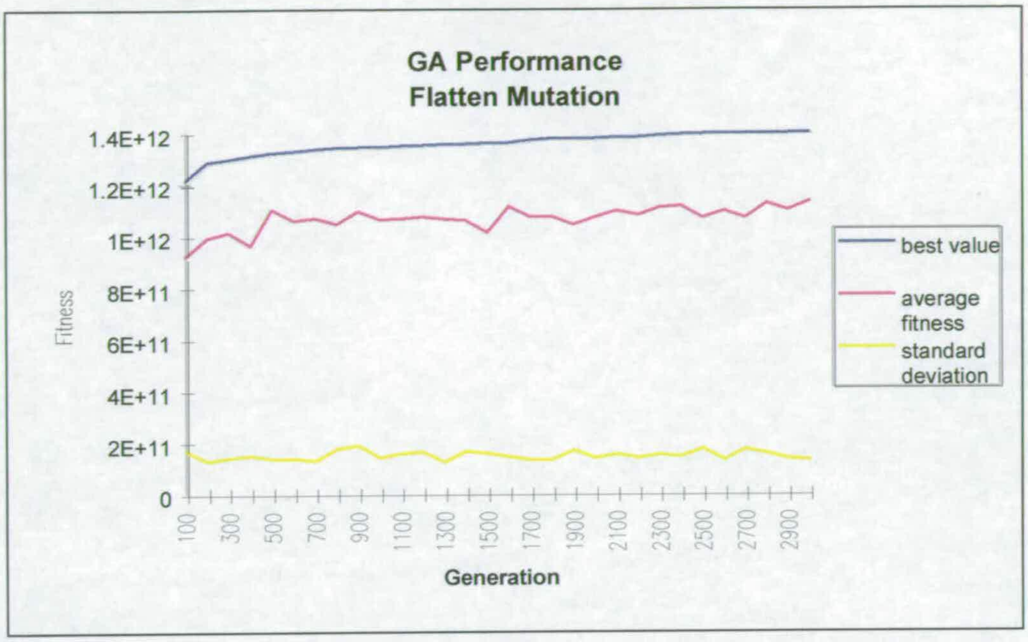

Figure 8.5 Graph showing the best fitness value, average fitness and standard deviation of chromosomes in a standardised run of GAMES with a heuristic flatten mutation operator added to the existing uniform mutation operator.

The major advantage of the flatten operator was that it accelerated the initial climb peaks in the search space. This can be seen by the high fitness value after only 100 generations. However, if left long enough, the penalties within the fitness function for inefficient generation schedules had the same effect as the flatten operator. The extra speed in the initial stages allows the rapid creation of approximate results which is useful for energy planners.

8.3.3 Non-Uniform Mutation Test

Settings

Flatten Mutation	=	Active
Mutation Factor	=	(Non-Uniform Mutation)
Recall	=	Not applied
Mutation Rate	=	0.025
Crossover Rate	=	0.8
Radiate	=	Not Applied
Seed	=	Not Applied

This test investigated the use of a non-uniform mutation operator along with the flatten operator discussed in Section 8.3.2. The operator reduced the size of mutations as the optimisation process neared its end. The reduction was an exponent of the fraction of generations completed raised to the power of the mutation factor. Figure 8.6 shows the average value began to converge on the best value at around 2500 generations. The operator improved the optimisation by increasing the selective pressure and reducing the diversity of the population during the final stages of the optimisation.

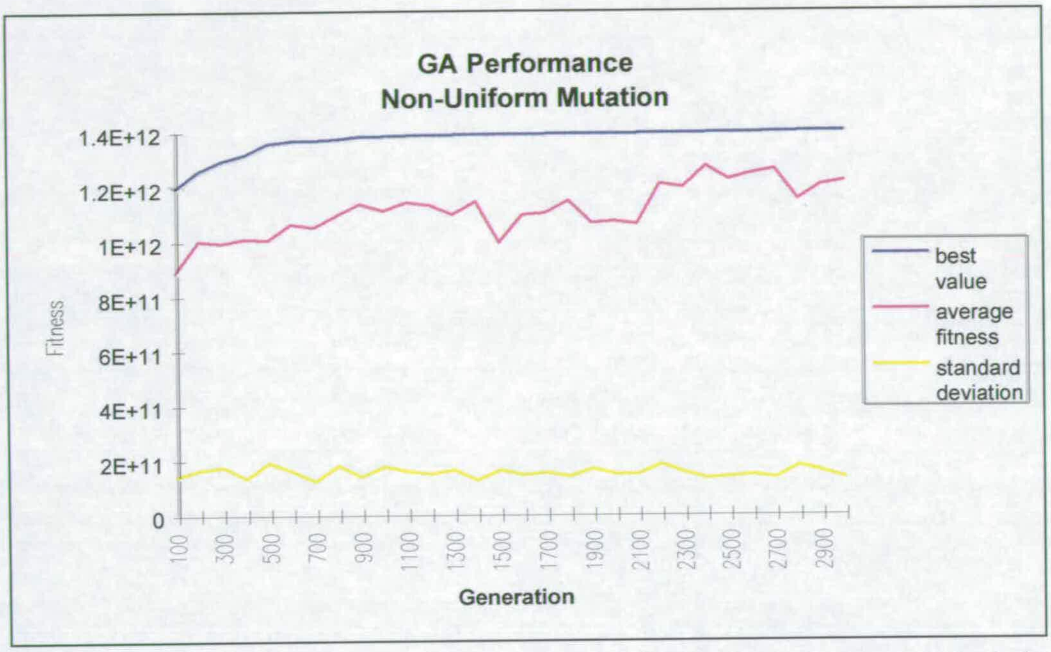

Figure 8.6 Graph showing the best fitness value, average fitness and standard deviation of chromosomes in a standardised run of GAMES with a non-uniform mutation operator.

Although non-uniform mutation only increased selective pressure towards the end of the search its benefits were also found in the initial search phases. This was due to initially higher mutation rates being acceptable as their effect was automatically diminished during the latter parts of the optimisation process. The net result was higher diversity in the initial stages where it was most useful. Because the flatten operator was also active the initial mutation rate was, in effect, doubled. The best value graph shows this improvement clearly between 600 and 1600 generations. It was therefore possible to use even higher mutation rates with non-uniform mutation in cases where a refined search was needed.

8.3.4 Recall Test

Settings

Flatten Mutation	=	Active
Mutation Factor	=	5 (Non-Uniform Mutation)
Recall	=	Active
Mutation Rate	=	0.025
Crossover Rate	=	0.8
Radiate	=	Not Applied
Seed	=	Not Applied

The Recall operator was a new operator specially designed for GAMES. It allowed old segments of chromosome to be stored and replaced into current chromosomes subject to mutation rates. This test also included Flatten and Non-uniform mutation operators as discussed in Sections 8.3.2 and 8.3.3. Recall provided a steeper initial best value curve without having increased the selective pressure. This is a good result as rapid optimisation is normally associated with convergence on local optima due to high selective pressure. The separation between the average and best fitness values reflects the low selective pressure, and high diversity, during this test.

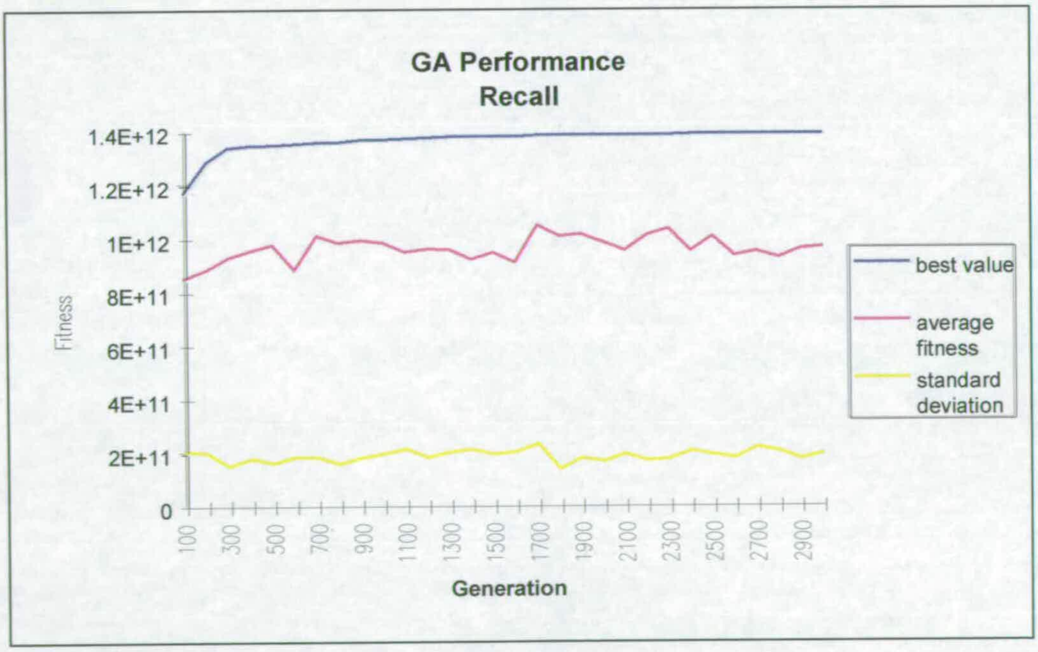

Figure 8.7 Graph showing the best fitness value, average fitness and standard deviation of chromosomes in a standardised run of GAMES with non-uniform mutation and Recall operators.

This operator increases the memory usage of the whole program. However as processor speed is the critical factor in optimisation times, this was not a great problem. The benefits due to the reduction in generations needed outweighed the drawbacks of increased time to process each generation. The overall time needed to find the optimum solution was therefore reduced.

8.3.5 Mutation Rate Test

Settings

Flatten Mutation	=	Active
Mutation Factor	=	5 (Non-Uniform Mutation)
Recall	=	Active
Mutation Rate	=	0.5
Crossover Rate	=	0.8
Radiate	=	Not Applied
Seed	=	Not Applied

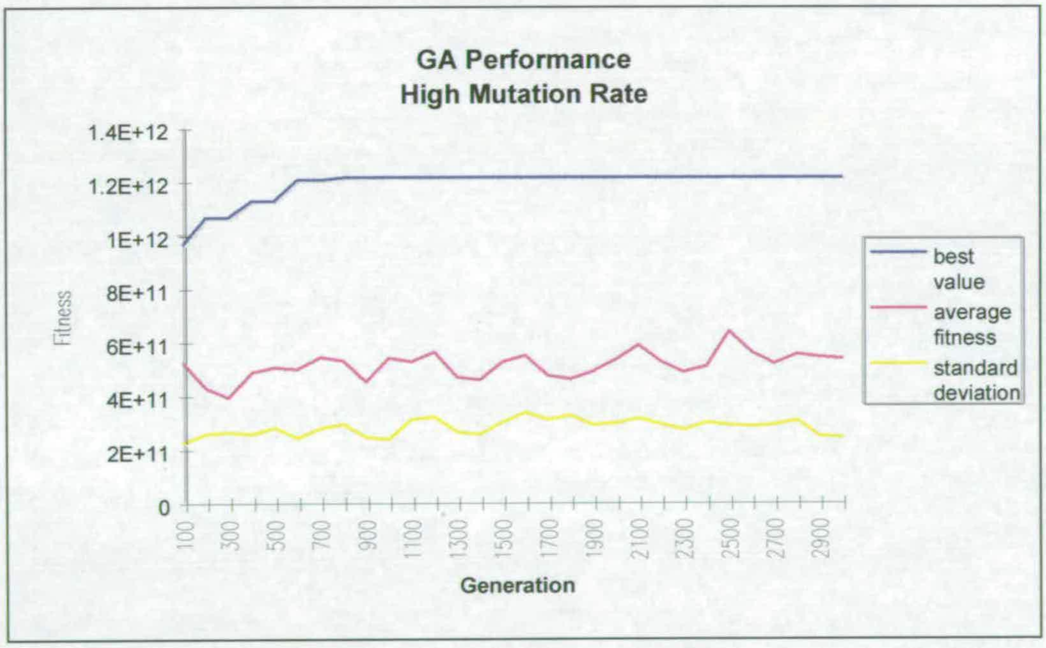

Figure 8.8 Graph showing the best fitness value, average fitness and standard deviation of chromosomes in a standardised run of GAMES with all GAMES operators. This graph shows the effect of a high mutation rate.

This test investigated the effect of an unusually high mutation rate. The test used non-uniform mutation and included the GAMES specific Flatten and Recall operators. The high mutation rate increased the random element of the evolutionary process to such an extent that the iterative procedure of crossover was almost nullified. The best value increases in steps reflecting large, possibly randomly found, improvements in chromosome fitness. Once a reasonably good solution was found no further improvements were made. The average fitness was especially low which indicated that it was thinly spread over the whole search area. The high standard deviation through out the search confirmed this. This proved that there was a maximum acceptable level of diversity against selective pressure which was exceeded in this case. The proportion of diversity to selective pressure and the size of both factors against population and problem size is critical. There are no absolute rules in GA theory to govern mutation and crossover rates to set these factors.

8.3.6 Crossover Rate Test

Settings

Flatten Mutation	=	Active
Mutation Factor	=	5 (Non-Uniform Mutation)
Recall	=	Active
Mutation Rate	=	0.025
Crossover Rate	=	0.02
Radiate	=	Not Applied
Seed	=	Not Applied

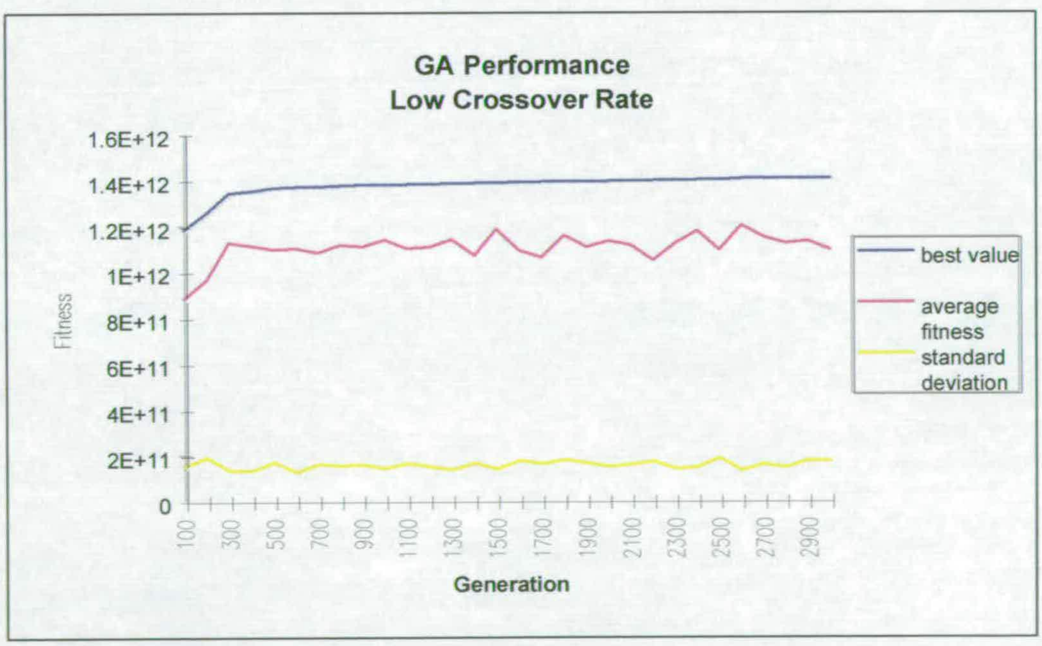

Figure 8.9 Graph showing the best fitness value, average fitness and standard deviation of chromosomes in a standardised run of GAMES with all GAMES operators. This graph shows the effect of a low crossover rate.

This test was performed to investigate the effects of lowering the crossover rate whilst using Flatten, Recall and Non-uniform Mutation operators. The test investigated a reduction in crossover whilst maintaining the previous mutation rate of 0.025. This increased the difference between selective pressure and diversity but reduced both these values against the population size. The reduced selective pressure balanced the level of diversity giving a higher optimum value. The average value trace followed the best value but did not converge on it, reducing diversity. The standard deviation remained constant and low throughout the optimisation which shows that the spread of the population remained even.

8.3.7 Radiate Test

<u>Settings</u>

Flatten Mutation	=	Active
Mutation Factor	=	5 (Non-Uniform Mutation)
Recall	=	Active
Mutation Rate	=	0.025
Crossover Rate	=	0.8
Radiate	=	From 5000 to 7000 generations
Seed	=	Not Applied

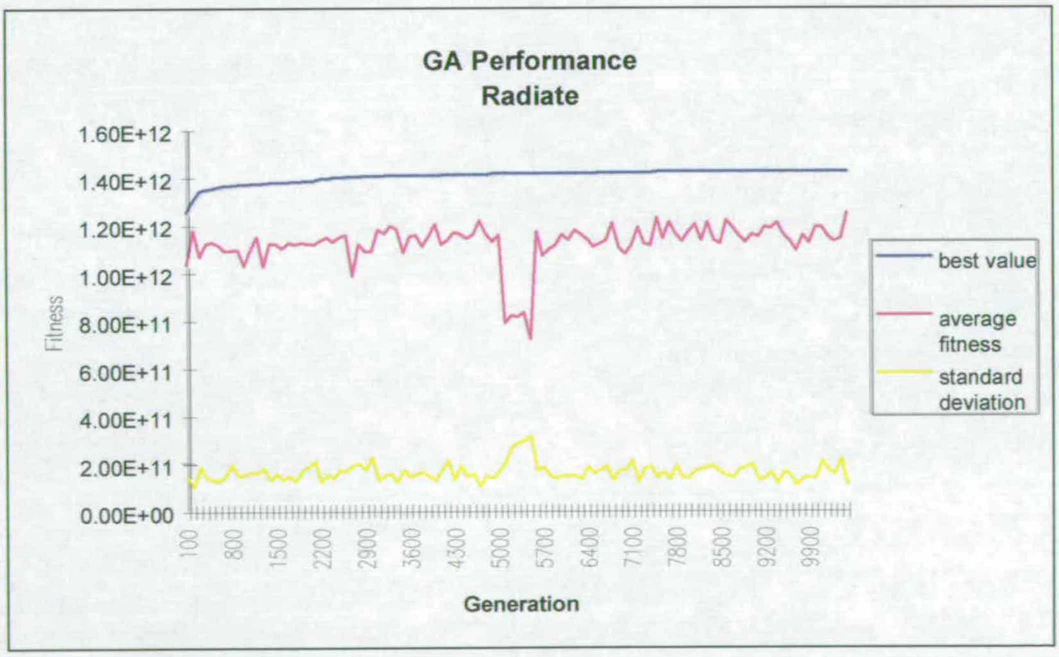

Figure 8.10 Graph showing the best fitness value, average fitness and standard deviation of chromosomes in a standardised run of GAMES. This graph shows the use of the Radiate operator applied between generations 5000 and 5700. Radiate is used to ensure that a global optimum has been found.

The Radiate operator is activated by the user by pressing the *Radiate* button on the GAMES GA graphical interface and deactivated by pressing the *Stop Radiate* button. The operator, when activated, increases mutation rates and sets the mutation factor to zero (uniform mutation). It was used between generations 5000 and 5700 to test if a local or a global optimum had been found. Figure 8.10 shows how this affects the evolutionary process. Because the GAMES GA uses an elitist function the best value cannot be reduced so the best value graph remained constant. Whilst activated the operator dramatically reduced the average fitness of the population indicating that the population had been pushed away from an optimum. The increase in standard deviation showed that the population's spread also increased during this period. Because the GA returned to the same optimum after Radiate had been deactivated it could be concluded that the GA was climbing the highest peak in the search space. It could also have been that Radiate could not find a better chromosome than the saved value and therefore the GA returned to that same point. This is quite possible as the high mutation rate would have limited the best value achievable whilst Radiate was active. To eliminate this the whole population was seeded with a known unlikely solution when Radiate was activated. The results from this further test are discussed in Section 8.3.8.

8.3.8 Radiate With Seed

<u>Settings</u>

Flatten Mutation	=	Active
Mutation Factor	=	5 (Non-Uniform Mutation)
Recall	=	Active
Mutation Rate	=	0.025
Crossover Rate	=	0.8
Radiate	=	From 20000 to 25000 generations
Seed	=	From 20000 to 25000 generations

This version of Radiate seeded the population with a known unlikely solution each time the operator was activated. The test was run over a longer time-scale to give a better view of the operator's effects. As in the first Radiate test, Section 8.3.7, there was a massive reduction in the average fitness of the population and an increase in the standard deviation showing increased diversity and population spread. The addition of a seed removed the effect of the elitist function allowing the best value to drop. The result was that when the Radiate operator was deactivated the GA continued in a totally different area of the search space. It took the GA approximately 3000 generations to return to the optimum found before the operator was activated. This point can be declared the global optimum.

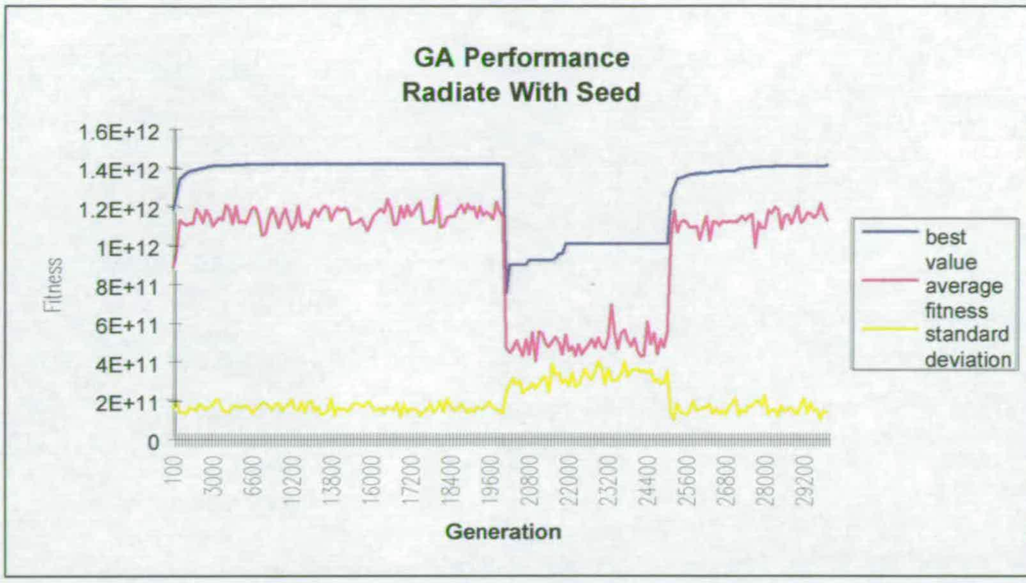

Figure 8.11 Graph showing the best fitness value, average fitness and standard deviation of chromosomes in a standardised run of GAMES. This graph shows the use of the Radiate operator applied between generations 20000 and 25000. In this case the best value was deleted when radiate was switched on so the climb back to an optimum can be seen more clearly.

8.4 Model Performance

This section serves to validate the GAMES model by comparing an ex-post forecast with actual data and by studying the results from five scenarios. The comparison between ex post and actual data could only extent back as far as the privatisation of the UK ESI in 1990. This result shows the accuracy of the model and validate the thesis that utility optimisation by GA can be used in forecasting. Each of the five scenario studies investigates a separate part of the model and tests the models sensitivity to different data inputs. These results show the stability of the model and prove the thesis that utility optimisation by GA is a reliable method of modelling in the long term.

8.4.1 Ex-Post Forecast

Ex-post forecasts are used to make comparisons between modelled and actual historical events. Such comparisons are mainly used to calibrate and validate models. The validation of GAMES cannot rely on a forty year ex-post forecast of the UK ESI as the industry, for which it was designed, was privatised in 1990. Privatisation changed the decision making process within the ESI and therefore ex-post forecasts before this time are not valid. Chapter four discusses the differences between forecasts of a nationalised and privatised industry. A comparison can be made between ex-post forecasts and past data during the period from initial privatisation in 1990 to 1998, the last date for public access data. Although it must be recognised that although the ESI had been privatised by 1990 the effect of privatisation on generation mix would be subject to a delay. This delay was due to the time taken to construct new plant and the inertia in replacing current plant.

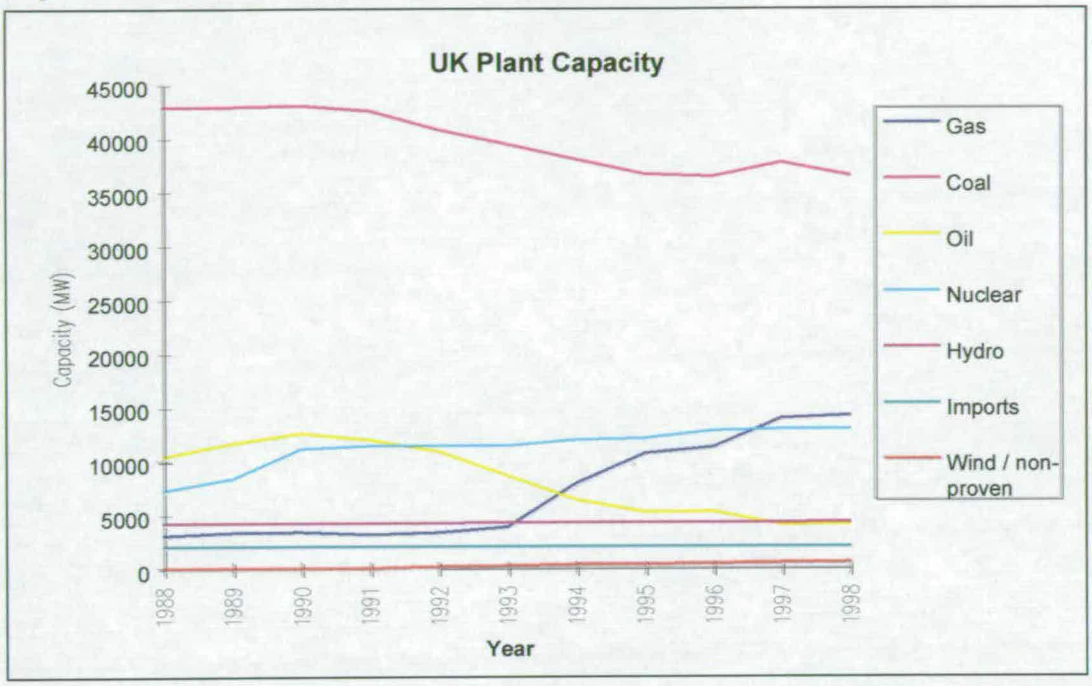

Figure 8.12 Graph of Actual UK Plant Capacity from 1988 to 1998[108, 109, 110]. Units given in MW to conform with actual data.

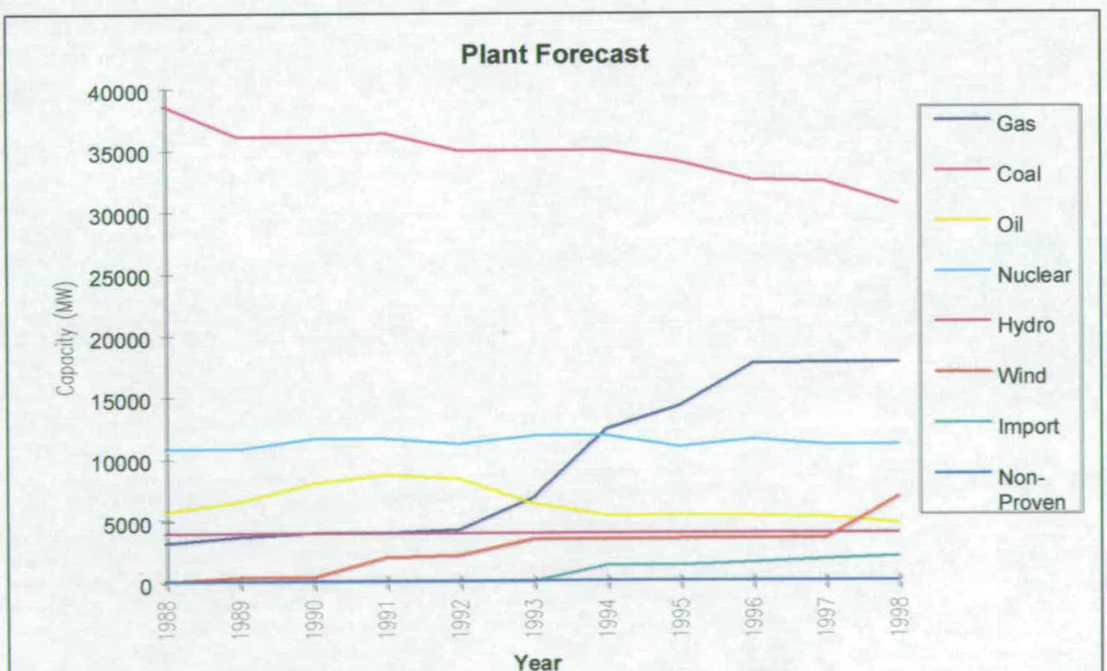

Figure 8.13 Ex-Post Forecast of UK Plant Capacity From 1900 to 1998 made using GAMES. Units converted to MW to conform with actual data.

Figure 8.12 shows the actual plant capacity as it varied between 1988 and 1998. Figure 8.13 shows a forecast of the same period. Note that the output from GAMES was set to give forecasted plant capacity in MW units to match the historical data provided whereas normal GAMES plant forecasts use GW units.

The trends shown by both graphs are very similar. As GAMES was designed to show trends this is good proof ESI that forecasts can be made using this method. Although the actual values are not as important as these trends an error analysis was performed on the data represented by the two graphs. The analysis was performed using a time series adjusted RMSE as described in Section 4.4.3. Table 8.1 gives the results of the time series errors:

Plant: Time Series RMSE:	Gas	Coal	Oil	Nuclear	Hydro	Wind + non-proven	Imports
From 1988 to 1998	1.67	1.16	0.87	1.03	1	1.34	0.92
From 1993 to 1998	1.68	1.18	1.65	1.05	1	1.33	0.76
From 1995 to 1998	1.47	1.27	0.78	1.05	1	1.37	0.78
From 1996 to 1998	1.4	1.26	0.77	0.98	1	1.47	1

Table 8.1 Time series RMSE figures for the error between ex-post forecasts and historical data.

The time series RMSE errors given in this table show the variation of error with time. A value of 1 represents no change which proves that the error between these two graphs does not change with time. The only discrepancy is between the oil plant figures between 1998 and 1993. This is due to the differences between the nationalised policy of encouraging the North Sea oil fields and market led influences which only came into effect in 1990 and would not have had an impact on plant construction until at least 1995.

Differences in the amount of coal, nuclear and oil plant between 1988 and 1992 can also be attributed to the delay in upgrading and converting plant to satisfy the change in market structure due to privatisation. There is also a discrepancy in the amount wind plant constructed from 1994. This is probably due to the recent increase in efficiency and decrease in capital costs for this type of plant; the model is aware that wind generation will become profitable and therefore associates a smaller risk cost to earlier turbines. In addition small variations in value can be attributed to the small scale of the data collection. A large scale data collection would have been beyond the scope of this study. Even with these discrepancies the trend correlation between the forecasted and actual results prove the thesis that accurate forecasting is possible through utility optimisation by GA.

8.4.2 Scenario 1 (Continuation of present policy)

Policy statements from this government in 1997 promise that 10% of the UK's electricity demand will be met from renewable generation by the year 2010. Targets for reductions in CO_2 emissions, set by the 1997 Kyoto agreement[111], should put pressure on fossil fuel combustion. In addition the present government has placed a hold both on nuclear and CCGT plant construction. The former due to political incentives and the latter to end the "dash for gas" [112] created by the previous government. If these policies are upheld there will be a strong drive towards renewables. However the United States has already withdrawn from the original Kyoto agreement. Although the UK continues to work towards the 10% reduction in CO_2 by 2010 much of the momentum created by Kyoto has been lost.

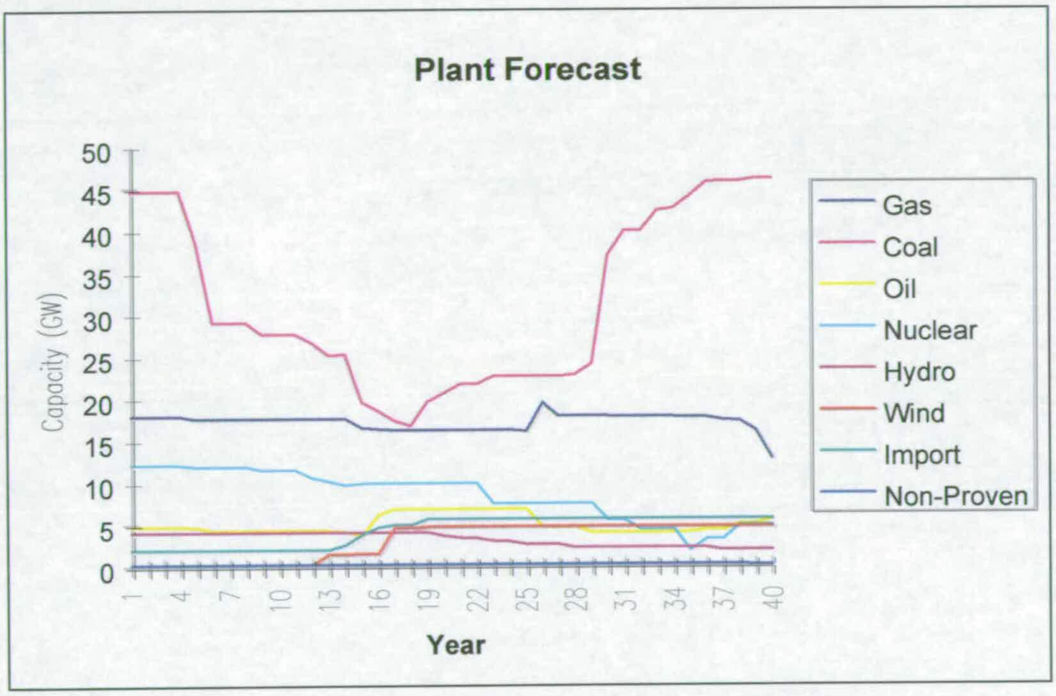

Figure 8.14 GAMES yearly point forecast, from 1995, of plant following present UK generation policy.

Figure 8.14 shows the plant forecast for scenario one; it starts in 1995 and represents an ex-post / ex-ante forecast projecting present policy into the future. It shows how the proportion of coal fired plant will drop as old plant is decommissioned and not replaced. This will continue until year thirty (2025) when gas generation becomes too expensive due to resource constraints. Coal fired generation is given as the major replacement for gas. In addition to coal, wind, oil and imported capacity will be increased to meet the generation deficit. Nuclear plant continues to be reduced following the obligation not to construct new plant. The reduction in hydro power is due to the ageing of Scotland's hydro plant. Although the generating plant can be easily replaced, the dams themselves weaken with time and are prohibitively expensive to replace. Most new possible hydro sites are a distance from the grid system where transmission costs become critical.

8.4.3 Scenario 2 (External Costs of Generation)

Scenario two was ex-post / ex-ante forecast from 1995 following the forecast in Section 8.4.1. It assumed that the external costs of generation starts to influence electricity prices by year ten. This is a highly likely event as electricity companies are already offering *green* electricity to customers at an increased tariff. The acceptance of this customer driven push towards less polluting generation methods serves to subsidise renewables and penalise those methods that have higher external costs.

Legislation will be influential in including external costs of generation. Taxation structures that will replace the Non-fossil fuel levy, Non Fossil Fuel Obligation (NFFO) and Scottish Renewables Order (SRO) are presently being discussed on a European level. These will also serve to penalise electricity generation that damages the environment and encourage methods that do not. The magnitude of these penalties should reflect the actual cost of environmental damage incurred along with the cost associated to the potential risks of each generation method.

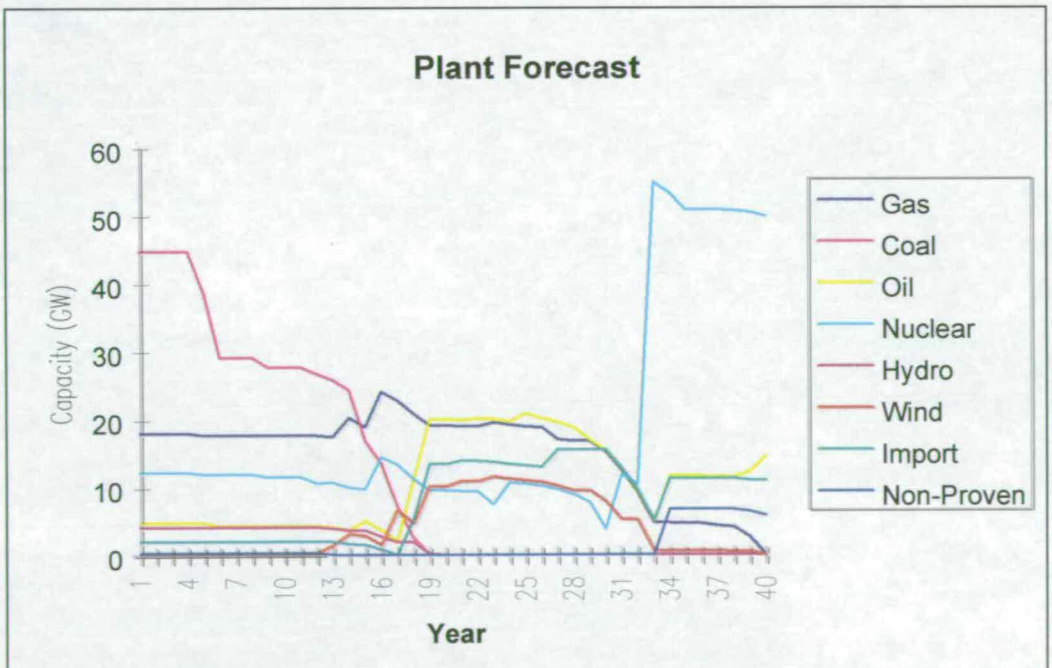

Figure 8.15 GAMES yearly point forecast, from 1995, of plant assuming the inclusion of external costs of generation are applicable from year ten.

Coal fired generating plant almost disappears by year 20 (2015); some of this plant is replaced by gas fired plant and the remainder is decommissioned. The reduction in overall plant caused by reducing the capacity of coal fired power stations is met by a combination of generation methods. Figure 8.15 shows how this consists of wind, oil, nuclear and to a small extent gas generation. Figure 8.16 gives the generation figures for this period and shows how gas generation reduces suddenly five years after the reduction in coal fired generation. This deficit is first met by an increase in imported electricity then by nuclear generation. To obtain such a large proportion of nuclear powered generation over 40 GW of nuclear plant comes on line in the space of two years which sounds unrealistic. However the quantity of nuclear plant suggested from this scenario is similar to that of France in 1994 where 395TWh, over 75% of the total electricity generated, was provided by nuclear power[113].

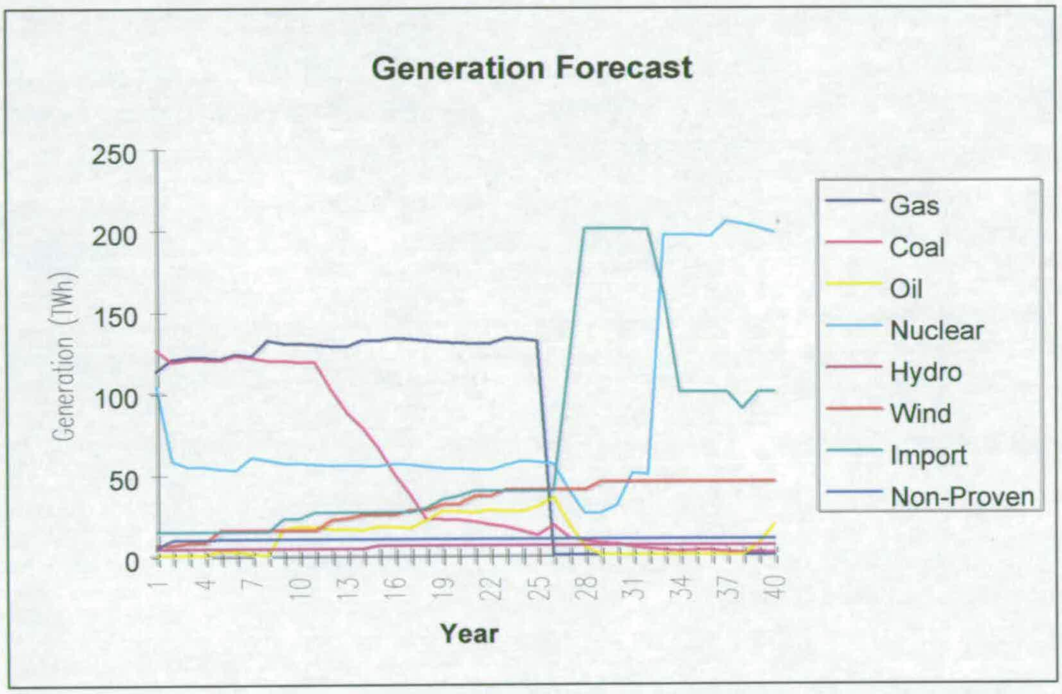

Figure 8.16 GAMES yearly point forecast, from 1995, of generation assuming the inclusion of external costs of generation are applicable from year ten.

This scenario shows the effect of charging electricity generators for the total cost of generation; including environmental, risk and resource costs. Some of these costs, such as risk and some environmental costs are already included in the electricity market and taxation structure. Although it is unlikely that all external costs will be accounted for it gives a good idea of the ESI's sensitivity to the inclusion of external costs. The results clearly show the role of nuclear power in an ESI that imposes heavy penalties on fossil fuel combustion. However nuclear power is politically sensitive and the threat of a nuclear accident increases the risk cost of this technology. If the apparent risk of nuclear generation were to increase, due to an incident, and nuclear generation was to cease, this model would suggest importing a large proportion of electricity from France. This represents the limitations of the data used in these scenarios as the majority of electricity imported from France is generated by nuclear power. Only by including data from France, and other European nations could this problem be solved. Such an increase in model and data size would not destabilise the model itself although the GA and its optimisation process would be slowed down.

8.4.4 Scenario 3 (European Oil Pipeline)

Scenario three was also an ex-post / ex-ante forecast from 1995 following the forecast in Section 8.4.1. Generators were expected to pay for the majority of their external costs by year ten (2005). The scenario also included the building of an oil pipeline from the Black Sea states into Europe. Oil from former Soviet states that is presently shipped down the Black Sea, through Turkey, then out into the Mediterranean would be piped directly into Europe. British Petroleum (BP) has been planning such a pipeline but political instability in the region has delayed in-depth feasibility studies. Scenario three assumed that this pipeline is operational by year thirty (2025). This was set to coincide with the depletion of easily accessible North Sea gas reserves.

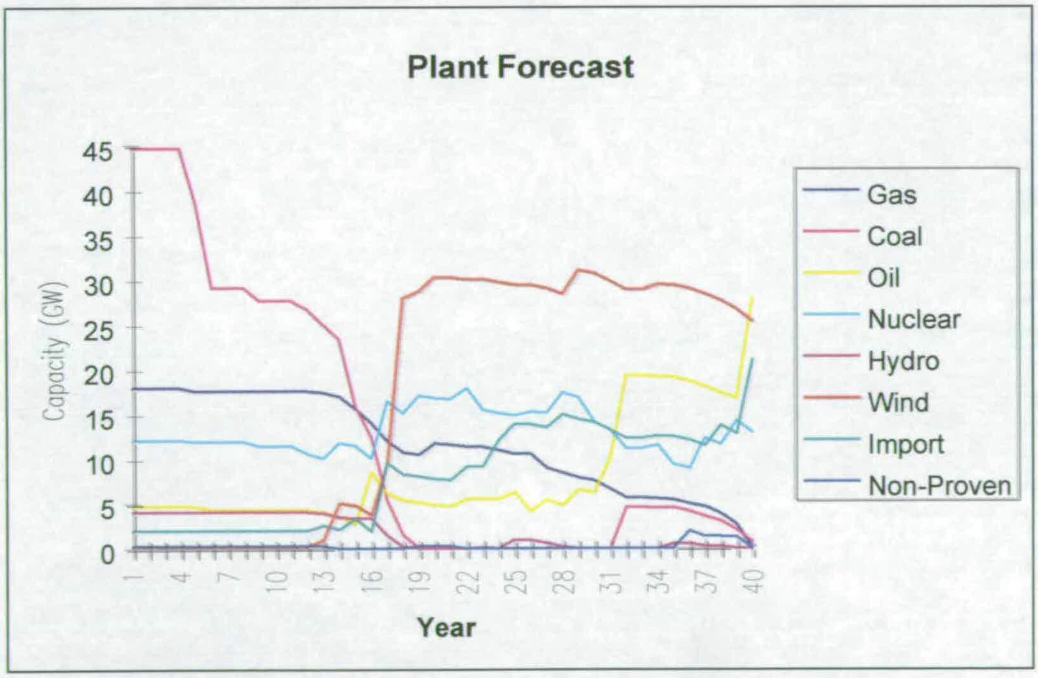

Figure 8.17 GAMES yearly point plant forecast, from 1995, that includes external costs of generation by year 10 and the completion of a European oil pipeline from the black sea by year 30. The model assumes that coal generation continues to decline due political influence and import insecurity.

The first twenty years plant capacity is similar to that of scenario two; a steady reduction in coal plant made up by an increased usage of nuclear, gas, oil and wind plant for generation. Imports also increase to meet the increasing demand. Oil plant is constructed between years twenty and thirty with the majority coming on line, in year thirty, with an oil pipeline bringing oil from the former Soviet states into Europe. 25TW of wind power plant is shown to come on line by year twenty. Figure 8.18 shows the generation figures for this time period. Although a large amount of wind plant has been constructed, the primary generation methods remain as nuclear, oil and imported electricity. The excess wind plant is used as a renewable *top up* to ensure that international agreements are met.

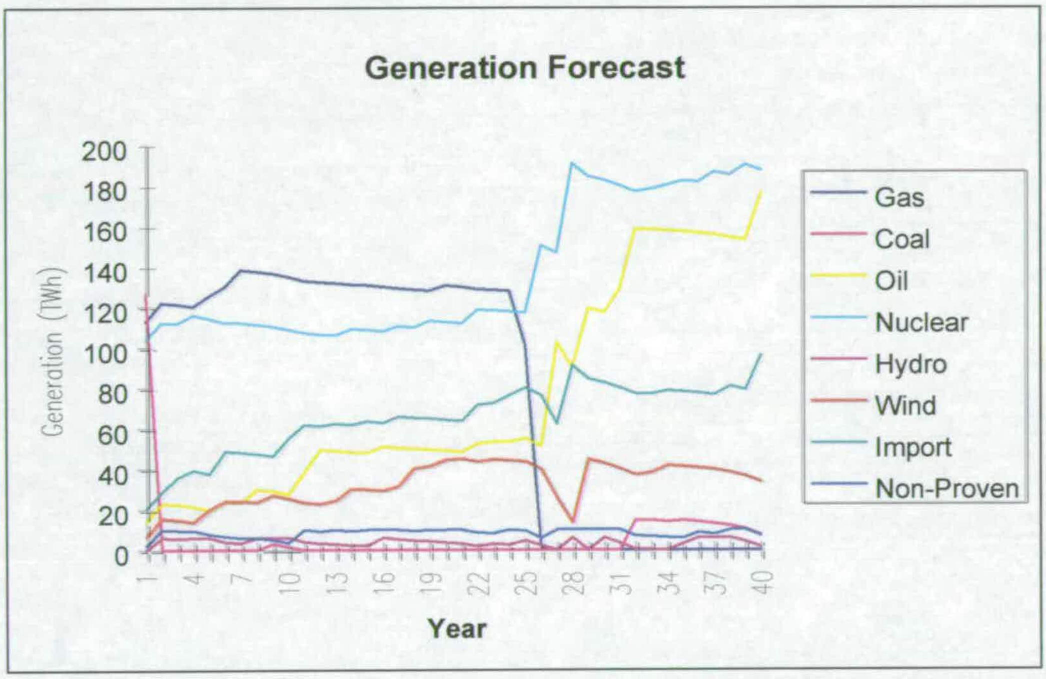

Figure 8.18 GAMES yearly point generation forecast, from 1995, that includes external costs of generation by year 10 and the completion of a European oil pipeline from the black sea by year 30. The forecast also assumes that coal generation continues to decline due political influence and import insecurity.

North Sea gas reserves are seen to become scarce by year twenty six. An initial increase in Imports, nuclear and wind powered generation make up for the immediate shortfall. The extra oil entering Europe by pipeline allows for a long term generation base of nuclear and oil powered generation.

8.4.5 Scenario 4 (Cross Channel Interconnector Fault)

Scenario four used the same ex-post / ex-ante forecast from 1995. Again the external costs of generation were applied to the generators in year ten. Once these external costs of generation had been included along with capital, operational, and maintenance costs the profitability of electricity generation was substantially reduced. However the implementation of these taxes will differ between countries. These differences in legislation and taxation structures across Europe will increase the incentive to import or export electricity. The major problems with this strategy are the risks in relying on a single set of interconnectors and the risks associated with foreign politics. As generators within the European community will be in competition a long term cheap imported supply cannot be guaranteed. Scenario four investigated a sudden closure of the cross channel interconnector in year 20 (2015) that does not reopen for five years (2020).

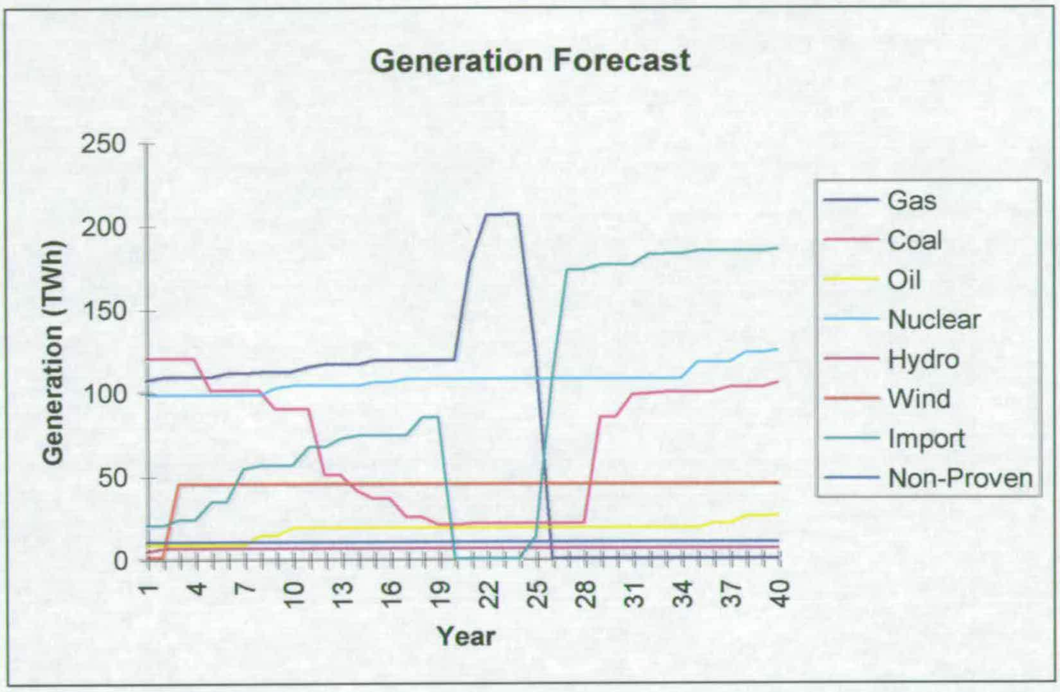

Figure 8.19 GAMES yearly point plant forecast, from 1995, that includes external costs of generation from year 10 and has the UK - French Interconnector go inoperational between years 20 and 25.

Figure 8.19 indicates a drop in coal fired plant with an increase in interconnector size to make up for the shortfall. This is most apparent between years ten and twenty due to the inclusion of external costs of generation. When the Interconnector is shut down new gas plant is built to take up the shortfall. However the graph shows a delay in gas plant construction as the halting of imports is an unforeseen event. In year twenty three imports are resumed but the rapid growth in interconnector capacity seen before the closure is not continued. This is because the apparent risk of importing electricity has increased. Coal generation will increase after the import crisis and the extra coal plant built between years twenty eight and forty will be used to take up the shortfall as cheap North Sea gas becomes scarce.

8.4.6 Scenario 5 (A Future for Renewable Energy)

Finding a balance in electricity generation is not easy. Legislation is the only control that a government has over the generation mix in a privatised ESI. Market forces can serve to promote non-renewables if left alone. This scenario was the result of gentle taxation structures that reflected the total costs of generation. This was fully implemented by year ten in an ex-post / ex-ante forecast that started in 1995. In addition it assumes that research and development of presently non-proven technologies is partly met by all the players in the industry.

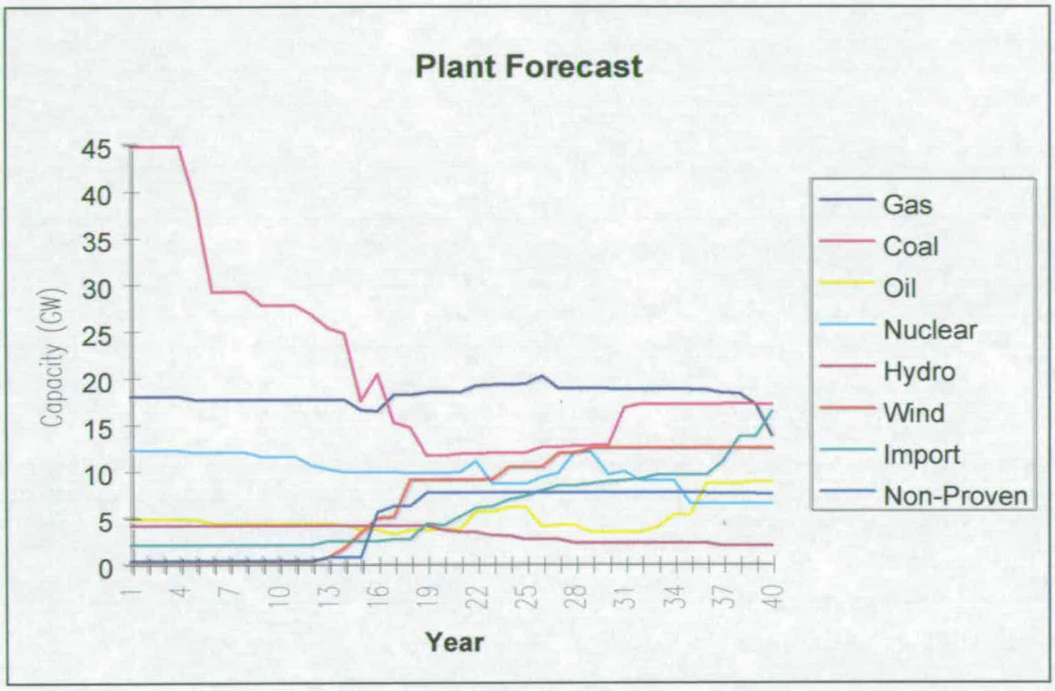

Figure 8.20 GAMES yearly point plant forecast, from 1995, that includes external costs of generation, must take contracts for all renewable generation and considers advances in unproven technologies such as solar, wave and waste combustion.

Figure 8.20 indicates a reduction in coal plant that continues until year 19 (2014). The generating fuel mixture then becomes diverse and balanced. Although the largest plant is gas fired plant each generation method reflects its overall costs and resource constraints. If the reduction in coal plant was continued past year twenty the deficit would be partly augmented by renewables. However the incentives to reduce fossil fuel combustion promote importing electricity and generation with nuclear power along with aiding the growth of renewables. If the pressure to reduce fossil fuel combustion is high, and electricity demand continues to increase, the incentive to import increases exponentially. Therefore when North Sea gas reserves diminish care must be taken to keep diversity in generation as the incentive to rely on another countries generation or solely on nuclear power will be great. This scenario shows that a balance can be reached using a mixture of renewables and existing fossil fuels. In this case there will be a place for approximately 7 GW of plant from presently unfeasible technologies. This will occur gradually starting in year 14 (2009). Even if the cost of such technologies is presently prohibitive the reduction of environmental impact should cover much of the extra cost.

8.5 Summary of Discussion

The feasibility study proved that long-term ESI forecasting using a GA optimisation process was possible. It led to the construction of a full-sized model which forecasted the mix between 8 generating methods over a forty year period. This model contained functions that described the ESI's market, finances, political influences, technical constraints and environmental impacts. It represents the first long-term forecasting model that contains all these factors in a manner that allows for feedback within the system and the creation of a number of equally likely outcomes to each scenario forecast.

Before the model was validated through a combination of ex-post and ex-ante forecasts the performance of the GA, and its ability to optimise such a large-scale model was assessed. Each genetic operator, and its relevant settings, were tested for their effect on the speed and quality of the optimisation process. The benefits, and drawbacks of each individual operator was discussed as they were added, in turn, to an initial control optimisation. This analysis was based on three statistical graphs for each test. The first was the rate of convergence of the best chromosome in the population on the global optimum, which indicated the rate of optimisation with respect to the number of generations passed by the GA. Secondly the average fitness of the population was assessed, giving an indication of the population's diversity as the optimisation process continued. Finally the standard deviation of the population was used to analyse the spread of chromosomes within the population. The results showed the added value of the new operators flatten and recall and showed the operation of the radiate function and how it tested for a global, rather than a local, optimum.

The validation results given in this chapter represent a selection of the outcomes to five different scenario forecasts that highlight critical issues for the ESI in the near, and distant, future. The first was an ex-post forecast of the generation mix in the UK ESI between 1988 and 1998. When compared to the real data for this time period large errors were found between 1988 and 1993. This was because this model was designed to forecast a privatised industry rather than a nationalised ESI. The privatisation of the ESI took place in 1990, but due to the lag needed to construct new plant, and decommission old plant, there should have been discrepancies between these two graphs until at least 1995. The fact that the general trends match from as far back as 1993 proves the power of GA optimisation based forecasting and the initial thesis that this method of forecasting can provide accurate forecasts of the ESI.

The five scenario forecasts describe different possible futures for the ESI. Their stability proves the thesis that GA based forecasting can provide reliable long-term solutions to possible future scenarios. The combination of all these forecasts allows an analysis of the critical factors that most influence the industry. The efficiency of CCGT plant and the price of its fuel are not the only factors that have made this technology so attractive to investment. The relatively short pay-back periods, the must-take contractual agreements between CCGT generators and suppliers and the low emission costs have established this method of generation at the cost of coal fired, oil fired and nuclear powered generation. Although, in the short-term, this represents an efficient and relatively clean generation policy the inevitable depletion of the UK's gas reserves within approximately 35 years indicates that this *dash for gas* is not sustainable.

As gas reserves run low replacement plant will be needed. It is inevitable that environmental pressure within Europe will have established stringent emissions regulation and taxation by this time. The gas replacement will need to meet an increasing electrical demand without exceeding these environmental constraints. Unless low NO_x coal burners and flue gas desulphurisation plant becomes more efficient and less expensive coal generation will not be able to meet the capacity deficit left by gas resource depletion without breaking emissions targets. The only feasible solution may be the construction of new nuclear plant to provide over 60% of UK load. This figure could be reduced through the increased use of renewables and imports from France.

Of the renewable potential in the UK, wind power is the only proven technology that has yet to be fully exploited. The majority of large and medium scale hydropower potential has been used, or is too remote to facilitate economic grid connection. There is much potential for offshore wind and wave power however, the technology needed to exploit these primary renewable energy sources remains unproven.

9. CONCLUSIONS

9.1 Overview

The conclusions given in this chapter are drawn from the results of the work detailed in this thesis. They include and identify contributions to knowledge in the fields of modelling and forecasting, Genetic Algorithm research and long-term planning in the privatised UK Electricity Supply Industry (ESI). This chapter starts with a detailed discussion of the conclusions drawn from the construction of a large-scale model of the ESI in Section 9.2; from the development of Genetic Algorithm (GA) and optimisation based forecasting in Section 9.3; and from the construction of the Genetic Algorithm based Model of Electricity Supply (GAMES) in Section 9.4. Section 9.5 draws conclusions from the results of the scenario forecasts given in Chapter 8. This is followed by a final summary of general conclusions from this thesis in Section 9.6. Section 9.7 concludes the thesis and the final Section, 9.8, gives recommendations for future work.

9.2 Large-Scale modelling

Mathematical models have been used to describe events from falling apples to share prices. Some of these models are more reliable than others. Larger models tend to be less stable, contain more errors and can be difficult to use. The errors in GAMES, a large-scale model of the ESI, came from two main sources: The first was data error, which could be amplified if the system suffered from positive feedback. This was minimised by selective data acquisition and the avoidance of mathematical expressions that might have amplified these errors. However, the large number of explanatory functions, which describe the ESI, and the difficulties in acquiring reliable and continuous data also caused some small discrepancies between ex-post forecasts and historical events. These modelling errors could have been reduced by increasing the number, and accuracy, of internal functions and including a statistical analysis of all exogenous data. Such a rigorous analysis would have been beyond the scope of this study which was to investigate the use, and best application, of GA optimisation in long-term forecasting in the ESI. The second cause of errors was due to the trade-off between complexity and the ability to solve the model. A high degree of accuracy could be obtained through the inclusion of all relevant factors. Unfortunately every function added increased the model's complexity. With complexity came the problem of organising and solving the model. It was important that the model had a pre-defined structure and that each function was classed correctly. If the model had become organic it would not have been possible to trace the origin, and therefore the validity, of the results; thus conclusions based on these results would have been void.

The use of a general utility function played a critical role in maintaining control of all the GAMES model's functions. The large number of functions that were needed to describe the ESI accurately created a non-linear set of simultaneous equations that could not be solved mathematically. In addition the number of possible solutions to these equations covered such a wide search space that they caused traditional iterative methods fall down. Using a GA to solve the model proved successful. Not only because it was able to solve such a large problem relatively quickly, but also because it allowed changes to be made in the model without manually re-solving sets of simultaneous equations. This combination of a general utility function solved by GA optimisation allowed easy reference and editing of functions, simple comprehension of the model's workings and a solid platform for scenario based forecasting.

9.3 Genetic Algorithm based Forecasting

Exact predictions of future events are notoriously erroneous. This study aimed to prove that the trends in electricity generation could be modelled and used to make forecasts of outcomes to possible future scenarios. Previous models that based forecasts on a handful of critical functions, such as least cost planning, were shown to be too simplistic and unreliable. A reliable forecasting model needed to include all relevant factors from politics to resources and use them in a complete study of the sensitivity of the system. This could only be achieved if the model was able to run quickly so that many results of different scenarios could be examined. The final forecasts would be the net result from the many sets of results.

It was found that it was not possible to solve the equations, containing the relevant factors needed to obtain a valid model, using traditional mathematical or computational methods. A feasibility study on a simplified model showed how a GA could be used to evolve an optimum solution to this large, non-linear problem. A full scale model was then created and tested. The results proved that GAs were ideally suited to the problem of long term forecasts especially in the ESI where the number of relevant factors was large. The time needed to obtain reliable results using GAMES varied from two to eight hours depending on the particular problem and accuracy needed. These tests were performed on an Intel Pentium Pro 200 processor which operates at one fifth the speed of today's fastest PC processors.

Although GAMES has not been tested on a faster machine it is reasonable to expect that reasonable results would available within 25 minutes.

9.4 The GAMES Forecast Model

The GAMES program was designed to be intuitive and easy to use without compromising the program's flexibility and power. The input fields were constructed to allow expansion without reprogramming the visual graphical user interface (GUI). The program itself was designed with expansion in mind and is therefore of an object oriented nature. The type of user that would be using GAMES was also carefully considered. The program was found to be suitable for energy planners with no prior knowledge of genetic algorithms; as the default GA settings achieved satisfactory results. Users with GA experience were able to edit, and make efficient use of, the genetic functions during the program's runtime.

Users of GAMES found the spreadsheet feel of the data fields intuitive and simple to use. The users had no problems obtaining and viewing results with little or no explanation. However there were no online help files as this study was concerned with whether such a package was feasible and was not dedicated to the creation of a commercial program. Producing a commercial GA based ESI forecasting model has been suggested as future work from this thesis.

9.5 UK Generation and Supply

This study aimed to use a GA to construct a reliable model of the ESI and prove that it could be used to make forecasts of how electricity will be generated in differing, but possible, future scenarios. The results given in Chapter 8 were some of these forecasts. They were not definitive forecasts of what will happen in the future, as exact predictions could not be made in such a complex system. They represented possible outcomes to pre-defined future events which, when considered together, gave a clear assessment of the critical influences within the industry. Sections 9.5.1 to 9.5.9 discuss each of the eight generating methods involved in the forecast scenarios. These sections represent relevant knowledge derived from the creation of the model and the combined results from scenario tests.

9.5.1 Gas Generation

Gas fired generation has been the generation method of the nineties. In 1990 0.5% of the UK's electricity was produced by gas, a figure that rose to 32.5% in 1998. The National Grid Company expect that by 2005 41% of the UK's electricity will be produced by CCGT[114]. The DTI believe that by 2020 gas generation will have peaked at 57%[115]. GAMES scenario forecasts corroborate this data. This increase in gas usage was mainly due to new, highly efficient, CCGT technology and the *dash for gas* policies of the last government. Gas generation proved to be the most lucrative of the 1990's generating methods and thus has succeeded in the privatised UK ESI. This trend was set to continue so long as there were no changes to legislation. Legislation changes came when, in 1997, the present government put a freeze on the construction of any new gas plant. This was due to the finite nature of the UK's gas supplies. If gas was burnt following predicted levels the North Sea's gas supply would only have lasted another thirty to forty years. This problem would be compounded by demand from countries that are presently considered to be developing. These countries are set to increase the global gas demand by as much as 60% before 2010[116]. New reserves may be found and new mining techniques may create new gas and oil field opportunities. Unfortunately these possibilities cannot be relied upon.

If market forces are left to decide gas combustion issues changes in the trend to gas depletion will only arrive when reserves have become scarce and expensive. Gas is vital to industry, in the home and for electricity generation as a part of an integrated supply. Only through controlling the large scale combustion of gas can this finite supply be conserved for the future. This does not seem likely as CCGT plant is the cleanest of the fossil fuels and will always be subject to less taxation than oil and coal combustion.

9.5.2 Coal Generation

In 1993 coal fired power stations accounted for over 50% of the UK's electricity generation. This figure now stands at 35% and is expected to fall to below 27% by 2005. GAMES scenarios that included a comprehensive accountability for all environmental costs put coal generation as low as 2% of the UK's total by 2015. Forecasts that assume it is unlikely that all external costs will be charged to the generators predict a minimum level of 18% for coal that will be reached in 2015. Coal generation will not disappear altogether as it will be a primary substitute for gas powered generation when these reserves run low. However directly replacing CCGT with coal fired plant will cause an increase in NO_x, SO_x and CO_2 emissions making government target levels difficult to meet. Fortunately, new combined cycle coal turbines, using gassified coal, are cleaner and more efficient than traditional coal power plant. There are also many new technologies dedicated to the cleaning of emissions from coal combustion.

9.5.3 Oil Generation

Oil generation, like coal generation has been on the decline over the past ten years. It has not had government support and CCGT technology has left it behind. The figures speak for themselves: Oil fired power plant dropped from 7.5% of total UK generation in 1993 to 2.5% in 1997. Most forecasts do not expect this figure to rise in the near future. GAMES based forecasts attribute this to high fuel costs and the range of environmental penalties attributable to oil combustion.

The concept of using Oil as a substitute for gas is not new. The third scenario showed how the construction of an European oil pipeline would facilitate this substitution. This scenario did include a gradual increase in base oil price as demand from the developing world increased. The exact extent of this increase is not yet known but if the increase was more than 4% per year, index adjusted and above yearly oil price deviations, GAMES suggested that oil will cease to be used as a major generating resource. The average annual oil price rise has been 1.5% per year since 1987[117]. However the price of oil products rose and fell by over 50% between 1978 and 1986. Memories of the 1970 oil crisis also add to the risk costs of oil powered generation as there is always an element of uncertainty in the fuel supply.

9.5.4 Nuclear Power

Nuclear power has been the most contentious of the generation issues since its inception in the 1950s. The benefits of nuclear power are that it does not cause the type of pollution that causes global warming, acid rain or local health problems. The power stations themselves are compact and the majority in the UK, which are based in coastal regions, do not have large cooling stacks that onlookers incorrectly associate with pollution. They are ideal base load generators that have proved reliable. Their safety statistics are far better than those of fossil fuel generating plant although there is the unknown effect of the numerous small scale leaks that are not included in the published figures[118]. Although uranium supplies are similar to those of oil[119], nuclear power resources will out-last fossil fuels as the reprocessing of spent fuel rods is highly efficient.

The drawbacks of nuclear power are as numerous as the benefits. The main issue is safety, although uranium supply problems do exist. The safety issues concern the mining and transportation of uranium, the process of fission to generate heat and the disposal of radioactive waste materials. Reprocessing the spent fuel adds further complications, especially when waste from abroad is shipped into the UK. The main fear is of a repetition of the accident at Chernobyl. The Chernobyl accident in 1986 highlighted the risk of a meltdown, where the chain reaction goes beyond a critical point and cannot be recovered due to the deformation of the reaction chamber itself. A year later, against international safety advice, the plants number three reactor was back in service. Thirteen years later the surrounding countryside is still deemed unsafe. The total loss of life on this radioactive land is still unknown. Leaks from ageing radioactive dumps also pose a great threat to public safety. Coastal dump sites in the UK have recently come under scrutiny as water ingress has compromised the safety at some of these sites.

The political nature of nuclear power makes forecasting its usage difficult. France and the UK have placed a moratorium on nuclear plant construction and the USA is closing down plant, without replacing it. Meanwhile Japan is extending its nuclear plant capacity. The present UK government has decided that the risks do not warrant new plant construction. However this will change as the cost of electricity generation increases and new technology makes nuclear powered generation safer. New fission methods are under test and much work is going into the possibility of fusion. When UK gas reserves become scarce a nuclear alternative will be necessary. This will be as part of an integrated supply and will probably include new and safer nuclear technology.

9.5.5 Hydro-Electric Power

Hydro-electric power is a well proven renewable energy source. Both pumped storage and traditional turbines have a place in future generation. Successful hydro schemes need the correct geographic formations and hydrological resources. The UK has used much of its feasible mountainous resource. Prohibitively high transmission costs have ruled out many ideal sites in the Scottish Highlands. In addition the threat of global warming increases the risk costs of hydro power. This, with high capital costs and long lead times, diverts investment from hydro power to generation methods with shorter pay-back periods and low capital costs, such as CCGT.

In 1997 hydro plant produced 1% of electricity generated in the UK. This was a 50% reduction on 1993 figures. As hydro dams age they weaken. As they weaken less water can be held in the reservoir behind them. Once the maximum allowable water head drops below a critical value generation becomes unprofitable. Strengthening the dam is presently too expensive and therefore the old dams are simply left in place. The result is a dwindling large-scale hydro capacity. Conversely small-scale hydro is on the increase. The new market, NFFO and SRO subsidies have provided a base for this proven technology. Unfortunately grid companies are resisting this drive towards embedded generation as the additional expense of managing and protecting such plant costs them money. It is likely that this will be overcome in the near future and that small hydro schemes will make a significant contribution to the UK's total renewable capacity.

9.5.6 Wind Power

Although there is some opposition to wind turbines, due to their visual and audible impact they are quickly becoming viable generators. The new standard for turbine output is 1MW which is twice the size of turbines constructed three years ago. There are some 1.5MW machines in operation. They can be used on a small scale, as a single turbine, or as part of a large farm of wind turbines. Over the past five years the cost of electricity generated by wind has fallen from 7p/kWh to 4p/kWh, comparable to the mainstream generators. The UK also benefits from the correlation between domestic demand and wind power availability. Due to the UK's island type climate the wind, on average, peaks in time with the midday and afternoon demand profile peaks. In addition winter months see substantially higher wind speeds, matching cold spell demand.

Scenario studies showed how wind turbines could be used to offset environmental taxation. Wind generation of up to 25TWh of electricity per year helped reach government emissions targets. Possible future European Commission penalties on excess emissions were avoided by employing such strategies. Onshore wind power is already increasing as the technology develops. The only problem is that onshore resource limitations and the technology for the anchoring of offshore wind turbines is still undergoing tests. The future of this technology is almost certain as it has proven to be a vital part of a future integrated UK electricity supply.

9.5.7 Non-Proven Technologies

This category includes offshore wind, wave power and solar power along with any technology that does not yet exist. It does not include advances in already proven technologies. This field was used for scenarios that investigated the impacts of new technologies on existing generating methods. Nuclear fusion is considered a non-proven technology and its impact on future generation was investigated using GAMES. Although there was no actual data for these untested generation methods the ESI's sensitivity to such change was investigated. As expected new technologies took time to be established unless their overall utility was far greater than existing methods.

9.5.8 Imported Electricity

The present the cross channel interconnector capacity between the UK and France is 1,988MW. Although expensive additional under-sea cable can be laid to increase this capacity. There is no maximum future interconnector capacity so long as there is power to send down it. It will prove useful in controlling the taxation structures of individual countries as imports are not subject to environmental taxation. Including imported generation did show the present limitations of the model. Because UK based environmental taxation did not apply to imported electricity, and the difficulties in collecting reliable French policy data, The model often suggested importing electricity as a means of avoiding taxation. This effect was reduced by including an import tax that correlated to expected French taxation policy. The sensitivity of this was proved to be low and imports remained a significant portion of the UK's future integrated supply.

9.5.9 Integrated Generation

The key issues in maintaining a reliable supply of electricity are security and diversity of supply. The security issue concerns the availability of substitute generation and the delay in these generators coming on line. This is due to the fundamental problems of power storage and the time lag in spinning up and synchronising plant. Small faults in the final electricity supply can have a catastrophic effect on industry, commerce and public safety. Therefore there must always be enough capacity to meet both expected and unexpected demand. This type of extra reserve capacity is not wanted by investors and market forces, without regulation, cannot guarantee that this margin will always exist. All the scenarios followed the models primary assumption that demand will always be met by supply. However, on some occasions, the model suggested reducing all reserve plant, sustaining large penalties instead. This proved that legislation is needed to ensure that there is enough plant to cover forced outages and sudden, long term closure.

Generation diversity plays an important role in securing supply. Resource, technological, environmental and political changes can remove a whole generating method from the grid system within a few years. An example is the UK's rapidly diminishing coal capacity; coal plant is being replaced by gas plant which will, in turn, need to be replaced itself. The scenario studies show a high probability that some of the capacity deficit resulting from gas depletion will be met by coal. The ideal solution is one where each method of generation is used by its merits and no individual method is asked to take the whole load. Such a future is possible so long as legislation and taxation are used wisely as part of a long term plan.

9.6 Summary of Conclusions

The ESI has performed a full circle from private ownership, through nationalisation and government control, and back to being a privatised industry. History has shown that government led intervention and regulation has always played an important role although some politicians like to state otherwise. Along with these changes in market and ownership, technologies, environmental impact assessments and resource constraints are also under constant change. Chapter 2 highlights the need for forward planning in this environment of change and concludes that a robust long-term model is needed to investigate the effects of changes to policy, market, environment and technology on the primary energy usage for generation in the ESI.

Chapter 3 outlines the many mathematical techniques that have been used to forecast small scale correlations, such as weather temperature and electricity demand, in the ESI. These techniques are limited by the number of possible explanatory variables and the necessity of linear data sets. Computer based forecasts, that apply non-parametric regression, can correlate non-linear data. These forecasts can be improved using AI techniques which enable the classification of data through fuzzy logic, the learning of complex correlations using artificial neural networks and the evolving of optimum solutions by genetic algorithm. The chapter concludes that GA optimisation is necessary for long-term forecasting of generation in the ESI due to the lack of relevant past data, the size of the problem and the non-linear nature of the relevant explanatory equations.

Chapter 4 concerns the theory behind long-term primary energy forecasting and the application of a new, utility based, model. It proves that a rigid structure is necessary to organise such a large scale model based upon the separation of exogenous and endogenous functions, and the classification of the latter by their role in the model. The chapter concludes that grouping all these functions, that together described the UK ESI, in a global utility function allows the conversion of the multitude of non-linear simultaneous equations into a single optimisation problem. This novel approach to energy forecasting unifies fiscal and relative numeric values in order to combine financial, environmental, technical and political factors in a single model.

Because the global utility function was non-linear with over 4×10^{416} possible solutions it could not be solved repeatably by any other means than an intelligent search method. Chapter 5 proved that a GA was the most suitable intelligent search method and described the GA that was specifically created to optimise the global utility function. The chapter outlined improvements which could, in this case, be made over the standard selection, crossover and mutation operators by using two point crossover, non-uniform mutation and including two new operators "flatten" and "recall". It can be concluded from the construction and testing of a Genetic Algorithm based Model of Electricity Supply (GAMES) that flatten, the heuristic mutation operator, made forecasts more realistic by removing unlikely peaks and troughs from trends in primary energy utilisation. In addition the recall operator gave the population a memory of previous generations allowing, through mutations, the reuse of old genetic material which improved the overall optimisation time. Both operators should be applied to other large-scale evolutionary algorithm applications.

GAMES was constructed for use by energy planners and used an intuitive approach to the user interface. Chapter 7 showed that the use of spreadsheet styled forms for data input allowed the easy access and editing of data sets. The default settings of genetic operator variables were adjusted to enable the use of the program without any prior knowledge of GAs and their operation. Users with some GA knowledge were able to manipulate these variables through novel interfaces, such as the hold operator interface, which represents genes as items in a fruit machine. The chapter also showed the program's facility to *radiate* the population and temporarily increase the level of diversity in the population to ensure that a global optimum, rather than a local optimum, had been found. Although this method of testing the optimum solution was not new, it had never been used as an integral part of a forecasting tool in this manner. The importance of a GUI is often underestimated resulting in forecasting tools that are difficult to use. This chapter shows the advantages of a simple, yet intuitive, GUI and concludes that, for real applications, the accessibility of a program decides its use to the same extent as its ability to solve the problem at hand.

It has never been possible to make exact predictions as to the future shape of the ESI. Existing models, which attempt to give an exact view of the future, have generated notoriously inaccurate forecasts. It can be concluded that this innovative approach, of forecasting through an optimisation process, enables the creation of multiple sets of near optimum solutions. This provides the energy planner with various, equally likely, outcomes to scenario forecasts and creates a wider picture of possible future events. Combining the results from a number of scenario forecasts gives enough information to assess the factors that will influence the future of electricity generation in the UK ESI. This extra analysis should prove critical in future forward planning decisions.

The results discussed in Chapter 8 represent the analysis of multiple sets of outcomes from five different scenario forecasts. The conclusions given below are based upon this sensitivity analysis and give a clear picture of the critical influences in future plant construction and generation scheduling choices. The continuity in these forecasts proves the stability and accuracy of the GAMES forecasting model and the theory behind using utility optimisation in long-term forecasting.

From the analysis of results given by the GAMES forecasting model it can be concluded that, in the short-term, Combined Cycle Gas Turbine (CCGT) generation has attracted private investment in the UK ESI because of the efficiency of the technology, the low fuel prices and attractive contract opportunities. In the long-term, the depletion of UK gas reserves will be a major energy issue in the next millennium. Gas depletion will have a direct impact on both industrial and domestic gas users, and an indirect impact on generation and the environment as contingency measures to meet the generation shortfall constrain planning possibilities. The main large-scale replacements for CCGT will be coal and nuclear powered generation. Oil prices are expected to rise due to increased demand from developing countries and the UKs available hydropower potential is already nearly fully exploited. Coal generation suffers from both gaseous and ash emissions which impact heavily on the environment. Unfortunately the technology needed to remove these emissions is expensive. It costs over £160 million to install flue gas desulphurisation on a 1000MW of coal fired plant which removes a high percentage of SO_x but still leaves NO_x and CO_2 emissions. Nuclear power does not have any emission problems and could be used to replace CCGT without breaking environmental targets. Unfortunately the potential hazards of current nuclear technology, and the issues relating to the disposal of radioactive waste cannot be ignored. History proves that accidents do happen and increasing the UKs nuclear capacity can only increase this risk.

Renewable generating technologies, which currently account for less than 2% of the UK total capacity, are encouraged through favourable contractual arrangements, European based financing and a high media profile. Their maximum potential is large but, as with all generation, the renewables have a specific place in the industry. Hydropower turbines can come on-line very rapidly, whilst wind power must be exploited whenever it is available. These are the critical constraints, along with taxation and resource usage that must be given a priority if renewables are to become influential in the future.

The UK is fortunate in that it has the resource, technical knowledge and wealth to enable it to formulate and execute a long-term future for electricity generation. This future could be sustainable if efficient use is made of domestic resources and adequate funds are made available for researching improvements in existing generating methods and developing new generation technologies.

9.7 Conclusion of Thesis

The thesis of this study, that a reliable long-term forecasting model of yearly generation, energy resource and available plant mix in UK electricity generation can be constructed using a global utility function solved by a Genetic Algorithm (GA) based optimisation has been proved. The removal of moral decisions from the energy planners, to the legislators, made it possible to model future plant scheduling decisions by optimising economic, technical and environmental functions within the constraints of known, or predicted legislation. This large, non-linear and discontinuous optimisation was solved efficiently and reliably using a dedicated GA. The comparison of an ex-post forecast against real historical data proved the accuracy of using this approach. The five scenario studies proved the long-term stability of the model and completed the validation of the GAMES forecasting model.

9.8 Recommendations For Future Work

This study has proved the application of GAs to complex long-term forecast problems and shows how the advantages of using a GA, rather than a traditional iterative technique, increases as the model's size, non-linearity and complexity increases. Therefore the recommendations for future work concern the application of the GAMES model structure and GA to existing and larger forecasting problems. The first recommendation is to use the existing GAMES model to continue the study of the UK ESI and explore the factors that will influence its future structure. The second is to increase the model's scope to include the European Community (EC). The third is to change the emphasis from generation to load flow through interconnectors across the whole European continent. Finally the fourth suggestion is to extend the knowledge behind GA based optimisation in large-scale problems.

9.8.1 UK based Studies Using GAMES

This study was primarily concerned with the development of a new type of model that could be used in long-term primary energy utilisation in UK electricity generation. Although the results obtained are valid, the objective of the work that produced them was to prove that the model was stable, reliable and able to predict outcomes to possible future scenarios. A full study of all possible scenarios, in order to find an ideal planning policy for the UK ESI, could be performed using GAMES as the forecasting tool. Such a study could include additional generating methods and their descriptive functions along with extra data and exogenous forecasts. France should be included within this study as environmental concerns in France apply to the UK which purchases electricity from France.

9.8.2 European Forecast Model

As computer processor speeds increase, so do the possibilities for applying GA based forecasting techniques. A forecasting model that encompassed the whole of the EC, with enough detail to provide accurate forecasts to possible future scenarios could aid the European Commission in their forward planning energy strategy. The vast amount of data needed for such a model would put this recommendation beyond the scope of a single researcher. A team of energy planners would be needed to construct, apply and derive planning strategies from a model that size.

9.8.3 European Interconnection Study

As the EC develops a network of interconnectors, between individual European nations, will be established. Each nation will be in direct competition for electricity generation and supply. A model which will be able to predict which nations will have an excess, or deficit, of generation capacity would prove invaluable in such a market. The economics, taxation structures, technical ability, and resource constraints of each nation would have to be included along with the costs of transmission across such a large geographical area. This large project would be ideal for multinational energy companies who are already investing in European generating companies.

9.8.4 Extension of GA Theory for Large-Scale Problems

During the past thirty years Genetic and evolutionary algorithm research has increased rapidly. Until recently this was on a theoretical basis as computer CPU speeds limited the application of these techniques to small, theoretical, problems. The standard tests for new GA operators are currently based on their ability to solve these traditionally small problems. The most popular of these is the Travelling Salesman Problem (TSP) which concerns the cheapest route that a salesman can travel between a set of cities based upon the transportation costs between each city. However, this history of proving GA theory through simple problems limits the addition of complex operators which benefit large-scale problems, but are inefficient in small-scale problems. Many biological theories, such as reversible mutation or the inclusion of dominant and recessive heredity, could be tested on large-scale problems. If CPU speeds continue to increase as they have over the past twenty years evolutionary algorithms will be regularly used to optimise complex large scale problems and in order to do so they themselves must evolve additional complexity.

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APPENDIX 1

PUBLISHED PAPERS

1. Silverton C.L., Wallace A.R., "Application Of Genetic Algorithms to Long Term Generation Fuel Resource Management" *32nd Universities Power Engineering Conference*, Vol. 2, p609-613, Sept 1997,

2. Silverton C.L., Wallace A.R., "Construction of a Genetic Algorithm Based Model of Energy Systems" *33rd Universities Power Engineering Conference*, Vol. 2, pp 501-504 Sept 1998,

APPLICATION OF GENETIC ALGORITHMS TO LONG-TERM GENERATION FUEL RESOURCE MANAGEMENT

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ABSTRACT

This paper discusses the problems associated with long-term fuel resource forecasting within the UK privatised electricity supply industry (ESI) and suggests the inclusion of market and economic effects along with emissions tax, plant and generation costs. A Genetic Algorithm (GA) based solution is offered as a means of modelling these non-linear factors to give proportions of energy sources to be utilised in electricity generation. A simple GA has been implemented to forecast the fuel mix between gas and coal as a means of testing the feasibility of such an approach. Results suggest that GAs are ideally suited to modelling long term fuel resource usage as this approach allows dynamic updating of input data.

INTRODUCTION

UK electricity generating capacity must increase to satisfy a steadily increasing demand for energy. In conflict, the future of fossil fuel generation is somewhat uncertain as these resources become scarce, expensive and emissions taxes rise. These so-called environmental taxes have, in the short-term, helped the growth of many renewable energy technologies (RETs) which are not subject to this type of taxation [1]. However the long term effects of these taxes are unknown. The ideal scenario would be that the ESI met electricity demand with minimal environmental impact. However, if the result is a future ESI that relies too heavily on a single unreliable technology or energy source, the impact on UK industry, economy and environment could be disastrous. To ensure that this does not happen there needs to be a coherent plan upon which future new plants and electricity generation mix can be based. To create such a plan the factors that influence decisions involving energy resource utilisation must be fully analysed. These factors include:

- Emissions Taxes
- Fuel Resources and Prices
- Electricity Demand & Existing Capacity
- Costs & Benefits of Technologies
- Managerial Strategy

A model based on the relationships between these factors and the choice to utilise each method of electricity generation could be used to predict the long term fuel-mix in the UK. Such a model must be active so that it can be adapted to investigate the effects of different taxation structures along with changes of environmental constants and technical developments. This can be done by taking forecasts of each factor and including them into a model that predicts, on a yearly basis, the proportions of electricity generated by each energy source. Although the accuracy of any long term forecast is entirely dependent on the quality of the input data, sensitivity studies on such a model will show the results of unexpected changes in the future. Such an investigation into the effect of these changes on the long term generation mix will give the factors most critical in energy resource planning. It is this sensitivity analysis, on a long term forecasting model, that will prove crucial in the validation of different long term plans for electricity generation in the UK.

PRIVATISATION OF THE UK ESI

Privatisation brought with it considerable restructuring within the ESI. The new economic structures of Regional Electricity Companies and Generators has affected, although sometimes only indirectly, their public policy [2]. Privatisation has transferred public responsibility from these private companies to a system of regulators and government legislation. This has created a separation between many of the firm's public obligations and the maximisation of economic performance: Until the majority of customers can choose their electricity supplier, all actions within the laws and rules of energy trading will be considered acceptable. As energy legislation is well defined and private firms' performances can be estimated, the removal of public responsibility from the firm has made it possible for ESI forecasters to use complex theories within the constraints of known legislation to model the outcomes of future fuel-mix decisions [3]. The reliability of such models depends on the industry - and market - specific assumptions made in the forecasting method.

FORECASTING IN THE PRIVATISED ESI

It is widely assumed that private ownership implies profit maximisation. Existing ESI forecasting methods assume a Least Cost Plan (LCP); that decisions concerning the choice of generating methods rely solely on a maximisation of generation profit. Although more recently some of these algorithms have included emissions constraints [4], Shlyakhter's study [5] on past forecasts in the US private energy sector showed that there was a *"... 7.5% probability that a value of a parameter predicted by a model would be seven standard deviations above or below the true value"*, suggesting something is fundamentally wrong with traditional LCP forecasting methods being applied to the ESI. For example many RETs only promise future high returns whilst profit maximisation, due to *"dash for gas"* policies [6], lies in combined cycle gas turbine (CCGT) generation . LCP models would predict that no RETs would be used until they became more profitable than CCGTs. In reality, the decision process is far more complex and companies have become involved in RETs long before they have become the most profitable forms of generating technologies.

Deviations from profit maximisation are related to economic inefficiencies in the decision making process created by the incentive structure of private firms. These inefficiencies are explained using the Principal-Agent theory [7]. The theory suggests that there is a conflict of interests between Principals (the shareholders in electricity generating companies) and Agents (the decision makers or managers within those companies). To incorporate this effect in a forecasting model sets of additional constraints must be added to the forecasting method. These constraints are derived from the major managerial decision making processes:

Contracts
In the electricity generating companies, where there are many shareholders, enforcing managerial contracts becomes too costly for the individual as the returns from such endeavours are shared. This limits managerial efficiency and so implies productivity constraints must be added to the model.

Threat of takeover
A perceived threat of takeover will set a minimum efficiency. However to avoid takeover a manager must often take action to manipulate profits and share prices. This constrains a firms growth.

Threat of bankruptcy
A perceived threat of bankruptcy causes a manager to either increase assets (through investment) or reduce liabilities (as a means of reducing debts). This will cause, at least, nominal investment constraints.

Risk management
Risk management strategies that do not follow profit maximisation are adopted to avoid worst case scenarios. These include:

- *Long term contracts* that span a time-scale that will not be affected by short term market fluctuations.
- *Vertical integration* through investing along the supply chain guards against supply price variance.
- *Horizontal integration* that aims to increase market share by absorbing the competition.
- *Risk sharing* by companies who would be unable to individually accept the risk of exploratory work
- *Diversification* by swapping a specific risk for a general market risk.
- *Hedging* to eliminate unwanted risks by offsetting one risk against another.

Risk management strategies must be included within the forecast as a set of constraints that vary depending on the probability of a future event. For example: reducing the probability of utilising generation methods that are too dominant in the market ensures diversification. This creates further forecasting problems; present decisions are altered by predictions of future events yet these events rely on those same decisions. This loop creates non-linearities that traditional optimising techniques find difficult to solve.

SOLUTIONS TO FORECASTING PROBLEMS

As any fuel-mix decision can be described as an optimisation based on forecasts and a set of known laws, predictions of such decisions must rely on a function other than simple profit maximisation [8]. Although adding the above constraints to profit maximisation creates non-linearities it gives a more accurate forecasting method. Optimising such a function cannot be time-dependent as these constraints vary depending on past and predicted future events. Complex non-linear, time-independent functions have traditionally proved difficult to solve.

The solutions to these forecasting problems lie within the construction of the forecasting model itself. To include the cause and effect of present and future events the model must solve for the whole time period at each iteration rather than solving on a yearly basis. Using this approach along with the inclusion of technical, economic and environmental constraints increases the models complexity. A complete ESI model, including a mix of eight generating methods over a forty year period, would have 10^{321} possible solutions. The algorithm most suited to solving the non-linear combinations of functions over the massive search space that describes the ideal ESI forecast method is the Genetic Algorithm (GA) [9].

GA REPRESENTATION OF ESI FORECASTS

A GA is an optimisation method based on evolution. The algorithm consists of a population of chromosomes. In this example each chromosomes represents a possible fuel-mix between gas and coal generation over a selected time period (6 years are shown in fig. 1). Chromosomes are made up of a strings of genes, each representing a possible single years proportion of gas to coal usage.

1. A number of chromosomes (possible solutions) are randomly generated

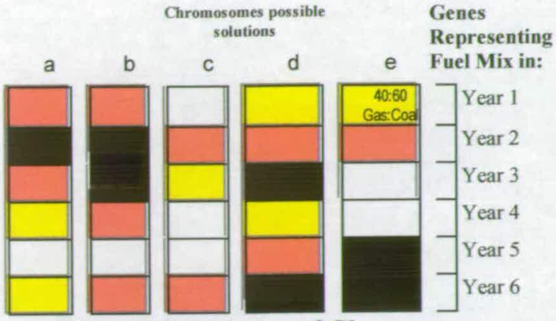

Figure 1 Population of Chromosomes

2. The fitness function, containing technical, economic and environmental functions assigns each new chromosome a fitness which affects its probability of selection. Two chromosomes are then selected as parents to be used in breeding new and better, against the constraints of the fitness function, fuel-mix solutions.

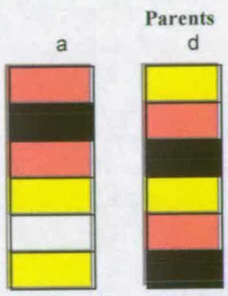

Figure 2 Chromosomes are selected as parents

3. Breeding involves splitting strings of genes off two chromosomes and swapping them. This is known as crossover (fig. 3). The children then replace the least fit solutions in the population.

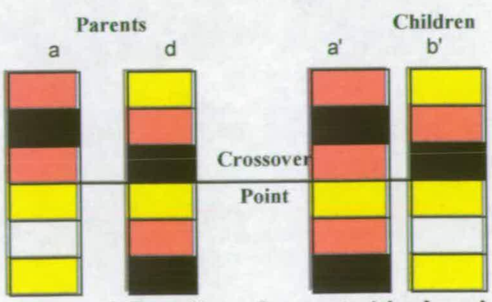

Figure 3 Breeding of parents (single point crossover)

4. A small number of the child chromosomes have a random number of genes, or strings of genes, randomly mutated (fig.4). This prevents the GA becoming stuck in local optima.

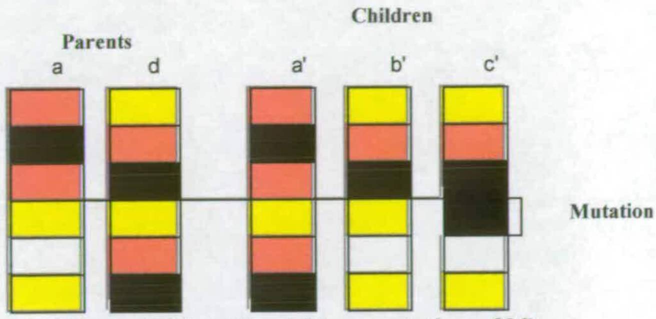

Figure 4 Mutation (c' is a mutation of b')

5. The GA returns to the fitness function (phase 2). This continues until the whole population converges (the population becomes similar and stops changing), providing the fittest or most likely set of possible fuel-mix solutions that satisfy the requirements of the fitness function.

APPLYING A GA TO ESI FORECASTING

A test model was initially created to investigate the feasibility of using a GA in ESI forecasting. This model assumed that all UK electricity was generated using either coal or gas. It incorporated forecasts such as emissions taxes, resource costs, technical advances and UK electricity demand, all of which could be altered for sensitivity analysis. The fitness function was constructed using functions based on economic theory and a knowledge of the ESI under environmental and technical constraints. The model's GA (Evolver by Axcelis) was constructed using fifty chromosomes, or outcomes of possible gas to coal mixes over a forty year period. These chromosomes consisted of forty genes, each representing a possible single years percentage of gas and coal generation.

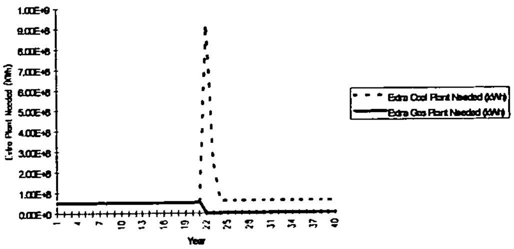

Figure 5 Starting (0 Generations) 50% Coal 50% Gas Seed of a GA Based Forecast of Extra Coal and Gas Plant Needed

All, bar one, of the chromosomes started with random values assigned to each gene. The remaining chromosome could be seeded with a fit or unfit solution; the former to speed convergence and the latter to aid divergence (fig. 5).

Selection was based on a standard roulette method which gives slightly higher breeding rates to fitter chromosomes. Once selected, breeding was performed using a two point crossover to allow the passing down of market and technical trends through generations. This involved randomly selecting two points along the breeding chromosomes and swapping the sections within these points. Both parents and children were then re-inserted into the population replacing the two least fit solutions.

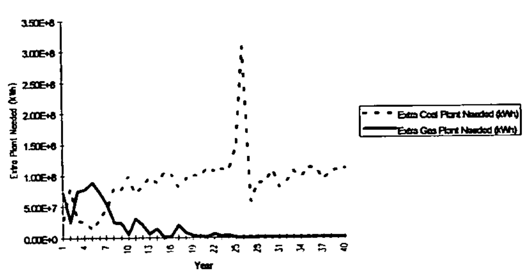

Figure 6 Mid point (2,000 Generations) GA Based Forecast of Extra Coal and Gas Plant Needed

The mutation rate was manually altered during runs. It was increased after initial convergence to help ensure a global, not local, optimum had been found. When an increased mutation rate had no further effect, it would be set to almost zero to aid final convergence. Figure 6 shows the GA's progression towards convergence on an effective energy resource utilisation plan (fig. 7).

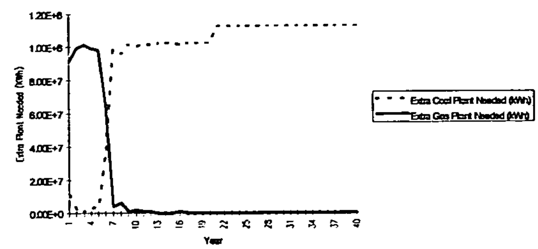

Figure 7 Convergence (200,000 Generations) GA Based Forecast of Extra Coal and Gas Plant Needed

The model converged after 200,000 generations. As the number of possible solutions was 10^{41} the GA was considered very effective. The results, for this scenario, indicated an increase in CCGT plant construction over the next six years. Further CCGT construction would be unlikely as the plant life would exceed present UK gas resources. To accommodate the resulting capacity shortfall extra coal plant construction would need to start in year five (fig. 7).

Sensitivity studies showed stability in the model when changes in fuel price, interest rate, taxation and electricity demand predictions were altered to see their effect on future generation fuel-mix. This was helped by the speed at which the algorithm adapted to these changes during run-time.

CONCLUSIONS

- By predicting the results of yearly energy utilisation decisions, a clear picture of the shape of a future ESI is possible.
- Existing ESI forecasting models are either too simplistic or insoluble using conventional mathematics.
- Using a GA based model allows the inclusion of economic, technical and environmental constraints.
- The ability of GAs to solve massive, non-linear, problems quickly allows comprehensive sensitivity analyses on forecast models.

- A scaled test model proved that this approach provided consistent and stable results suitable for sensitivity analysis.

A future model will consider 8 energy sources, each with up to 32 variables, over a 40 year period. Sustainability and the role of renewable energy technologies (RETs) will be tested when subjected to predicted and random changes such as: global-warming reduction of large hydro resources; price shocks in heavy hydrocarbon fuels; depletion of gas reserves and emissions-taxed pollution reduction.

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CONSTRUCTION OF A GENETIC ALGORITHM BASED MODEL OF ENERGY SYSTEMS

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ABSTRACT

This paper discusses the construction of a long-term UK fuel resource forecasting model. The model gives likely fuel mixes in the privatised UK electricity supply industry (ESI) and includes market and economic effects along with emissions tax, plant and generation costs. A Genetic Algorithm (GA) based solution is given to model these non-linear factors to give proportions of energy sources to be utilised in electricity generation. The GA has been implemented to forecast the fuel mix between gas, coal, oil, nuclear, hydroelectric, wind and non-proven generation methods. These are set into competition along with imported electricity as a means of finding fuel mix outcomes over the next forty years. Results suggest that GAs are ideally suited to modelling long term fuel resource usage as this approach allows the inclusion of many non-linear functions and the dynamic updating of input data.

INTRODUCTION

UK energy policy preaches reductions in emissions, more renewables, sustainable electricity generation, and effective energy efficiency. Unfortunately commitment to one of these policies can have an adverse affect on another. The recent hold on combined cycle gas turbine (CCGT) plant construction will bring an end to the "*dash for gas*" [1] and will arguably increase the long term sustainability of the UK ESI. However increasing the combustion of Coal, the suggested replacement for CCGT, will make the 1997 Kyoto CO_2 emissions targets harder to achieve.

Total fuel cycle CO_2 emissions[2]:

- Natural gas 401 g/kWh
- Coal 880 g/kWh
- Lignite 1166 g/kWh

Environmental taxes and incentives such as the Non-Fossil Fuel Obligation (NFFO) and Scottish Renewables Order (SRO) have, in the short-term, helped the growth of many renewable energy technologies (RETs) [3]. However the long-term effects are unknown. Ideally the ESI would meet electricity demand with minimal environmental impact. However, if the result is a future ESI that relies too heavily on a single unreliable technology or energy source, the impact on UK industry, economy and environment could be disastrous.

There needs to be a coherent long-term plan upon which future new plants and electricity generation mix can be based. To aid such a plan a model based on the relationships between social, economic, environmental and technical factors and the choice to utilise each method of electricity generation has been created. The model, Genetic Algorithm Model of Energy Systems (GAMES)[4], is active so that it can be adapted to investigate the effects of different taxation structures along with changes of environmental constants and technical developments. A Genetic Algorithm (GA) is used to solve the model due to the non-linearity of the many functions and the massive search space (10^{321} possible solutions). Relevant predictions of interest rates, emissions taxes, fixed and variable costs, external costs [2] and technical advances are used as inputs. GAMES predicts, on a yearly basis, the proportions of electricity provided by eight different energy sources. Although the accuracy of any long term forecast is entirely dependent on the quality of the input data, sensitivity studies on the model show the results of unexpected changes in the future. It is this sensitivity analysis, on a long term forecasting model, that will prove crucial in the validation of different long term plans for electricity generation in the UK

MODEL STRUCTURE

In order to perform a quantitative, long term, forecast of energy utilisation for electricity generation, a model of the system, that is solved by the GAMES GA, was created. The construction of this model involved a balance between defining the system in greater detail, thus increasing the model's size, and keeping the model manageable in both understanding and in computational expense. Model size is dependent on the proportions of:

- Endogenous variables; calculated within the model. The functions that perform these calculations are known as endogenous functions.
- Exogenous variables; variables provided to the model.

A model with more endogenous than exogenous variables will explain more but will be larger[5]. As the problem of energy utilisation is multi-dimensional and non-linear its model can only be solved by iterative methods, in this case using a GA. The inclusion of extra endogenous variables slows down the GA and reduces the final accuracy of the model when set to run within a finite number of iterations.

The calculation of endogenous variables is performed by the application of sets of functions which often have exogenous variables embedded within them. These functions can be classed in three groups:

- Behavioural functions that describe the aggregate actions of economic agents such as consumers, producers and investors.

- Technical functions which approximate institutional arrangements such as taxation structures related to electricity generation costs.

- Accounting identities which are exact relationships that hold for all points in time. These are usually variable costs based on fuel usage, emissions, distribution, being related to fuel expenditure in a particular plant.

AGGREGATION

Behavioural functions, technical functions and, to some extent, accounting identities are all subject to aggregation, or averaging over time, techniques. By averaging the actions of microeconomics systems, such as, fuel prices over time many simplifications can be made in a large scale model. The aggregation approach can even be applied to natural effects such as the weather. A long term forecast of the minute by minute temperature, to the nearest ±5°C, of a small town within the UK is simply not possible! However an long term view of the average yearly UK temperature to within ±3°C is, at present, considered reliable. The model of the ESI utilises aggregate solutions to give:

- Yearly fuel prices
- Wind speeds
- Rain precipitation
- Temperature
- Electricity demand (Base and peak loads)
- Generation costs or particular plant types
- Plant life expectancy in relation to the plant's lifetime load factor

DERIVING FUNCTIONS

Some of the exogenous variables, used in GAMES, have to be separately derived if the behaviour of that particular system is complex. For example forecasts of UK electricity demand are based on many variables such as weather, prosperity and industrial output and there are not enough known endogenous functions to provide an accurate model. Such exogenous variables are calculated by looking at past data to find the trends in the relationships between relevant input data and finding the outcomes that result from these relationships. Processes such as simulated annealing, or the application of neural networks have proved successful for the derivation of endogenous functions.

The structure of the UK generating system has recently undergone substantial changes as a result of privatisation, the new economic structures of Regional Electricity Companies and Generators has affected, although sometimes only indirectly, their public policy [6]. As a result there is no reliable past data. The derivation of endogenous functions for the GAMES model must therefore be theoretical, using proven economic and technical theories to describe the new market for electricity and how it affects the competitiveness of different methods of electricity generation. Privatisation has transferred primary public responsibility from these private companies to a system of regulators and government legislation. This has created a separation between many of the firm's public obligations and the maximisation of economic performance: Until the majority of customers can choose their electricity supplier, all actions within the laws and rules of energy trading will be considered acceptable [4]. As energy legislation is well defined and private firms' performances can be estimated, the removal of public responsibility from the firm has made it possible to use complex theories within the constraints of known legislation to model the outcomes of future fuel-mix decisions [7].

OPTIMISATION OF FUNCTIONS

As any fuel-mix decision can be described as an optimisation based on forecasts and a set of known laws, predictions of such decisions must rely on a function other than simple profit maximisation [8]. Although adding political and environmental constraints to profit maximisation creates non-linearities it gives a more accurate forecasting method. Optimising such a function cannot be time-dependent as these constraints vary depending on past and predicted future events. Complex non-linear, time-independent functions have traditionally proved difficult to solve.

The solutions to these forecasting problems lie within The construction of the GAMES forecasting model itself. To include the cause and effect of present and future events GAMES solves for the whole time period at each iteration rather than solving on a yearly basis. However using this approach along with the inclusion of technical, economic and environmental constraints increased the complexity of the model. The complete ESI model, including a mix of eight generating methods over a forty year period, has 10^{321} possible solutions. Because GAMES uses a GA it can solve the non-linear combinations of functions over the massive search space that describes the ESI forecast model [9].

GA OPTIMISATION OF FUNCTIONS

A GA is an optimisation method based on evolution. This model uses an evolutionary process to forecast the distribution of eight electricity generating methods over a forty year period. These include:

- Gas fuelled generation
- Coal fuelled generation
- Oil fuelled generation
- Nuclear powered generation
- Hydroelectric generation
- Wind powered generation
- Generation from non-proven technologies
- Imported electricity

The GA used in GAMES is based on one described by Michalewicz[10]. The GA operators (described below) have been chosen to provide the most effective GA representation of the model.

Population
A number of possible solutions (chromosomes) are generated, either randomly or seeded to influence the starting direction of the GA. Each chromosome consists of a number of genes. As it is assumed that electricity demand will always be met, each gene represents the distribution of additional generating capacity needed to satisfy the demand by each of the eight generating methods.

Fitness
The fitness function, containing endogenous technical, economic and environmental functions assigns each new chromosome a fitness which affects its probability of selection. The exogenous variables that effect the fitness function can be adjusted before and during the running of the GA.

Selection
By evaluating the fitness of each chromosome and the fitness of the whole population, the probability of selection can be assigned to each chromosome. This method of selection is called Roulette selection as the fitter chromosomes have a higher chance of selection but are not guaranteed success.

Breeding
Breeding involves splitting strings of genes off two chromosomes and swapping them. This is known as crossover. A two point crossover, as used in this model, takes two random points along the length of the chromosome and swaps the genes between the points. This method allows much diversity whilst still keeping some linking between genes. A new population is made from the children, although the fittest parents have a chance of surviving themselves.

Mutation
A small number of the child chromosomes have a random number of genes, or strings of genes, randomly mutated. The mutation rate (chance of mutation) takes a non-uniform distribution that reduces the mutation rate as the GA reaches a pre-defined number of generations. This aids convergence in later populations thus allowing for greater

mutation initially.

Next Generation
The GA returns to the fitness calculations, then selects and breeds. This continues until the whole population converges (the population becomes similar and stops changing), providing the fittest or most likely set of possible fuel-mix solutions that satisfy the requirements of the fitness function. It is then possible to restart the GA with a large mutation rate to insure that a global optima has been found.

RESULTS

In addition to a GAs ability to solve large non-linear functions their flexibility is invaluable in modelling.

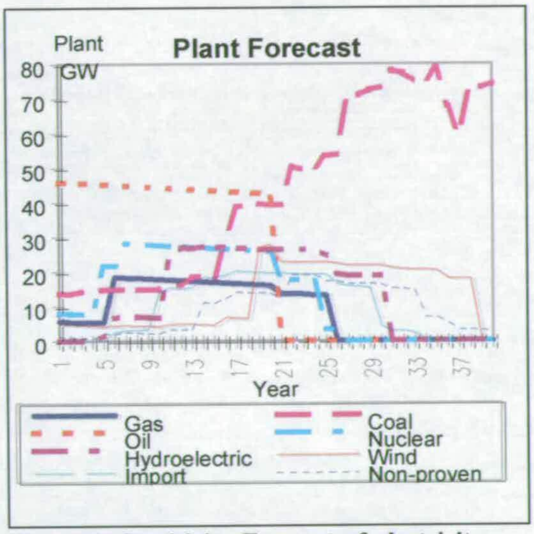

Figure 1. Sensitivity Forecast of electricity generation and imports over forty years (endogenous risk functions NOT included)

Because a GA is used to solve the energy model the addition of endogenous functions to GAMES is a simple process. A non-linear endogenous function can easily be added to the fitness function in the form of a constraint or as part of the optimisation.

Figures one and two are separate forecasts for generating plant over a forty year period. The first forecast (fig 1) includes no risk reducing policy. The second (fig 2) includes risk management strategies within the forecast as a set of constraints that vary depending on the probability of a future event. For example: reducing the probability of utilising generation methods that are too dominant in the market to ensure diversification. This was done through sets of penalties in the GA's fitness function that apply to over usage of any individual generating method at the expense of other generating methods.

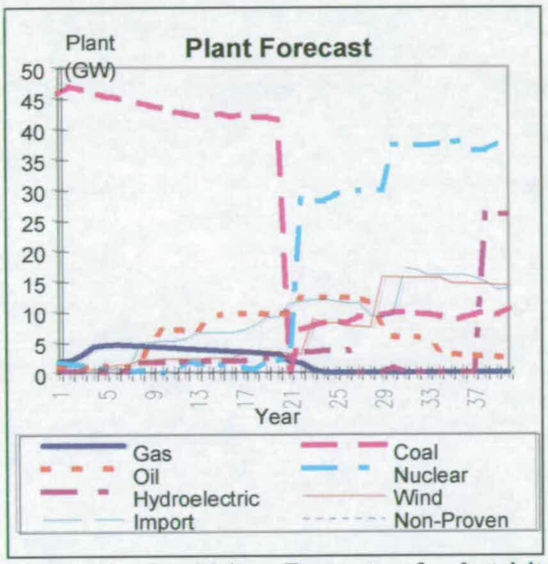

Figure 2 Sensitivity Forecast of electricity generation and imports over forty years (endogenous risk functions included)

This sensitivity study on the GAMES model shows how the inclusion of endogenous risk functions (fig 2) results in a diverse ESI which would prove a robust strategy. It can be seen that even if the forecast started from a predominately coal based generation scenario the model returned to give a mixed generation outcome. Conversely omitting risk analysis results in a purely coal based generation after thirty eight years even if the forecast is started from a mixed generation scenario (fig1). Only after a complete sensitivity analysis of the GAMES forecasting model will any results derived from its use be valid for UK energy resource planning.

CONCLUSIONS

- By predicting the results of energy utilisation decisions, a clear picture of the shape of a future ESI is possible.
- Using a GA based model allows the inclusion of economic, technical and environmental constraints.
- The ability of GAs to solve massive, non-linear, problems quickly allows comprehensive sensitivity analyses on forecast models.
- Sensitivity analysis on the GAMES model have proven it to be robust and useful as an energy planning tool

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