Mathematical Modelling and Risk Management in Deregulated Electricity Markets

Stephen Davis

This dissertation is prepared in fulfilment of the requirements for the degree of Master of Science in Operations Research at the University of Cape Town.

Supervised by Professor Theodor J Stewart.

March 2005

Acknowledgements

My sincere thanks go to Professor Stewart for your brilliant insights and guidance in writing this dissertation, and to Jacqueline for all your support and encouragement.

Synopsis

In this thesis we aim to explore how electricity generation companies cope with the transition to a competitive environment in a newly deregulated electricity industry. Analyses and discussions are generally performed from the perspective of a Generator/Producer, otherwise they are undertaken with respect to the market as a whole. The techniques used for tackling the complex issues are diverse and wide-ranging as ascertained from the existing literature on the subject. The global ideology focuses on combining two streams of thought: the production optimisation and equilibrium techniques of the old monopolistic, cost-saving industry and; the new dynamic profit-maximising and risk-mitigating competitive industry. Financial engineering in a new and poorly understood market for electrical power must now take place in conjunction with — yet also constrained by — the physical production and distribution of the commodity.

Contents

Glossary

(I)SO The (Independent) System Operator who controls the scheduling of electricity production for a particular grid, 14

Basis Risk the risk resulting from the difference in price between the same product (or between a product and its spot value) in different markets, 56

CFD 'Contracts-for-differences' is a commonly used synonym for a financial swap agreement, 49

Convenience Yield the net benefit of either holding a commodity in storage or entering into a forward agreement for future delivery of the commodity, 37

DSS Decision Support System, 23

E&W Acronym for the England and Wales Power Pool, 16

EPP Eskom Power Pool, 6

GBM Geometric Brownian Motion, 39

Genco A generation company in a deregulated market for electricity (also refers to the client in the simulation model formulated for this thesis), 11

IPP Independent Power Producers are privately funded generation companies in a liberalised market for electricity, 66

LMP Locational marginal price is the price at which the market at a locational node of a power system is cleared, 19

Lognormal A lognormal variable is random variable having the property that its logarithm is normally distributed, 30

MC The Marginal Cost of producing 1 MWh of electricity; may be SRMC (Short Run) or LRMC (Long Run), 66

MCDM Multiple-criteria Decision-making, 82

MWh The megawatt-hour is the basic unit of production and sale of electrical energy and is the amount of power produced (or consumed) by an entity in a specified hour, 15

NER The National Energy Regulator of South Africa, 94

NETA The New Electricity Trading Arrangements implemented in the England and Wales market, 16

NYMEX New York Mercantile Exchange: an exchange offering energy futures and options contracts for the U.S. market, 5

OTC Derivative contracts arranged privately between too parties and which are not traded on a recognised exchange are termed 'Over-the-counter', 48

PPO The Power Pool Operator for the Eskom Power Pool, 101

RED A regional electricity distribution company, 13

RED The Regional Electricity Distributors in South Africa, 96

RETA The Revised Electricity Trading Arrangements implemented in the England and Wales market prior to NETA – proposed bilateral trading in favour of the E&W Pool, 17

SMP System Marginal Price at which the market is cleared in a pool clearing price auctions for electricity. Very often it is the price paid to Genco's whose offers for production offers were successful, 36

Unit Commitment is the responsibility of an electricity producer to obtain an optimal schedule of all of its units while satisfying all of the plants' technical requirements i.e. deciding when and which units to start-up or shut-down, 2

VaR Value-at-Risk is a confidence interval for the distribution of profits or losses on a portfolio in a particular time interval, 29

Volatility Smile When the distribution implied by market option prices differs from lognormal the true volatilities are non-constant — often observed when prices exhibit stochastic volatility and jumps, 47

List of Figures

List of Tables

Chapter 1

Introduction and Problem Statement

1.1 Structure of the Dissertation

In this chapter the justification for the study that has been undertaken is outlined, setting the stage for the analysis of the behaviour of a market participant in a deregulating market for electricity. In order to proceed, it will be necessary to define the broader area of research which currently relates to the financial economics of energy markets, and the strategic analysis of market participants. The area of specialisation is then located within the global changes that have taken place in the world's energy markets — particularly in those for electrical power. Having located the specialisation, a practical context for the development of a simulation model for an actual participant will be presented, followed by the development of a model and subsequent analysis of the insights gained from the model and the modelling process. Some summaries and conclusions of the study will then be given, providing an overview of the success of this research endeavour. After this introductory chapter, the remainder of the thesis will proceed as follows:

Chapter 2 will give a general overview of the current types of issues tackled by researchers in the field of electricity markets, thus providing a broad survey of the topics which are dominant in current worldwide research on the subject.

In Chapter 3, the literature review of Chapter 2 will be refined to a survey of the techniques and issues which currently prevail in the modelling of generation companies' trading strategies, particularly in pool-type markets.

Chapter 4 will present the context for a simulation study of a local generating company. It will thus describe the current state of transformation of the South African power market, and in particular the current changes within Eskom: the original parastatal enterprise producing the bulk of the country's electrical energy requirements. It will also provide the background for the simulation study conducted in subsequent chapters.

In the context of Chapter 4, the development and construction of a stochastic simulation model, as an aid to strategic decision-making, for a single generating unit will be described. This is undertaken in Chapter 5.

The results, findings and associated experimentation of a unique simulation model are outlined in detail in Chapter 6, with some concluding remarks, discussions and suggestions for further research summarised in the final Chapter 7.

1.2 Global Reform in Energy Markets

Worldwide there have been recent radical transformations in the economics of electricity trade. This is amid the reforms of many other industries, ranging from telecommunications, to primary energy commodities, to bandwidth and emissions to name a few. Characterising these reforms is a move toward the ideology of a free market, including the unbundling and privatisation of large-scale monopolies and parastatals which have traditionally operated these large-scale technical systems.

The intentions are for the industries to have a structure and regulatory framework which allows the price of the relevant commodity to be efficiently and cost-effectively determined, solely through the interaction of supply and demand for that commodity. As will be discussed in later chapters, there are many difficulties in achieving the so-called ideals of a completely fair market, where price essentially reflects the underlying costs of production, extraction or management of the commodity, as the case may be. Furthermore, it is hoped that replacing centralised control in one industry with cooperative behaviour of smaller sub-participants will allow the sector to function more efficiently and cost-effectively as a whole.

The new market participants are therefore exposed to financial risks to which all firms engaged in economic competition are exposed, but are further compelled to meet the technical constraints of a national (or sometimes cross-border) electrical grid. In such a grid, demand must continually be satisfied on a real-time basis with strict adherence to frequency, voltage levels, safety measures and any other constraints that assure proper operation of the system.

The themes of this dissertation that are to be covered in the survey of literature and the subsequent modelling process are motivated by a conglomeration of the following concepts:

Electricity market reform

Transformation of the electricity sectors in various countries from monopolies to industries dominated by competitive forces [20] is investigated, including the unification of free market forces with electric power system (unit commitment) concepts and the commoditisation of electricity. **Unit commitment** is the responsibility of an electricity producer to obtain an optimal schedule of all of its units while satisfying all of the plants' technical requirements i.e. deciding when and which units to start-up or shut-down. **Generation dispatch** is the decision on what the individual power outputs of the scheduled units should be.

Financial markets, derivatives and risk management

Invoking a discussion on the development of financial markets for the electricity commodity, including a description of derivatives markets that were soon conceived in response to the commoditisation of electricity. The derivatives markets have routes in the management of risks associated with the trade of a commodity whose prices are highly volatile, and whose required volumes are also very uncertain. These tertiary markets have subsequently been engulfed by the speculative trading activities prevalent in other markets, especially in developed countries such as the United States.

Literature review

- summarising the types of problems tackled by researchers in the evolving research area of *electricity economics* and discussing some of the ways in which to tackle these issues.

- Additionally, classifying the changes that have taken place with respect to market design and structure in various countries' electricity sectors, highlighting the ways in which these changes have emphasised the need for strategic decision-making tools.

Specialisation

Focusing on the South African market and its dominant supplier, Eskom. There is little to no research that can be found on the subject of restructuring in South Africa's electricity market, even though the intentions to transform were declared some years ago, during the same era when drastic changes had commenced in other countries. Eskom being the original monopoly (and now the subject of current unbundling and privatisation efforts in the country), a study is envisaged which considers one of its subsidiary generators as a market player. The study is conducted with a view to ultimately developing a representation of the entire market, though the building block for such a representation is given the immediate and direct attention.

Mathematical modelling

Following on from the above point, we aim to develop, in the light of other research, a mathematical modelling and simulation tool for understanding a competitor's behaviour in the South African market for electricity generation, and using such a model to improve and understand an individual participant's performance in the market. Regarding the literature, a survey will be undertaken which includes an account of the types of modelling techniques used by researchers, describing their endeavours in other markets. Although the model of this thesis will be somewhat unique, it will be motivated in the light of techniques and aims of those reviewed in the survey.

1.2.1 Development of Energy Markets

Structure

The financial engineering of national energy markets has resulted in various constituents. The grid itself forms a market place where buyers and sellers meet. It may not necessarily participate in any power trading, but can act as a facilitator. A spot market may serve as the primary power pool, providing a medium for the physical commodity to be traded in hourly time periods. At a higher level we find a financial futures market providing the instruments for price hedging and other risk management tools for power procurement and cost mitigation.

Markets vary by nature (day-ahead, real-time and ancillary services) and can be sub-classified according existence of demand-side participation, firm bids and offers, location-specificity, presence of financial markets and existence of bilateral agreements.

Electricity spot markets are the short term markets where energy is traded for immediate delivery, or for the following day depending on the design of the auction. The spot market will therefore serve as a reference market for long to medium term transactions. In many countries, the spot market constitutes a day-ahead market, a congestion management procedure, an adjustment market, a reserves market and a market for ancillary services. Of these the day-ahead mechanism constitutes the largest transaction volumes and is therefore considered the most important for research purposes, though some researchers [4] explicitly consider the adjustment and reserves market in their analysis of optimal offers.

According to [30] there are four different types of energy markets:

forward energy market which is the day-ahead auction of electricity to the pool.

planned production market is the day-ahead market for the power generation plan in order to meet demand forecasts and system constraints.

real-time production market meets the second-by second demand for energy and assures safe delivery and satisfies other system objectives.

ancillary services market is needed to assure reliable system operation.

In this dissertation the literature on systems encompassing the first two of these will be surveyed, followed by the development of an associated simulation model for analysis of strategic behaviour. In addition to these four markets, one further market is considered in the literature review of Chapter 2 for the sake of completeness:

derivatives market the tertiary level of trade where financial risks may be hedged using instruments based on the underlying commodity (in this case electrical power).

Electricity and other commodities such as coal, natural gas and oil may all be traded (on paper) through a commercial exchange that trades in the more conventional interest rate and paper equity commodities, for example the trading which occurs on NYMEX (New York Mercantile Exchange). Full scale commoditisation of electricity can clearly only take place in the most advanced of the world's energy markets, where there is sufficient liquidity to enable free trade in both the commodities and the derivative instruments.

Derivatives are on old concept in all markets: contracts were frequently arranged to hedge exposure to price fluctuations, with *ad hoc* methods of valuation. Nowadays the agreements are formalised and standardised in the hope of improving the efficiency with which they may be used as effective risk management tools, and must consequently be priced to reflect their optionality and minimise the possibilities of speculative arbitrage inefficiencies.

System-wide models try to capture aspects of the whole supply system (as discussed in [51]). Such models treat the system price of electricity as an endogenous variable such that supply and demand are matched *within* the system. These models are useful for utility planners and policy makers in the sense that they measure the market performance by comparing the resultant market price under different market scenarios. The researchers in this instance, rightly caution against over-consideration on the total scope of scenarios. This could result in an a low long-run system price under perfect knowledge of the future. A policy-maker using these kinds of models can examine price-scenarios as a result of a participant's actions, but cannot use them to make policy decisions for the participant itself.

Differences to Financial Markets

Energy commodities have an evolving tertiary market unlike the already established tertiary markets for equities and interest rates. This is particularly true of electricity in which the evolution has been spurred on by the widespread deregulation and subsequent unbundling and privatisation of the traditional industry monopoly that has been occurring worldwide.

The line between secondary and tertiary markets for energy is not as clearly defined as it is in the conventional financial markets. Correlations between short and long term pricing are much less pronounced in energy markets, both between and across commodity types. Modelling difficulties are rife as the markets are new and less understood. Therefore a greater part of the behaviour is attributable to the stochastic or random element, as constrained by our understanding of the market mechanisms governing prices. An example is the effect of supply constraints which initiate price shocks. Having said this, there is also much to be learnt from the developed tertiary sectors of other markets.

The derivative products in energy markets are often contingent on functions of the underlying asset price e.g. an average, a maximum, a minimum, a range, or any other function depending on the needs of the parties to the contract. The pricing must capture this underlying functionality. Further difficulties arise in the market transition from traditional to deregulated. In the former, many pricing inconsistencies existed and these need to now be managed alongside the newer contracts of the latter, and the respective risks aggregated, even though these risks are vastly different.

1.3 Development of a Simulation Model for a Market Participant

The aims of the simulation model developed in the later chapters will be to mimic the actions of a single trader, acting in the market on behalf of an individual electricity generation unit over a specified time period. Initially — and albeit in a simplistic manner — it is hoped to be able to represent both the unit commitment and the trading strategy (or supply function) characterising the daily operations of the unit, including production and sales through an auctioning mechanism in the EPP. The intentions of the model and its resultant formulation are motivated by the following ideas and aims:

- Examining the long term effects on the benefits accruing to a generator as a result of a particular strategy adopted. This will be explored through the inclusion of various endogenous parameters or experimental factors. The choice of parameters will be justified and explained in Chapters 5 and 6.
- Including sufficient exogenous and contextual parameters to enable an assessment of the extent — if any — to which the trading environment affects the total benefit accruing to the market participant.
- Gaining insights from the apparent significance (or insignificance) of any interaction within and between the two groups of factors above, and explaining the significance or otherwise of these interactions as revealed by the simulation outcomes.
- Using the model to confirm whether altering the levels of the factors affects the benefits according to our expectations, thus confirming any intuitive understanding we may already have.
- When levels of the factors are changed and results do not coincide with our expectations, it is hoped that these anomalies can be explained and new insights revealed.
- Revealing the scope for using the model for determining an optimal supply function/bidding strategy and explain the conditions under which this strategy may be adopted.
- Determining whether or not the results obtained are consistent over various time horizons, and explain any inconsistencies should they arise.
- Ultimately revealing how satisfactory the model is in its current form, suggesting and — where possible — implementing amendments and improvements to the formulation. The identification of any deficiencies and associated implications will also be an important aspect of the exploration.
- Identifying areas for further research and development of the model in a real-life situation: In keeping with trends in the current scientific research on the subject we may, for example, postulate the amalgamation of several units into generation

clusters (otherwise referred to as generation companies), and then take a further step by forming an aggregate model of the entire generation sector through the amalgamation of all the clusters and then ultimately with the remaining market entities (these being the grid, the consumers and derivative markets). Theoretically, should the latter be achieved, we shall have obtained a representation of an entire system describing the entire power economy.

It is also prudent to make clear that the express intentions of the model are NOT - at least for the purposes of this dissertation - to achieve the following:

- Providing exact numerical answers or recommending strategies to be adopted in reality. Any results and insights would need to be first explained to a representative of the generation company concerned in the light of the model formulation. For practical purposes, further interaction and co-operation would be required to achieve a desired level of practical representability. To some extent the research in this thesis is possibly more of theoretical interest.
- Although some of the parameters suggest the need for optimisation routines to determine the best trading and production strategies, we shall first be identifying the importance of the factors in the context of the model, after which recommendations will be made on how to adapt these to obtain realistic and workable strategies for finding the optimal behaviour.
- Formulating an entire representation of the electricity market in South Africa which would enable advice to be given on regulatory or system management issues.
- Including to any great degree the use of derivative instruments and risk management tools, or suggest the use and valuation of such instruments and tools for the market participant. The sections on risk management and energy derivatives are given for interest, completeness and in keeping with current research topics in electricity markets, but must be covered owing to their peripheral importance for any model.

It will become apparent that the modelling approach adopted later in this dissertation is unique when compared to the approaches of other researchers. This is justified in many respects.

Firstly, each researcher bases their study on a different market, and each of these markets has a unique structure with regard to its design, type of auction, stage of transformation, existence of derivatives market, types of generating plant and regulatory environment; each model that is developed will then depend on the individual characteristics of the selected market.

Secondly, the intended aims of research will differ, thus necessitating different modelling techniques for say, analysing participant behaviour, analysing market design, finding optimal offering strategies for generators, analysing proposed reforms in market structure, managing risks or designing and valuing derivative contracts.

Thirdly, most of the techniques revolve around the concept of one or other kind of simulation methodology. Such methods are adaptive in nature, enabling and encouraging learning through experimentation. As such, a great deal can be gained from trying new approaches and then noting the relative advantages and disadvantages of the technique in the light of others. Many of the methods adopted in the works referenced by the bibliography are claimed (by their authors) to be useful in a wider modelling sense, in that they enable a self-critical development of modelling tools for systems as dynamic as, and with the unprecedented uncertainties, which characterise electricity markets.

Hopefully the nine aims stated above can be achieved, and if not, the reasons for the deficiencies can be explained. Regarding the four intentions which are not fundamental for this dissertation, it is hoped that suggestions will arise during the modelling process that would offer insights into how to achieve them, and where possible suggest ways of incorporating them into the developed framework. In both instances, the resulting discussions will at least provide a platform for suggesting further research into this wide-ranging and rapidly developing field of study.

Chapter 2

Characteristics of Modern Power Markets

A broad coverage of the most pressing and relevant research areas in electricity markets is given in this chapter. The topics covered are those which crop up with abundant frequency in the sample of literature listed in the bibliography. Although the sample is from a huge volume of material that is currently available on the subject, there are some common threads that crop up time and again, even in the relatively small sample of this thesis. Power markets are a research area that has experienced an overwhelmingly rapid growth since their very recent initiation. The aim of this chapter is therefore to attempt a classification of the main threads in the selected sample, giving a brief history, defining some important concepts, and elaborating on a few of them in detail.

The chapter is divided into six sections. The first one outlines in an introductory manner the changes that have taken place in power sectors worldwide, and will define the context for research, describing the types of markets, the participants, thus motivating the investigative studies that have been observed in the literature. Section 2.2 will examine strategic decision-making by market players and Section 2.3 will look at risk assessment and management in competitive markets for electricity. In the fourth section we look at the characteristics of electricity prices, particularly their importance, how they are modelled, and some of the available methods for forecasting and modelling them. Section 2.5 will cover electricity derivatives and associated financial risk management, and the final section will give a brief overview of the chapter.

2.1 The Economics of Electricity Production

2.1.1 Introduction

Great effort has been invested in restructuring traditional monopoly power industries, the objectives being to introduce fair competition and improve economic efficiency. The design of the market is crucial to providing the necessary mechanisms to enable vigorous competition without disrupting the operations for the supply of electricity or unfairly distorting prices.

Recent research in the field of power markets is both wide-ranging and far-reaching. Topics range from studies on different types of markets such as regional and cross border, though are predominantly conducted intra-nationally. Researchers have attempted to model the competitive environment, drawing on expertise from other areas of financial economics, while explicitly modifying the approaches to allow for the special characteristics of the electricity commodity.

Studies have been undertaken in order to examine the extent and success of competition in various markets, and for scrutinising auctions as a viable means of enabling the sale of electricity through pools. Other work has concentrated on the appropriateness of bilateral trading in markets and whether it is preferable to a pool as a means of facilitating the trade of electricity.

Often, the question arises as to whether particular participants in a market are capable of exerting untoward levels of market power [13]. Significant market power is an undesirable feature of efficiently competitive markets, and which can be a consequence of unwanted levels of concentration in the market. Models have been proposed to assist regulators in determining flaws in, or suggesting improvements to, the market structure, as well as for identifying collusion among participants or the abuse of market power.

Authors have also commented on the stability of electrical energy markets [2] and questions have been raised about the appropriateness of the new market structures and, which try to assess the extent to which the reforms have achieved their intended outcomes. Some challenge whether the reforms have resulted in any improvements at all by attempting to quantify the changes, and others investigate proposed changes in the structure before they are implemented by pre-empting the outcomes with system-wide simulation models. Improvements are recognised through reduced spot prices, efficient production scheduling and uninterrupted supply.

A substantial amount of work has looked at finding the optimal strategies for individual market participants, particularly generators, including the analysis of supply (and demand) functions and improving the strategic decision-making of these participants. Search for optimal strategies is expanded upon in Chapter 3, and provides the motivation for the model of electricity trade developed in subsequent chapters.

Lastly, a growing area of research, attributed to the sudden liberalisation of the electricity industry and the associated uncertainties, is that of electricity derivatives. Later in this chapter (Section 2.5), summaries are given on issues surrounding the design, valuation and risk management of derivative instruments that are traded in the world's more advanced power markets. Adjacent to derivatives issues are some topics on the valuation of generation assets and the study of real options. A few studies on the effects of capacity payments and network effects have also been found in the survey of the literature.

2.1.2 Power Market Development

There has been a worldwide restructuring of the public sector as a consequence of liberalising political ideologies which commenced in the early years of the last decade [34]. A primary benefactor of the change has been the electricity industry where the restructuring is driven by expectations of lower prices, greater efficiency and increased need for investment. The global trend began with Chile in the 1980's and escalated rapidly in the 1990's with many other countries following thereafter.

Many questions arise as to how the transformation should take place while ensuring the focus is concentrated on the industry's most pressing needs. In particular, questions have arisen such as how to restructure, how to create the right market mechanisms, and how to regulate both the changing environment and the newly established market. In such a dynamic environment there are huge strategic uncertainties; changes are accepted by participants on an act of faith and there is little historical evolution from which to evoke an understanding. Clearly countries whose markets have so far lagged in the development should have the distinct advantage of hindsight with the experience of others at their disposal, but cannot be too complacent as their needs will be very specific to the way their local market has been constructed.

A crucial difference has arisen amid market reforms with regards to the ways in which generation plants were operated. Under the regulated regime, the operator of the unit only needed to consider technical aspects of the production, where simple minimisation of costs resulted in the maximum attainable profit. In the deregulated system, profits depend on the success of the strategies chosen for offering production capacity to the pool, and the subsequent market-clearing process.

The methodology of system dynamics is one that has been widely suggested as a tool for solving a broad range of strategic problems and for developing potentially dynamic strategies [34]. Where no history of market evolution is available, it is common to use simulation as a tool for testing the appropriateness of modelling strategies through sensitivity analysis. Strategies can be assessed through the use of simulation tools.

Gary and Larsen [19] address the issue of new capacity investment in electricity generation with particular reference to the long-term production capacity in the UK. They advocate the need for moving away from the traditional methods – in particular equilibrium models that rely on a reserve margin approach – toward disequilibrium models that incorporate information feedback systems and behavioural policies. (Reserve margin in this context is the percentage excess generation capacity over peak demand.) They also stress that their methods are preferable to the (often costly and detrimental) 'trial-and-error' approach that has often previously characterised the making of decisions in transforming industries. The approach presented in [19] does not apply to the (bidding) strategies of an existing generating company (hereon referred to as *Genco*), but has the potential of being adapted accordingly, as the methodology is contextually important. Their theories are verified using a simulated comparison of equilibrium versus behavioural policy assumptions and a strategic scenario analysis. The improvements to the market are significant when measured by the increase in resultant reserve margin and electricity pool price reduction.

Characterising the changes in power markets is the move from a sector with traditionally monopolistic features to a competitive industry requiring rapid adaptation. Some of the challenges include price uncertainty, the forces of capital markets, ownership uncertainty, transition regulation and the availability and disclosure of information. Electricity is also the victim of furious development of a tertiary market where the commodity may now be traded many times before it is consumed, and where huge corporations now run an enormous trade in energy without even producing any of it. Sioshansi [46] documents the dramatic increase in resales of power in the US from virtually none in the mid-nineties to $452 million in the third quarter of 1997. The existence of such intermediaries is aimed at improving the efficiency of the trade and the supply of electricity by effectively 'outsourcing' the decisions to a third party. It is hoped such a party would provide the time and resources in order to improve the performance of their clients (at a cost) through managing their risk exposures, reducing their costs and increasing their revenues. The obvious dangers of large-scale power trading have been proven with the collapse of *Enron*.

In industrialised countries the primary goals of the restructuring and privatisation of the electricity industry are to improve both operational and economic efficiency through lower costs and improved technology. Maintenance of the grid is also an important issue, a good example being the collapse of the power supply in the northeastern United States in August 2003. The incident sparked off much political debate, and resulted in blame being laid upon the lack of upgrades to old capital assets. (The actual failure was initiated by a lightning strike on a power station near Niagara Falls, though the overriding cause was said to be the subsequent overloading of the region's antiquated grid in the aftermath of the strike [see archives of UK Telegraph newspaper, 15 August, 2003]. Italy was hit by similarly disastrous outages in both June and September of the same year.)

Changing technology with regard to electricity production and environmental concerns also play a role in industrialised countries. Examples include the increasing use of renewable energy resources such as wind, solar and geothermal energy, and the establishment of emissions trading arrangements to address the environmental impact of the burning of fossil fuels.

Regarding political and economic concerns, there are four key factors supporting the need for industry reform [12]:

- Poor performance of the state-owned or state-run supply and inadequate expansion of service.
- Inability to finance new capital investment and maintain existing assets.
- Transfer of subsidies to more pressing public issues.
- Revenue potential through the sale of state-owned generation and transmission assets.

In developing countries, the primary aims of privatisation are to create financial independence of large enterprises and to raise capital for other concerns.

2.1.3 Methods of Reform

There are two principal changes that are possible with regard to deregulation of state-run enterprises, namely changes in ownership and structural changes.

Ownership changes

There are four definable changes in ownership that characterise market reforms:

Commercialisation: a change in the behaviour of the owner in the form of greater market orientation.

Corporatisation: a relinquishing of control of enterprises with regulatory influence remaining. The entity becomes a company registered in terms of the Companies Act.

Privatisation: a complete change of ownership and sale of enterprises so that the performance of the economic activity is carried out by a private sector business.

Liberalisation: occurs when an industry adopts of a free market model through private sector participation.

It can be noted that the pace and order of the changes in ownership has differed dramatically between national power sectors.

Structural changes

Alongside the methods are reform there are three main structural changes that prevail in the electricity sector. The changes are:

- Unbundling of the single enterprise into separate, independently run entities of Generation, Transmission (in its own right a natural monopoly) and Distribution.
- Further hierarchical unbundling of the generation and distribution entities into individual, competitive business units consisting of:
  1. in the case of generation, individual power stations or clusters of production units under the umbrella of a single company, and;
  2. in the case of distribution, individual regional electricity distribution companies (RED's).
- Moving away from wholesale markets where large quantities of electricity are sold for fixed tariffs for an extended period to more flexible sales and purchase arrangements over shorter time horizons.
- Tending toward full-scale retail competition where electricity is purchased close to the hour of its generation (and consumption) at the prevailing spot price.

2.1.4 Electricity Pools and Contracts

A **pool-type market** is characterised by a central dispatch and pricing mechanism, first created for England and Wales, with similar markets now operating in Australia, New Zealand and parts of Latin America. In contrast to centralised pool are the **decentralised** markets where participants trade power bilaterally (or even multilaterally) in advance of the dispatch to consumers. The advance trades are then forwarded to the Independent System Operator (ISO) for dispatch at the time of production. A commonly discussed version of a decentralised market is the California Power Exchange [3]. Examples of hybrids of bilateral or multilateral markets and centralised bid-based markets can also be found in the literature [43].

Power pools were established with the aim of realising cost savings [33, 45]. Power pools are also an ideal location in which a derivatives market can be established. A pool is a coalition of market actors, created to improve efficiency and reduce prices by increasing trading possibilities. It is hoped that the creation of pools will more effectively capture the value of the power commodity through pricing on an hourly basis, rather than the traditional fixed cost, long term-type contracts that were common in the regulated era. Pools can be classified according to their type of membership into energy producer, distributor, extractor and consumer pools. The analysis of power pools is a broad field with its own unique academic merits.

Markets for electricity may exist within pools (say between generators), or across pools, or even across national borders. Power systems may consist of one or many pools (of varying or similar types) at the same level of hierarchy [30].

Analysing power pools

Makkonen and Lahdelma [36] do a simulation study to analyse power pools in the deregulated energy market, focusing on the situation in the Northern European countries (Finland and Norway in particular). In so doing they emphasise the need for sophisticated techniques for deciding on actions to be taken by distributors and pool members in an increasingly complex environment. A simulation study is conducted for long-term market analysis. The model is based on energy optimisation software known as *EHTO*, and is used to calculate the benefits of different types of pools and to compare policies for allocating the common benefits of the pool among its members.

They begin by describing the evolution of the Northern European market to one in which the grid, a natural monopoly, forms a marketplace for power trading between producers, distributors, and industrial consumers. They claim this introduction of competition has drastically reduced the spot price of electricity in those countries. Along with improved technologies for metering and accounting, competition has resulted in new types of electricity contracts and derivatives being introduced alongside the older existing ones. A consequence is the difficult problem of managing complex portfolios of contracts.

Three types of pools and their associated functions are defined:

Producers' pools permit central optimisation of production reducing the need for shutdowns and start-ups.

Consumers' pools benefit from economies of scale, diversity of load curves, increased marker power and centralised demand side management.

Distributors' pools combine the benefits of producers' and consumers' pools, and can be sub-classified into: Long-term supply; Short-term supply; Spot market and; Trade pools.

Contracts

Three types of old contracts that are traded in the pool are described by the same authors:

- A long-term multi-tariff contract with capacity limits and separate capacity and energy fees (determined with reference to indexes of cost factors such as fuel prices and currencies). The durations of the contracts are from one to several years.
- A fixed bilateral contract with a fixed contract fee and an hourly energy fee (varying according to intra-day time periods).
- Adjustable bilateral contracts are like the fixed ones except that the amount of energy to be bought is only specified up to a maximum amount an hour or more before delivery.

The duration of the bilateral contracts is often between a week and a year in length.

A monthly settlement of the energy traded in the three contract types takes place. Deregulation has resulted in the older contracts being overpriced and distributors of electricity are no longer able to forward their increased costs on to the consumer owing to competitive market fears. Costs are higher because the acquisition of energy is higher (relatively speaking) for the old contracts than for the new.

Optimising the contract portfolio under the above circumstances requires advanced risk analytical techniques and an understanding of various financial instruments. The new contract structures must reflect more accurately the hourly variation in electricity price and demand. There is typically no capacity fee and energy fees vary from hour to hour according to actual spot price, marginal production costs, or forecasts of the two; power limits may vary hourly. Dynamic contracts such as these are sensitive to the volatile market and include risks to the purchasers.

In addition to the new short-to-medium-term contracts are the instruments of the spot and futures markets designed to replace (or used alongside) old contract types for minimising energy procurement costs and hedging risks. An example of the most basic commodity traded in the newly established markets is a fixed forward contract for 1 megawatt-hour (MWh) of electricity for a particular hour. In Finland, trade for the forwards is open a week ahead and closed two hours prior to delivery.

Other forward instruments are formed as aggregates of the hourly contracts to intra-day periods, whole days, weeks and four-week blocks to summer/winter season forwards. Instruments for price hedging and risk management are traded on a separate exchange, settled on the spot market price and are financial contracts with no requirement for physical delivery.

Maximising the profit of a pool involves an intractable dynamic, combinatorial multi-criteria decision problem under uncertainties, where risks also need to be minimised. An opportunistic decision strategy is assumed to avoid the combinatorial nature of the problem. The assumption is questionable given the realistic presence of inaccuracies in price and load forecasts, as well as other uncertainties. Risk analysis is conducted based on simulation techniques using different scenarios. In the medium-to-long term scenario tests are run to determine the potential risks, or derivatives are used to hedge the risks. In the spot market, risks are smaller and the pool can act as a risk-neutral decision-maker. Similar methods are used for independent market actors if three conditions are satisfied:

1. forecasts are available from all members
2. pool members are informative of all contracts made
3. pool members cannot trade simultaneously with the pool.

Various pool benefit allocation methods are discussed, then pool performance is analysed using a simulation model with three components (namely an optimisation model, a balance booking application, and spreadsheet application). The approach uses an upper-level spreadsheet framework allowing interactions between the three components and is similar to that used in Vlahos et al. [50]. Three of the distributors' pool types are analysed and four different benefit allocation methods are compared numerically using a pool containing three regional distributors. Their research is therefore largely descriptive of the types of pools and the participant behaviour, though is does prescribe a benefit allocation strategy.

With their integrative modelling approach, Vlahos et al. [50] hope to tackle issues such as the long term impact of developments in the electricity pool on the contract market, the effect on the competitive position of market players after regulatory changes, ability of generators to tactically manipulate the pool, and analyse the effects of abrupt changes in circumstances. Their work is similar to Makkonen and Lahdelma [36] who examine profitability of pools under spot markets, new contract structures and old contracts.

The England and Wales Experience

1. NETA: The England and Wales (E&W) Experience [26]

   Before the implementation of the New Electricity Trading Arrangements (NETA) in March 2001, the generation market consisted of a pool which was a centralised mechanism to dispatch day-ahead electricity on a marginal pricing basis in order to meet forecast demand. The arrangement (established after liberalisation of the electricity industry in 1990) aimed to reduce prices through competition, however only a few of the generators were setting the prices and exploiting their market power, so supply-side pressure to force prices down was limited. In addition, a centrally forecasted demand reduced the corresponding demand-side pressure. The resultant situation was an illiquid, rigid market with inhibited derivative development and reduced liquidity, resulting in increased margins and raising prices. Moreover the arrangements in the pool were inflexible to the needs of all market participants.

The structure of NETA was a two-sided market with simple, firm bids and offers with bilateral contracting chosen in favour of a centralised market. It allows flexible governance and real-time (at least until the 1 hour gate closure) balancing and settlement arrangements with hourly trading. Real-time trading represents a full-scale commoditisation of electricity with increased competitive pressures on the generators. Characterising the change is a forward and futures market for electricity allowing long-term trading and short-term power exchanges where participants can 'fine-tune' their contract positions. At the time of writing of this paper, the new arrangements had proven successful for the particular industry and therefore provided an instructive lesson to other energy companies and policy makers.

2. Bower and Bunn [8] do a "Model-Based Comparison of Pool and Bilateral Market Mechanisms for Electricity Trading" in which the Revised Electricity Trading Arrangements (RETA) in place prior to NETA are compared (in advance) with the proposed bilateral trading characterising NETA. The arrangement in place at the time of RETA was the centralised pool market described above. The researchers develop a computer simulation model of the electricity market allowing the agents (generators) to compete with each other under the proposed new arrangements, and develop their own trading strategies (modelled via artificial intelligence). Their (ironic) conclusion is that the new arrangements would result in increased prices. The increase had two causes:

   (a) Firstly, hourly bidding would allow generators to more effectively segment the market between on-peak and off-peak hours allowing more consumer surplus to be extracted than under daily bidding, so that tacit collusion would be easier.

   (b) Secondly, the potential for over-bidding by baseload generators is made easier, reducing competitive pressure on generators with mid-merit plant.

   In their final conclusion they note that neither of the industry structures (existing or proposed) would be more effective in the England and Wales situation because of factors specific to the national context, and that a more thorough reform would be required. Both arrangements have been successful in the countries where they have been implemented. The bilateral market has in fact proved effective as shown by Hesmondhalgh [26], though the idea they proposed in this paper of assessing the impact of a proposed change prior to its implementation is a good one. A possible reason for failure of the new arrangements (as foreseen by the authors) is that two initiatives were timetabled at once making it difficult to identify which one of the changes had the required or unwanted impacts on the market.

The paper by Hesmondhalgh [26] is a worthwhile demonstration of the use of simulation tools to analyse the effects of potential changes in trading arrangements in pool-type markets.

It can be seen from this subsection that the question of how to allocate benefits that arise from pool-type markets among the parties in the pool is an important one, and has been addressed by a few researchers [36, 50]. They tackle the benefit-allocation problem under the premise that pools are indeed an efficient way of aggregating suppliers, and that cost savings can actually be achieved when compared to non-pool arrangements.

2.1.5 Auctions

The auction mechanism has been the widely accepted tool for setting electricity prices since deregulation in markets first commenced. Although auctioning has been effectively implemented in areas such as resource allocation and commodity trading, electricity trade requires modifications to the traditional process, because of the commodity's non-storability, and its constraints with regard to production, transmission and distribution [24]. The various types of auctions and market rules will now be described.[1]

Uniform price versus pay-as-bid auctions

In uniform price auctions every winning bidder receives the same market clearing price. Price-taking generators in these types of markets will be systematically encouraged to offer their production at close to their marginal cost. According to Rajaraman and Alvarado [42] most power markets adopt the uniform-price type of auctioning mechanism. Contrastingly, in pay-as-bid auctions, every winning bidder gets paid at its winning bid. Generators in pay-as-bid markets will bid close to their expectations of market price. The obvious question that arises here is which method results in the lowest overall price to consumers.

Multi versus single-round bidding

Certain markets allow for bids to be revised after the initial auction results, thus it is possible to have two or more rounds of auctioning. Where multiple rounds are possible we have what is known as multi-round bidding. Where no revision is allowed we have a single-round bidding/sealed auction.[2] Similarly, certain markets enforce fixed bidding blocks for the day (e.g. E&W) [39], while others allow the offer stacks to vary throughout the day (e.g. New Zealand). A further refinement of the variable, intra-day offer curves ideology, is to allow generators the opportunity during the day to vary their quantities

[1]Note that many of the particular designs mentioned in this section – and in the thesis in general – are subject to changes, so inconsistencies may arise where regulatory structures have changed.

[2]There is some ambiguity in the meaning of 'sealed' in auctions, some authors use the term to imply offer prices in the auction are confidential, others suggest that the auction is closed after the first round of bidding.

offered (though not their prices) for five minute (e.g. Australia) or half-hour intervals (e.g. E&W) [3, 40].

Supply functions

Some markets have restrictions on the number of tranches that can be offered in a particular period, e.g the New Zealand market is limited to five per half-hour period [37]. Another restriction on the type of supply function may be that it must be increasing in price, or even linearly increasing over the range of volumes offered. Auctions which allow participants to submit several offers (from sellers) and several bids (from buyers) are termed *multiunit* as each firm will submit tranches on behalf of each of its units (in the case of sellers) [4]. The reader is referred to Section 3.3 for a detailed definition of supply functions.

Multi and single-part offers (bids)

Markets which allow separate prices for unit start-up, no-load operation and energy are often termed *multipart* bid markets (e.g. E&W). Those which only permit a single energy price, inclusive of fixed or variable costs are termed *single-part* bid markets (e.g. California). In the latter, firms must internalise all costs and constraints in preparing their bids as the bidding structure does not explicitly allow for recovery of the costs. Either of the two market types may still permit the inclusion of several price tranches for blocks of energy that they wish to produce [54].

Discriminatory pricing

Some markets (e.g. New Zealand) may adopt *discriminatory pricing* which depends on the location of the supplier and requires the implementation of a Locational Marginal Price (LMP) mechanism [24]. Discriminatory and uniform are the two main pricing arrangements in deregulated power markets.

Double auctions

Both offers from producers (e.g. Genco's) and bids from buyers (e.g. distribution companies or retailers) can be submitted to each auction [4].

Day-ahead markets

Auctions are often of the *day-ahead* type such as the E&W and South African markets. In day-ahead markets the clearing takes place 24 hours before the actual generating day begins. Generators will submit a supply function for each hour of the following day before a specified deadline [9].

Other variations

Markets can also vary by virtue of the timing and availability of information flows which may depend on the information technology at the disposal of the participants and the system operators [43].

2.1.6 Generator-only market

A *generator-only* market is characterised by a vertical demand function. Most markets have, to date, not progressed far enough to have enabled full-scale demand-side bidding, resulting in the inelastic demand curve against which supply is matched. Even in markets where consumers can respond to the daily price publication, the prices are still set based on a point forecast of demand for each hour. In addition to the initial response by consumers in such markets, there is a limited amount of real-time demand response as well [9]. As markets tend toward fuller competition we will see the emergence of a downward sloping demand curve for electricity. The demand curve has also been treated to some extent in [53, 54].

Techniques have been devised by many researchers which address the question of finding the optimal structure for an electricity industry that maximises competition without compromising reliability of supply [50]. Such research is useful for regulators who must make structural decisions. Tools are also required by the regulators for determining the most appropriate regulatory framework for providing the correct incentives to competitors (such as generators) without compromising the quality of supply received by consumers.

2.1.7 Monopolies and Oligopolies

It is becoming very uncommon to find traditional monopoly power industries as the wave of liberalisation sweeps throughout the world with its well-meaning intent of introducing fair competition and improving economic efficiency.

The topic of oligopoly is separate, though not indistinct from the issues of price-takers and price-setters in competitive markets. By definition, an oligopolistic generation sector will consist of both price-setters and price-takers, and a monopoly will consist solely of one price-setting Genco. Even in completely fair markets, some companies will have the ability to influence the ultimate price outcome because of the type of plant they operate as well as the effects of peaks and troughs in demand (both expected and unexpected). For example, baseload thermal generators (coal and nuclear power stations) will automatically have the greatest say in the resultant price during hours where loads are fairly stable, whereas peaking-type units (fuel/gas-fired, pumped storage or hydro-schemes) can more-or-less dictate prices in peak periods (which by nature tend to be more uncertain) or times of uncertain sudden load increases.

In oligopolies, some of the generators are large enough to influence prices through careful choice of their supply function. Price-influence is a consequence of the economies of scale in generation, barrier to entry, a limited number of producers and also due to the spatial distribution of customers resulting in transmission constraints and losses from distant suppliers [3, 54]. An oligopoly is the common status of an industry that has had the best intentions of reaching pure competition, but has become stuck in waves of regulatory uncertainty, abuse of market power and information flow problems.

Reasons for the tendency to oligopoly (rather than perfect completion) are the special features of the electricity supply industry, and can be summarised by the following points:

- There are usually a limited number of producers.
- Investment size is generally large causing barriers to entry.
- Location:
    1. transmission constraints isolate particular customers from the reach of many generators
    2. transmission losses discourage sales/purchases over large transmission distances

Much of the research in the above realm has been conducted in order to identify loopholes in the design that may worsen the effects of the above features and seek ways of choosing/improving a design to create sufficient competition and limit the scope for gaming, and decreasing the tendency to oligopoly.

2.1.8 Participants and their behaviour

Many authors have identified their version of the participants in an electricity market. A particular overview can be found in Ghosh and Ramesh [20] who postulate the existence of following participants in a modern market:

- Generators
- Suppliers
- Customers
- Speculators
- Intermediaries(Power marketers/Power traders)

The challenge for the participants (and for researchers) is how to cope with uncertainty and the challenge for regulators (and again for researchers) is to find the optimal industry structure and best regulatory environment for the participants to interact.

2.1.9 Other aspects electricity generation markets

There are many other challenges facing the deregulated power industry. A particularly pronounced one is:

Changing technology Examples include improved metering and accounting advances that allow the markets to function more efficiently and advances in generation technology which result in new investment in generation plant. On a related front, there are increasing environmental concerns and the tendency in (mostly developed) countries toward the implementation of renewable forms of energy procurement.

2.1.10 Tools for investigation and analysis

A wide range of tools have been developed and adapted by researchers. Among the tools are: game theory and equilibrium concepts for analysing behaviour of market participants; Markov decision processes for incorporating various market states; algorithms for optimising decisions that affect the profit outcome of market participants (see section 3.4); Optimisation of offers (producers) and bids (consumers) allowing for system constraints, clearing prices, transmission and network constraints, outages, and ramping rates.

There are two main groups of models of that have been developed in the wake of reforms and generator competition [4]:

Models representing all of the generation companies. Models representing all Genco's are largely simulation or equilibrium-type models.

Models that focus on a particular generation company. Single Genco models can be categorised according to:

1. the manner in which the company may affect the spot market i.e is the company a price-taker or a price-setter?
2. treatment of uncertainty: is the spot market modelled in probabilistic or deterministic terms?
3. detail of representation of generation units:
    (a) an aggregate model of all the companies units with one unique cost curve and a maximum output.
    (b) models which distinguish the individual generation units but ignore intertemporal constraints.
    (c) models which consider units' intertemporal constraints.

Models of electrical power systems – as with strategic system models in general – can be described as being descriptive (conjecturing a picture of reality) or normative (determining an exact course of action) [18]. The modelling activities of electricity markets exhibit characteristics of both of the two types of models, resulting in prescriptive analyses which are neither exclusively descriptive or exclusively normative.

This section has given some important definitions and described the types of markets underlying the trade of electricity, as well as the characteristics of the markets. The types of contracts and trading arrangements have also been described. Much of the literature surveyed for the remainder of this chapter, and subsequently in Chapter 3, relies on a knowledge of the terminology introduced in this section, as authors assume an understanding of the terminology, concepts and assumptions as part of their platform for model development.

2.2 Strategic Decisions by Market Players

2.2.1 Needs for Strategic Decision-making

Companies in newly deregulated markets, need assistance in formulating and implementing strategy at a corporate level, as well as in adapting their traditional methods of strategic analysis to the new and transforming market environment. Albuyeh and Kumar [1] engage in an outline of the requirements for decision support for electric power market participants and also emphasise the need for models to be flexible. Their article is largely a written account of the needs for decision support, and the necessary features of such tools.

Generators, the suppliers of electricity in competitive energy markets, are challenged with exposure to a great deal of financial risks which necessitate the need for decision support models. Particular decision support is required with regard to scheduling, followed by the selection of an appropriate bidding strategy [30]. The difficulties arise, for example, in the treatment of uncertainties such as rival behaviour. Other market participants (distributors and consumers – both small and large) will also have the need for such models.

There are also various terms or horizons over which decision support is required e.g. from long-term planning (such as capacity investment and resource planning) and contracts administration to intermediate to short-term planning and spot market offer preparation. A related issue is the management of complex portfolios of contracts from pre- and post-reform eras where contractual obligations between suppliers and consumers that were agreed in the regulated era must now be met by the suppliers. The contractual obligation must be met alongside the management of the new types of contracts of the deregulated era. Management in this context also implies quantifying and managing the risk exposures attached to all types of contracts.

One of the main goals of research in strategic decision-making is to maximise the supplier's profit from selling electricity through whatever medium is available (e.g through the pool or through bilateral contracts). Real-time tactical and operational decisions are crucial in highly volatile energy markets and motivate the need for a reliable Decision Support System (DSS) in choosing the optimal unit commitment and generation dispatch.

Strategic decisions must also be made in the face of new market opportunities, for existing and new suppliers. The strategic decisions will assist in the identification of opportunities as well as in assessing their viability.

One of the most important needs for strategic decision support has been in assisting the adapting market participants in the transition from traditional (engineering-type) production cost models to a financial market environment.

2.2.2 Methods of Conducting Strategic Decision Making

A stochastic short-term planning model for a price-taking generating company is used by Kaleta et al. [30] as a key analytical tool within the decision support process. Price uncertainty is treated by imposing a set of possible price scenarios with associated probabilities. Several risk criteria are then considered and the problem (i.e. the generation scheduling and bidding strategy) becomes a multiple criteria optimisation problem. The criteria include various risk measures as well as some extreme events risk measures and the solutions are adjusted to the risk preferences of the generator.

System dynamics in conjunction with sensitivity analysis has been proposed as method for adapting and formulating strategies in [34]. The authors suggest the use of such tools as a means for learning where no industry evolution, experience or history exist, if not for the decision-making itself, then for simply understanding the strategic and regulatory risks that prevail. In this context, simulation is not used as a means for predicting the future evolution of the market, but rather a means of understanding the important connections and boundaries in a complex system without trying to capture abundant detail. The marked differences which are visible across different countries' markets reinforce the need for highly adaptive simulation models. Additionally, the aim should be to benefit from the traditional advantages of system dynamics models, namely that they are behavioural, high-level and depend on feedback.

In an article by Vlahos et al. [50], an integrative modelling approach for understanding competitive electricity markets is presented as a vehicle for systems thinking, allowing optimisation and spreadsheet models to exist within an overall strategic simulation model. The approach used by the authors in this instance was termed OO/DEVS: Object Orientation and Discrete Event Specification Formalism. The OO/DEVS platform allowed the integration of the strategic modelling tools into an industry simulation model, thus addressing the deficiencies of the solitary use of system dynamics, namely:

1. Inability to generalise and aggregate models representing entities in a system.
2. Insufficient level of detail being modelled.
3. Lack of re-usability.
4. Continuous rather than discrete time structure.

Decision support systems

An example of a computer-based decision system for Scottish Genco's is given by Robson et al. [44]. Such models demonstrate the importance of reliable information and also on improving access to such information. The models can improve response times and provide reliable prescriptive methods for meeting the trading requirements of a Genco. More specifically, the models can be used to assess a Pool or trading partner's requirement for energy, value the energy available for trade, and ultimately recommend an offer price for the energy to be traded. The ideas in their paper are useful, although specific to the spot trading of an external Genco to the E&W pool, and are based on a somewhat dated market design (1996). The latter point is a common difficulty in the fast-changing markets for electrical power.

Strategic gaming has been used for supporting the evaluation of business strategies and policy options in evolving power markets. Kleindorfer et al. [32] emphasise the importance for accurately representing institutional details in the analysis of regulatory and bidding strategies for network investment in the E&W pool. As with other approaches mentioned in this section, the executives of the companies concerned can learn/pre-test strategies in a realistic setting. The particular model developed by the authors was termed *EPSIM* (Electric Power Strategy Simulation Model). The EPSIM model was built with a view to implementation in different markets and for different types of strategy support, which makes it very versatile compared to the approaches of other authors, who are confined to a specific market design, and solved only one specific problem. Model versatility is essential for dynamic industries, and appears to have been implemented successfully in various applications, including the modelling of the E&W pool, and a large regional power pool in the United States, as well as in evaluating the desirability of a joint Argentine-Chilean interconnection agreement. They are also used more traditionally in modelling bilateral contracts between Genco's and distribution companies under transmission constraints (similar to [8]). Their approach also has the added advantage of integrating software packages with spreadsheets and mathematical models such as linear programming.

Other researchers have examined:

- Integrative modelling approaches for understanding competitive electricity markets [50].
- The use of system dynamics [34].
- Stochastic short-term planning models [30].
- Multicriteria Decision Support [30].
- Scenario testing (on exogenous factors such as hydraulicity, demand and fuel prices).

2.3 Risk Management in Power Markets

Two areas of risk management prevail. The first is that of general risk management in electricity markets and the second relates to that of energy derivatives (which is covered more explicitly in [10, 41]. The general risk management issues of this section are tackled directly in [7, 15, 16, 46, 55]. Indirectly they have been tackled in the models for strategic decision support of the previous section, and in generator trading strategy models of Chapter 3. The risk management of energy derivatives will be covered in Section 2.5 of this chapter. The management of electricity price risk, however, is important in both the contexts of general risk management and derivative risk management, and is covered in this section.

Sources of Risk

The main sources of risk in power trading are:

- Trading in a commodity that requires real time delivery and must (generally) be consumed immediately.
- Market risks such as credit risk, uncertainty of demand, and uncertain competitor behaviour.
- Adaptation of a monopoly to a competitive environment, with constantly changing market structure and regulatory influences.
- Taking into account the specific properties of the electricity market such as the characteristics of electricity prices and system constraints.
- In developing countries, or even in countries with developing electricity markets, there is the additional risk of having to cope with the uncertainty in a deregulating environment [50].

Caution is required with the application of complicated risk management strategies to a young, unadapted market. A notorious example of too little attention being drawn to the implementation of risk management strategies was the *Enron* collapse. Additional caution is due when conducting empirical tests of models in pricing and risk management in an illiquid market as there is little data to conduct such tests, resulting in a greater reliance on modelling assumptions.

In a privatised market with increased competition, price volatility is exacerbated, so tools need to be developed that minimise the exposure to the risks associated with the increased volatility. Note that volatility need not always reduce the potential profits of market participants: large losses due to extreme price movements experienced by one participant could imply large gains to another. Nevertheless, it is therefore also imperative to quantify this volatility and incorporate it into pricing models. A dynamic environment stresses the need for the appropriate management of the instruments within a company's investment framework. The parameters of the models we use for valuation and management are also dynamic, so any portfolio containing these instruments must be frequently updated and recomposed as these parameters change. This must be done within the constraints imposed through transaction costs and other similar market inefficiencies.

There will often be a choice between using an approach of testing various scenarios to determine trade constraints versus the utilisation of derivative instruments for risk hedging. Naturally, the relative costs and the existence of a sufficiently liquid market for these instruments, will determine which would be preferable.

2.3.1 Classification of Risks

Suppliers, distributors and traders in a competitive market place are all subject to a variety of risks. Broadly these risks are related to either market (price and quantity, volatility, correlation and liquidity), commodity (storage, capacity, delivery and transmission) or human behavioural (trader, analyst, manager, credit and model) risks.

One of the variables which incorporates and summarises most of these risks is the electricity price, so much of the research is directed at managing the risk associated with uncertain electricity prices.

Electricity price risk

Electricity price risk is the risk associated with uncertain electricity prices and is one of the most important risk factors in energy trading, as it is fundamentally driven by many other risk factors. Bjorgan et al. [7] (among many others) focus on the risks represented by fluctuating electricity market prices.

Being a commodity with a very complex physical characteristics, and one which is being treated to a greater extent like a free-market commodity in recent times, electricity poses a variety of risks for those who buy and sell it. The long-term, fixed pricing of the regulated era is no longer applicable. As a result, the price of the commodity is volatile (i.e. high frequency of change) and the magnitude of the price movements are larger than those of other commodities. There are manufacturing, transportation, delivery difficulties, as well as speculative trading, which all contribute to electricity price risk [10, 41, 55].

In regulated markets, the price risk resultant from this volatility was effectively passed on to consumers. Nowadays the risk is shifted to producers, emphasising their need for risk management. The use of standard hedging tools is not always an option since the possibility of extreme price movements increases the risks of trading (i.e. pricing and hedging).

Weron [55] uses time series and autocorrelations to prove that the price of electricity is far more volatile than other commodities. Some of the implications of the price uncertainty are that caution is required when using traditional valuation techniques for financial instruments in the electricity markets, and that more complex models should be used to capture the unique price dynamics.

Owing to the influences of weather, volatility, seasonality, technology, political and/or regulatory uncertainty, plus possible interactions between these factors, there is a substantial resultant price risk to buyers and sellers of energy commodities. There is also the added concern that the introduction of the derivative markets — though originally intended to enable reduced levels of price uncertainty, and besides inducing the participation of all parties concerned — creates an ironic additional price volatility that needs to be managed.

Market Risks

Denton et al. [15] categorise market risks encountered by energy asset operators (i.e. electricity producers) in terms of the risk horizon:

1. Short-term/operational risks (less than 1 month) related to the most economic dispatch and scheduling.
2. Intermediate-term/trading risks (1 month to 1 year) related to fluctuations in forward prices and their inter-period correlations.
3. Long-term/valuation risks (greater than 1 year) related to the long-term viability of generating plant, in the wake of uncertain technological, regulatory and pricing influences in the future.

Other sources of risk which have been classified by various authors are:

- Market rules, market segmentation and regulatory risks. The power markets exhibit uncertain environments with poorly understood risks which are unquantifiable and which may arise from unknown sources.
- Risks associated with the uses of financial instruments such as derivatives.
- Basis risk is a cross-commodity risk that arises when a firm is exposed to price differentials between two commodities. An example is a coal-fired generator who sells electricity at the spot price and buys fuel at the coal price. Such a company is exposed to the uncertainty of the price differential, which ultimately is what determines their profit margin.
- Credit risks equate to the probability of trading partners defaulting on their contractual arrangements and obligations.
- In energy markets there are often cross-locational or geographic risks related to production and distribution. These are related to transmission and network constraints (for example failure and/or reliability of the grid).
- Modelling and management risk related to the appropriateness of both modelling approaches and risk management strategies adopted by a company.

For this thesis, and in the studies mentioned in Chapter 3, the focus of risk management is predominantly related to price (and quantity) risk, as these are the most likely to mitigate the profits of a Genco. In any realistic risk management application, due consideration will also have to be given to the other risks mentioned in this subsection.

2.3.2 Risk Assessment and Quantification

An important aspect of risk assessment is consistency with asset valuation methods. It is also necessary to combine and quantify the physical and financial risks in any assessment.

Some of the techniques proposed for risk quantification include:

- The *Riskmetrics* and *Creditmetrics* methods of *J.P. Morgan*, though these relate more to firms in equity and other financial commodity markets.
- Immunisation and portfolio analysis.
- Value at Risk (VaR).
- Sensitivity analysis (e.g. the 'Greeks' of the next subsection).
- General tools of financial engineering.
- Models of bidding behaviour.
- Scenario testing.
- Simulation e.g. of power portfolios and optimal portfolio selection [49].
- Mixed and comparative methods.

Within the general framework of a simulation tool for supporting risk analysis, Batlle and Barquín [5] focus on the forecasting of fuel prices, these being the key risk factors which influence electricity market prices and their inherent stochastic volatility. Hence a quantitative rather than fundamental approach is adopted. A multivariate Generalised Autoregressive Conditional Heteroscedastic (GARCH) model is designed to generate future fuel price paths, using a Principal Components decomposition to deal with the difficulties of multidimensional conditional covariance between the base-fuel indexes.

Dhalgren et al. [16] summarise risk assessment in energy trading, especially that of price-risk. The common thread of their paper as in other related research is that of adapting risk management/assessment techniques to a newly competitive power industry.

2.3.3 Methods of Risk Management

A discussion of the growth of trading and risk management services in liberalised electricity markets is discussed and motivated in [46].

- General risk management can be handled with real options models and stochastic optimisation techniques. Denton et al. [15] give an example of the application of real options models to the risk management requirements of Genco's.
- The 'Greek' hedging techniques mentioned in the section on derivatives later in this chapter, namely Delta, Gamma, Vega, Theta, Rho, and other factors.

- Financial instruments such as futures and options.
- Portfolio analysis.
- Market analysis.
- Production limits.
- Transmission hedging.

These are the general techniques of risk management. Some examples of the specific research on risk-management in electricity markets are now described in some detail.

Managing Electricity Spot Price Risk

Bjorgan et al. [7] focus on the risks represented by fluctuating electricity market prices. A particularly useful application is discussed in the context of contractual decision making, and in particular the determination of the optimal portfolio when offering energy to a spot market. The situation is simplified by assuming a particular cost structure and no market power. A formula is derived for the number of futures contracts that minimises the variance of the profit distribution.

Vehviläinen and Keppo [49] do an interesting application of financial risk management methods to deregulated electricity markets. They present a method of solving for the optimal risk-aware electricity portfolio taking into account the important aspects of electricity price behaviour (namely seasonality and non-storability). The approach used is to maximise the expected utility from an electricity portfolio in order to allow for an agent's preferences with respect to profit and risk. This they achieve by converting a stochastic utility problem to a deterministic non-linear programming problem with the use of Monte Carlo simulation to create the VaR measure for complex portfolios. The advantage of Monte Carlo simulation over scenario-based analysis in this case is that several stochastic variables may be evaluated simultaneously without seriously affecting computational performance.

Elaborating on the approach in [49], a general stochastic framework is developed to model all uncertainties in the market (for example, electricity spot price, marginal production cost, demand patterns and weather indexes). A liquid futures market is assumed, with transaction costs and taxation both ignored. They simplify the spot price process by assuming that all the information about the future behaviour of the spot is contained in the forward price curve (see also [10, 41]). They also assume a **lognormal** distribution around the expected value by assuming that the *fat tail* of the true spot price distribution is mitigated through the use of price averaging in each discrete time period. To estimate volatility, they use historical rates, maintaining that implied volatilities are not practical owing to both illiquidity in options markets and a lack of analytical (closed-form) pricing formulae.

Next, the stochastic processes for the above factors are expressed simultaneously in a multivariate Ito process, and the derivative contracts dependent on these factors are similarly expressed by application of Ito's lemma (see the Appendix, page 179). The factors, instruments and electricity contracts (physical and financial) are combined into a portfolio from which an expression for total wealth can be derived at the end of the simulation period.

They then find the optimal portfolio for the agent by converting the stochastic utility function to a second order approximation thereof, resulting in a non-linear programming formulation. Specific assumptions regarding utility functions are made and tradeable assets are assumed to be linearly independent (i.e. they have non-identical payoffs). The estimates of the factors required for solving the formulation are obtained through Monte Carlo simulation. In the case of constrained optimisation, a wide variety of non-linear programming methods may be employed to arrive at a solution.

A mathematical formulation is then given for pricing the instruments, evaluating the portfolio (hence obtaining a distribution of simulated outcomes), and solving the optimisation problem.

Finally, a practical example is given within the framework of the Scandinavian market and numerical results derived from two perspectives: the first being that of an industrial electricity end user with a fixed consumption, and the second a generator of baseload electricity. In both cases the agents are able to reduce their VaR by optimising their portfolio (and hence their hedging level) according to their specific risk preferences.

The framework presented in this paper certainly permits risk management in the case of agents with more complex portfolios than those given in their examples (assuming the processes determining the uncertainties are known and can be modelled, and that market instruments can be described by these processes). One necessity is that futures contracts for electricity can be used as tradeable assets, so as to overcome the non-storability/tradeability of the spot asset. A limitation of these methods, as acknowledged by the authors, is that the data for model parameter estimation is limited and price processes are to date not well understood. The idea of using VaR as the appropriate measure of risk is justified and motivated in this paper. Scenario analysis is suggested to discover more about the risks of the portfolio. As indicated in many other instances, the use of financial methods in risk analysis can be useful if the unique properties of electricity markets are taken into account.

Batlle and Barquín [5] present a simulation method for risk analysis in a wholesale competitive electricity market. Within the general framework of a simulation tool for supporting risk analysis, they focus on the forecasting of fuel prices, these being the key risk factors which influence electricity market prices. The other factors not focused on in this paper include items such as short-term demand and hydraulicity (hydro inflows), and the strategic behaviour of agents in the electricity market (which itself influenced by the other three exogenous factors).

This paper is once again motivated by the common thread in this field, namely the introduction of competition in the energy industry, and in particular among generators. They advocate the use of economic and statistical models (such as game theory and time series) over those used in engineering science, the latter being unable to (easily) cope with the inherent uncertainties of electricity markets (over and above the classical uncertainties in the monopolistic industry).

Their focus is therefore on the building of a time series model of base fuel prices (e.g. oil, gas and coal), ignoring the other generator-specific variable costs which would be over and above the fuel costs. As mentioned on page 29, a multivariate GARCH model is designed to generate future fuel price paths, using a Principal Components decomposition to deal with the difficulties of multidimensional conditional covariance between the base fuel indexes.

The (Monte Carlo) simulation framework for the risk analysis within which the fuel price modelling takes place is outlined in this paper. The aim, via a fundamental approach, is to model the uncertainty on the price drivers' behaviour and obtain a future price distribution using a market model with scenarios dependent on the above-mentioned exogenous factors. Each variable represented within the factors must not be correlated with any other variables within that factor; clearly a questionable criterion in the case of fuel prices. A further necessary assumption is that the agent is a price-taker and is therefore unable to exploit their power in the fuel purchasing market. Having said this, the individual agent's strategic behaviour must be captured to reflect the fundamental aspect of the analysis, as must the time period over which the analysis takes place. The outcomes of the scenario analysis will be market prices, production costs and profits, along with their associated density functions. From these outputs, VaR (or other feasible risk measures such as factor sensitivity) may be derived. This approach allows the multivariate GARCH model to take care of the most important input determining a generator's behaviour, allowing the clustering within the scenario generation process to take care of the other factors. This considerably reduces the number of key variables in the general market simulation.

The multivariate GARCH model suggested also helps overcome some of the problems of applying a Black-Scholes-type model of asset prices (i.e. lognormal prices), in particular with regard to the assumption of constant volatility. Commodity prices — as confirmed in many other references where market implied values have been calculated — display mean reversion, and a strong correlation between price level and volatility exists clearly violating the crucial B-S assumption. Being a multivariate model, it is able to capture the strong correlations between the various fuel prices. The price behaviour of the fuel commodities can thus be captured in a vector GARCH model as follows:

Let $S_t = (s_{1t}, \ldots, s_{Kt})'$ be a vector at time t of K variables (commodity prices). The evolution of the variables is captured in a vector autoregressive process of order p

$$S_t = M + A_1 \cdot S_{t-1} + \cdots + A_p \cdot S_{t-p} + U_t$$

where M is a vector of dimension K; $A_i, i = 1, \ldots, p$, are fixed coefficient matrices of dimension $[K \times K]$; U_t is a white noise with non-singular covariance matrix Σ_U and,

$$\Sigma_U = \begin{bmatrix} \sigma_{11} & \cdots & \sigma_{1K} \\ \vdots & \ddots & \vdots \\ \sigma_{K1} & \cdots & \sigma_{KK} \end{bmatrix}$$

Here the mean-reverting model is implied in the case of $p = 1$.

In the case of a vector GARCH(m, r) model, Σ_U of U_t depends on the last r residual vectors and its m previous values.

$$\Sigma_t = V + \Delta_1 \cdot U_{t-1} \cdot U'_{t-1} + \cdots + \Delta_r \cdot U_{t-r} \cdot U'_{t-r} + \Theta_1 \cdot \Sigma_{t-1} + \cdots + \Theta_m \cdot \Sigma_{t-m}$$

where V, Δ and Θ are square matrices of dimension K.

A Principal Components Analysis of Σ is then made. From this the multivariate GARCH process can be decomposed into a set of K univariate models of the form:

$$\sigma^2_{kt} = \nu_k + \delta_{k1} \cdot \varepsilon^2_{kt-1} + \cdots + \delta_{kr} \cdot \varepsilon^2_{kt-r} + \theta_{k1} \cdot \sigma^2_{kt-1} + \cdots + \theta_{km} \cdot \sigma^2_{kt-m}$$

Each of the $k, (k = 1, \ldots K)$ is then weighted by its corresponding eigenvalue. The weights of the eigenvalues will correspond to the relative importance of the model variables. The parameters of each GARCH process are estimated using maximum likelihood by means of the *Berndt, Hall, Hall and Hausman* algorithm.

After the estimation is complete, the scenario analysis is then undertaken by simulating a large number of fuel price paths and the density functions of the clustering criteria are thus determined. As stated in the general model, the agent-specific variable costs (and the proportions thereof which are attributed to fuel costs) are calculated from a weighted aggregation of the scenarios.

Finally, a case example is summarised, and the authors conclude by stating the importance of being able to quantify the impact of various inputs' effects on the electricity market price.

Unit commitment in conjunction with financial markets

This topic is discussed to some detail in the short term/operational risk section of [15]. Here 'short-term' implies less than one month. (Hourly) unit commitment along with (minute by minute) economic dispatch represent the well-studied scheduling problems of the regulated industry. The authors specify how to schedule units in the most economic manner taking into consideration unit economics, physical constraints and incremental transmission losses while meeting the total commitment to power. In the regulated world, revenues from the scheduling were known and rates fixed; sales and purchases were analysed in an equivalent manner across Genco's. The deregulated regime requires a market-price-based unit commitment.

Trades over shorter and longer periods have been valued using a *spark spread* model (see Section 2.5). Decisions to trade or schedule were based on the value of the spark spread option which is effectively a *real option* available to the generator on whether it is profitable to enter the market for trading, and if it is then the optimal sales level can be determined with the same model. Since a spark spread instrument models the conversion of a fuel to electricity (pricing takes into account the volatilities of the underlying fuel price), the pricing mechanism is deficient. It will tend to overvalue the plant by failing to consider:

- physical constraints on operations e.g. hourly minimum and maximum operating ranges; maximum hour-to-hour changes in output, or ramp rates and;
- cycle time constraints, or minimum hours 'on' and 'off'.

The models also fail to account for variable costs other than those relating to the fuel itself e.g. maintenance, tax and labour. Another especially important consideration is the *heat rate* (or energy conversion efficiency) which is treated as linear in traditional spark spread models, and is in truth a non-linear parameter. This latter notion is supported by Deng et al. [14].

Two scenarios, deterministic and stochastic, were discussed.

Deterministic case: A unit commitment formulation is given using a decision tree (Discrete State Space model) showing paths of possible output changes (including ramps or shutdowns and on or off-times at each node) and the possible cost and revenue scenarios are then mapped out by the branches of the tree. In the deterministic case, the known variable costs (including the fuel price) and the power prices are superimposed at the relevant nodes on the decision tree, and net profit is maximised using a backward-iterating dynamic programming algorithm. The tree then yields the optimal dispatch path and asset valuation at every node along the path.

Stochastic case: In the situation of uncertain market conditions the authors propose an approach whereby a mean-reverting stochastic process with drift and time-varying volatility, for the logarithm of the spot price is assumed in the most general case. Otherwise a simpler process could be assumed. As mentioned in the section on derivatives and in reference [10], this is equivalent to a one-factor futures price model, and the process is discretised into steps in keeping with a discrete space formulation. Parameters for the model are estimated using maximum likelihood. This is a common method of price-mapping in derivative valuation (see Section 2.5).

The process is discretised and a *multi-level trinomial tree* or *trinomial forest* is created through an amalgamation of the energy price tree with a tree as outlined in the deterministic case above. The result is a trinomial forest with each node having four values characterising the state of the generator with respect to time, price, output level and run-time. It is not clear whether the authors have a separate tree for power and fuel prices, or the price captured at each node is the differential between the two. The latter however seems more likely as they then proceed to value the option directly from the tree using a backward induction technique.

The stochastic optimisation algorithm returns two results:

1. The value of the asset over the operation period which equals the expected profit earned under optimal dispatch.
2. The optimal dispatch rule at each time period and operating state and price.

Several benefits are visible from this approach:

- The effect of price volatility on plant valuation is shown.
- A set of decision rules i.e. what actions to take at a given node of the forest.
- Random outages could be included in simulations of optimal unit operations.

The effects of non-constant heat rate on the spark spread model is shown graphically. It is similarly shown that ramp rates also lead to an over-valuation of a unit on the spark spread model. Similar results would hold for start-up costs and minimum run times, with the effects compounded when these are coupled with non-linear heat rates and ramp rates.

No mention is made of the auctioning process in the short term. The authors have focused their attention on the technical aspects of generation in a deregulated market, where deregulation (in at least the short term/operational risk sense) simply implies that power and fuel prices are stochastic. It is effectively assumed above that the trading environment is perfectly liquid, and the unit is neither a price-taker nor a price-setter. In truth, a unit operator exists in a world with elements of the regulated load fulfilment/cost minimising world and the trading and derivatives world, played out in a less than liquid market, with sales structured to seek the maximum profit. A method analogous to Lagrangian relaxation techniques is used for handling the real options model in an illiquid market where power prices are adjusted iteratively until supply matches demand. Despite being computationally expensive, the real option model can produce a distribution of the value of a unit as a function of the underlying energy prices; from this the appropriate risk metrics (*'Greeks'* and VaR's of Section 2.5) can be obtained.

In the intermediate term (a few weeks to a year), forward prices are the dominant factors, and trading and hedging require attention. Monthly forward prices must also be consistent with the short term (hourly) forward prices. The appropriate risk measures in this time frame are VaR, and alternatives EaR (Earnings at Risk) and CFaR (Cash Flow at Risk). Methods for attaining these using the real options approach are discussed. Further relevant risks in the intermediate term are credit exposure, transmission congestion and portfolio optimisation.

Long-term asset valuation (several years in length) are discussed and the risks resultant from markets and regulation e.g. with respect to environmental policy. Key techniques used include scenario analysis with production cost models, examining fundamental market drivers and developing scenario-based price projections. The traditional models will — especially at high levels of demand — undervalue generation assets owing to the effect of strategic bidding behaviour on prices. An attempt to overcome this is made with the use of game-theoretic approaches, however this fails under non-equilibrium market conditions, a fact which many other researchers have also identified as a weakness.

Drawbacks of the production cost models are:

- Their inability to adequately address market price uncertainty.

- They assume perfect information transparency — an unlikely scenario in deregulated markets where information is commercially confidential and potentially unavailable.

Given improved computational ability, the stochastic real options models lend themselves to longer term scenario valuation exercises and therefore have the ability to overcome the described shortcomings. In conclusion this paper demonstrates the use of real options models for valuing generation assets and managing risks of trading, investment and portfolio optimisation, over various time periods in increasingly complex environments. A major drawback is its failure to examine the intricacies of the auction-type trading mechanism that now prevails in modern power markets.

A literature survey of techniques of portfolio analysis and price-risk hedging is given in [16], and is described in an industry-wide sense rather than with a specific focus on Genco's. Methods are surveyed from the two separate areas of analysis, namely power systems and financial analysis. Further research is identified as being necessary in the following areas:

- Modelling the electric power grid to understand the risk of gaming using transmission capacity.
- Modelling the bidding behaviours of market players for accurate risk assessment.
- Designing market rules to mitigate risks inherent in gaming.
- Transmission enhancements for removing bottlenecks and congestion.
- Methods for valuing transmission rights to hedge transmission system congestion.

2.4 Electricity Spot Prices and Forward Curves

This section describes the characteristics of electricity spot prices (interchangeably known as System Marginal Prices or SMP's), then discusses the types of models that have been proposed for modelling them, followed by a summary of the various uses of the price models in real-life applications. The last part discusses the electricity forward curve.

2.4.1 Characteristics of Electricity Prices

The electricity price is an important variable in any modelling activity which takes place in power markets. It has different characteristics from most commodities (including those of other energy commodities) and has therefore served as a worthy contender for the attention of many researchers. Though power prices may incorporate some of the behaviour of traditional commodities, they are riddled with intricacies.

One of the unique characteristics is that the electricity price economics is characterised by young, immature markets where the price drivers are complex. Additionally, the effects of economic cycles are subdued (owing to the ever-present demand for electricity) and there is a high frequency of market events. Furthermore, there is a notable impact of convenience yield (due to storage difficulties), a low correlation between short and long-term pricing, prevalent seasonality, and levels of regulation varying from highly regulated/low-activity to deregulated/high-activity in decentralised markets.

Electricity spot prices can therefore exhibit extreme volatility – more extreme than what is understood as extreme in the conventional markets – and are completely unique in that respect. The uniqueness is due to the balancing of various supply and demand factors, particularly owing (on the supply side) to storage problems and (on the demand side) to weather influences and grid reliability [55].

Prices in particular power markets may also be location-specific (leading to the formation of Locational Marginal Prices (LMP's). Formation of LMP's may be due to the structural design of the market making allowances for production, transmission, consumption or regulatory constraints across various regions of the grid.

The resultant distribution of electricity price returns exhibits a noticeably *long tail*, which means that the probability of large price increases occurring is substantial. Ghosh and Ramesh [20] also attribute this volatility to the interface between the trade of electricity and the physical realities of producing it. Additionally electricity prices can sometimes be negative when suppliers are forced to sell their energy to avoid the costs of shutting down – forced sale of a commodity is something generally unheard of in any other market. The fundamental price drivers in energy markets in general are very different to those in other developed markets for equities and most other commodities.

Seasonality, mean reversion and jumps are characteristics of electricity prices that have drawn the attention of price-modelling analysts. They are now described in more detail.

Mean Reversion is the tendency of energy spot prices to revert toward a long-term equilibrium level. The tendency is noticeably strong in electricity as confirmed by empirical studies on historical prices. Some analysts explain that the prices gravitate toward their long-term level, which in turn is determined by the cost of production. If the cost of production is identified as the main determinant of price, it has been suggested that cost-based models for pricing the energy (usually for energy producers rather than extractors) are used for predicting long-term mean levels of prices.

Along with the concept of mean reversion, we obtain the notion of price equilibrium half-life. The half-life is the time taken for the price to return half-way to its long-term equilibrium. A sufficient time-span of data are required to ensure that the effects of mean reversion are not smothered by stochastic variation.

Stochastic Volatility refers to the unpredictability of the asset price standard deviation itself. The concept can be used to explain the seasonality inherent in electricity prices. The stochastic element itself may be analysed in two components:

1. A deterministic element (explicable changes in volatility) that has a time-dependent functionality (i.e. we know the type of function which governs the randomness).

2. A true random part containing noise which can't be accounted for in the functionality (the unexplainable variation in volatility).

Jumps are sudden and large changes in the spot price. They are usually unexpected and discontinuous; empirical examples can be found in many electricity markets. Spikes in one direction are often neutralised with an equal and opposing spike in the other direction, particularly when mean reversion is very strong.

Seasonality is applicable to both price and volatility. It is effectively a consequence of supply and demand factors across regions and climate/weather differentials between seasons. The effects will be dampened when using models of average prices because the averaging of prices (say over a year) would hide the (intra-annual) seasonality. This element of the price dynamic can be represented by a separate deterministic function in a pricing model.

2.4.2 Methods of Modelling Spot Prices

In the regulated era, prices of electricity were calculated with reference to the long-run marginal costs of electricity production, and the energy was produced at least cost with few competitive forces affecting the prices. Various cost-based models were developed to meet the pricing requirements.

In deregulated markets, electricity prices have fundamental price drivers which differ from other commodities, so researchers have been driven to find new methods of modelling them. Fortunately, complex pricing models have been developed for interest rate, bond, equity, and other commodity markets. A prevailing difficulty with using the models is that many of them have to be adapted for the special characteristics of energy commodities, and even more so in the case of electricity prices.

This section describes a few of the stochastic models that have been suggested by several authors on the subject e.g. [10, 41]. Generally, all of the stochastic models will have two components, one allowing for drift and the other for stochasticity. Some have a deterministic function added to the drift and stochasticity terms to allow for seasonality influences.

Elsewhere in this thesis, other methods of modelling electricity prices will be found. Section 3.2 in Chapter 3 examines how prices are formed as a result of interactions between buyers and sellers, and for the most part, treats the electricity price as endogenous to the system models. In Chapter 4 [p. 100], the model prescribed for use by Genco's in the Eskom Power Pool is given, though it is somewhat simplistic as it only contains a seasonality function plus a random error component. The price model (and the demand model) developed in Chapter 5 is a lognormal model with seasonality factors and stochastic volatility, but no mean reversion or jumps.

Stochastic spot price models begin as the simple lognormal, Black-Scholes-Merton type. Then we progress to a 1-factor mean reverting model. To accommodate the volatility of the spot price we can use a 2-factor model that extends the single-factor to include a stochastic convenience yield that itself is also mean-reverting. A 3-factor model extends the 2-factor analogy by permitting interest rates to be stochastic, introducing an added source of variability. The model-type depends on the ultimate use of the derived prices; specifically the type of derivative instrument being valued determines the appropriate spot price model. Typically, the numerical methods of trees and Monte Carlo simulation are applied to the chosen price model when calculating the values of the instruments. Cost-of-implementation is a determining factor with regard to the level of model complexity permissible in any price-modelling methodology.

The stochastic models below are in increasing order of complexity. The more complex the model, the more accurately we can emulate the price behaviour, but complex models are more difficult to handle. The associated dependent models for risk management, derivative pricing, and others, increase proportionately in complexity (and with a greater cost for implementation). In each of the models that follow, the discretisation for the stochastic process is given. Discretisation necessitates the use of Ito's lemma which is discussed in detail in [10, 28, 41]. The application of Ito's lemma produces an algebraic formula which could be included in a simulation or pricing model, where the electricity price is being modelled as an exogenous variable which changes over discrete time intervals.

Geometric Brownian Motion (GBM)

GBM is the simplest representation of electricity price behaviour and is characterised by constant parameters, μ and σ. The model is also known as the (single-factor) *Lognormal Price Model* as the *price returns* are assumed to be normally distributed. In reality, both parameters can be expected to vary over time, so the model is not realistic for modelling electricity price behaviour in general, although it can be used as a simplification for modelling the SMP variable in specific applications where the exact price path is not crucial for the analysis.

$$dS = \mu S dt + \sigma S dz$$

where

$S =$	stochastic process for the asset price
$dS =$	change in the asset price process in an infinitesimally small time increment
$dt =$	size of the time increment
$dz =$	change in a Wiener process during dt and represents the underlying uncertainty driving the model
$\mu =$	instantaneous drift rate
$\sigma =$	instantaneous volatility

The process can be discretised for simulation modelling as follows:

$$\Delta x_i = \mu x_i \Delta t + \sigma \sqrt{\Delta t} \varepsilon_i$$

where

$x_i =$	the level of the price at the i'th time increment
$\Delta x_i =$	the discrete change in the asset price in Δt at the i'th time increment
$\varepsilon_i =$	an independently sampled number from a $N(0,1)$ distribution at time i

Mean reverting process

When prices show a tendency to revert to their long-term mean, the following stochastic differential equation provides a simple description of the price behaviour when volatility is still assumed to be constant.

$$dS = \alpha(\mu - \ln \bar{S})Sdt + \sigma Sdz$$

where

$\alpha > 0$	is the mean reversion rate
$\mu = \ln \bar{S}$	where $\bar{S}$ is the long-term level of the spot price.

Letting $x = \ln S$ and applying Ito's lemma gives:

$$dx = \left[\alpha(\mu - x) - \frac{1}{2}\sigma^2\right] dt + \sigma dz$$

The process can be discretised for simulation purposes as follows:

$$\triangle x_i = \left[\alpha(\mu - x_i) - \frac{1}{2}\sigma^2\right] \triangle t + \sigma\sqrt{\triangle t}\varepsilon_i$$

In reality, $\bar{S}$ is not constant and more complex models would be needed to obtain a more realistic view. Essentially, the (log of) price modelled by this process will exhibit an equilibrium drift with oscillations around the drift.

Stochastic volatility

Stochastic volatility is the instability of the spot price volatility itself. When the volatility parameter of electricity price process is assumed to be non-constant over time, then we have an accompanying equation which governs the behaviour of σ in the simple GBM process above:

$$dV = a(\bar{V} - V)dt + \xi\sqrt{V}dw$$

where

V	$=$	σ^2 is the spot price return variance
$\bar{V}$	$=$	long-term level of the variance
$\xi\sqrt{V}$	$=$	volatility of the variance
a	$=$	mean reversion rate
dw	$=$	underlying uncertainty (correlated to dz with correlation coefficient ρ)

The process can be discretised as follows:

$$\begin{aligned} \triangle x_i &= \left(\mu - \frac{1}{2}\sigma^2\right) \triangle t + \sigma\sqrt{\triangle t}\varepsilon_{1,i} \\ \triangle V_i &= a(\bar{V} - V_i) + \xi\sqrt{V_i \triangle t}\left(\rho\varepsilon_{1,i} + \sqrt{1-\rho^2}\varepsilon_{2,i}\right) \end{aligned}$$

where (other variables defined as above)

$V_i =$	the level of the variance at the i'th time increment
$\triangle V_i =$	the discrete change in the variance in $\triangle t$ at the i'th time increment
$\varepsilon_{i,1}, \varepsilon_{i,2}$	are independent identically distributed $N(0,1)$ variables sampled at time i

A variation on this model by Pilipović [41] suggests treating the long-term mean as the second factor rather than the volatility.

Jump models

Electricity prices commonly exhibit sudden, unexpected and discontinuous changes. The changes are commonly followed by a quick reversion to long-term levels and are often explained by a sudden surge in demand, or large-scale failure of generating units, which would result in the sudden price increase. The simple GBM model can be modified to include sudden and significant, large changes in electricity prices. The first of two mentioned in Clewlow and Strickland [10, Chap. 2] is a simple extension allowing for jumps, and the second, an equation allowing for jumps *with* mean-reversion:

1. Pure jump diffusion model:

$$dS = \mu S dt + \sigma S dz + \kappa S dq$$

where

dq	is a discrete time process governed by ϕdt
ϕdt	$= Pr[dq = 1]$ is the average number of jumps per year
κ	= proportional jump size such that $\ln(1+\kappa) \sim N\left(\ln(1+\bar{\kappa}) - \frac{1}{2}\gamma^2, \gamma^2\right)$
$\bar{\kappa}$	= mean proportional jump size
γ	= standard deviation of $\ln(1+\kappa)$

Discretising we get:

$$\begin{aligned}\triangle x_i = &\left(r - \phi[\ln(1+\kappa) - \frac{1}{2}\gamma^2] - \frac{1}{2}\sigma^2\right)\triangle t + \sigma\sqrt{\triangle t}\varepsilon_{1,i} + \\ &+ \left(\ln(1+\kappa) - \frac{1}{2}\gamma^2 + \gamma\varepsilon_{2,i}\right) \times I_{[u_i < \phi\triangle t]}\end{aligned}$$

where

$$I_{[u_i < \phi\triangle t]} = \begin{cases} 1 & \text{if true} \\ 0 & \text{otherwise} \end{cases}$$

and u_i is a Uniform(0,1) random variable (other parameters as previously defined).

2. Jump diffusion with mean reversion:

$$dS = \alpha(\mu - \ln S)S dt + \sigma S dz + \kappa S dq$$

(All parameters defined as above)

There are other variations on the above themes which are not given here in detail as this subject is very much a research topic in its own right. Examples include allowances for seasonality functions (such as phase and shift Fourier models) and 3-factor (or even multi-factor) models.

In summary there are three main methods of modelling electricity prices:

1. The cost-based models of the regulated era used by electrical utilities and also for pricing long-term contracts. Cost-based models will depend on primary fuel costs and running costs.

2. The stochastic models of this chapter and the model developed in this thesis which may or may not include mean-reversion, jumps, stochastic volatility and seasonality factors.

3. The endogenous methods of determining price via equilibrium or supply function methods described in Chapter 3

Some authors have suggested methods which incorporate characteristics of more than one of the above methods. Examples include pricing based on the behaviour of the underlying primary energy commodity price (as per reference [49] in Section 2.3 above), or more directly on the demand profile for electrical generation with the inclusion of weather variables (often temperature, illumination and wind cooling) or looking at future prices as implied from market forward curves [47]. Artificial neural networks are yet another technique being used for modelling prices.

Parameter estimation

The plethora of parameters introduced in the above stochastic equations will need to be estimated if the models themselves are to be implemented. The essential tools for estimation are time series, method of moments, maximum likelihood, least squares, empirical examination of historical price data, and the intuition of market analysts and traders. Time series, for example, can be used to analyse prices and calibrate the parameters by way of extracting seasonality and identifying events e.g. negative autocorrelations will demonstrate a tendency of prices to mean-revert. There are many options for estimation and the choice of method will depend on the level of complexity permitted, the type and purpose of the model being developed, and the amount of data at the disposal of the modeller. Most of the methods are outlined in more detail in the references [10, 41].

2.4.3 Uses of Spot Price Models

As explained in the previous section, the type of model being used will depend on the purpose of the modelling. The purposes range from:

- Evaluating optimal bid/offer or scheduling strategies for market participants, in both day-to-day trading and long-term strategic decisions such as capacity investment. Here the forecasts of SMP's will be important for the decision-making process.

- Valuing derivatives based on underlying electricity spot prices as well as valuation of generation and transmission assets.

- Risk assessment and risk management: quantifying exposure to price uncertainty and managing portfolios of electricity supply/purchase contracts and derivative instruments.

- Analysing market power, design and participant behaviour, where the SMP is a (benefit) measure of the effectiveness and efficiency of the market.

It is important to note that the ultimate use of the price values and the type of model being used are mutually dependent. For example, many of the stochastic models described above will have applications in derivative valuation and risk management, whereas the endogenous price models will be used in conjunction with the uses in the fourth point above.

2.4.4 Electricity Forward/Futures Curves

Forward curves[1] contain information about the electricity spot prices at various points in the future and are used for locking into prices for future trades in the spot commodity. A futures curve is a standardised form of forward curve that is published on an exchange where standardised contracts for future trade are regularly bought and sold. Contrastingly, a forward curve may be an individual Genco's view of the expected future spot prices, or the collective view of a few Genco's in the same market. Forward curves may be in *backwardation* or *contango*, the former implying that futures prices are lower than spot prices, and the latter implying that the futures prices are greater than the spot.

So far, the definition of a forward curve is the standard one used in other markets. However, with electricity (and some other energy commodities), the forward prices will not (in general) be equal to the expected future spot price. The reason for the inequality is the convenience yield or cost-of-carry, which represents the relative advantage (or disadvantage as the case may be) of storing the electricity as opposed to having a long (agreement to buy) or short (agreement to sell) position in the paper market for the commodity. Although electricity can not as a rule be stored (unless, for example, the Genco owns a pumped storage facility), the primary energy used to generate the fuel can be stored. Consequently the difference between forward prices and expected future spot prices will imply a specific convenience yield on the underlying fuel price.

The well known problem of being unable to create an arbitrage-free portfolio in the electricity spot market results in pricing difficulties not experienced in other markets (very

[1]the terms 'futures' and 'forward' will be used interchangeably. Strictly speaking, futures agreements are forward agreements that are standardised and traded on a recognised exchange.

large to infinite cost of carry). The solution here seems to lie the creation of a futures and forward market on expected future spot prices and an option/swap market, which is not based on the underlying spot price, but rather on the newly-formed futures/forward market. The creation of the notional futures/forward market is a very important concept tertiary markets for electricity. It seems logical given the non-storability (in the conventional sense of storing a commodity) [14]. The implications are that a convenience yield differential will arise between the spot and futures/forward market. The creation of the latter markets will thus enable arbitrage free pricing to proceed in the way commonly practised in conventional markets. The need for a way around dealing in the spot market for commodities has been partially met by the establishment of the forward market, and the associated forward curve analysis. The forward prices then become the price discovery mechanism and form the basis of derivative construction and valuation. Forward curves are still sensitive to the important features of the underlying, namely transaction costs, seasonal changes and convenience yield. In immature markets the forward curve is unique to individual participants. Methods for deriving the forward curve (in electricity) include arbitrage pricing (based on the cost of the generating fuel), an econometric approach (based on a simulation of all the underlying variables which determine price) and a spot price modelling approach (based on the modelling of the stochastic parameters that drive the price).

It is more common in developed electricity markets to model the forward prices rather than the spot prices which are comparable to market values and which often form the basis of inputs for derivative pricing and risk management models. Modelling of forward prices is done in an analogous manner to non-energy markets provided there is an established and reliable forward curve, and traded instruments are based on forward contracts rather than spot energy. Forward curves define the basis of the covariance/correlation structure across all underlying commodity prices. Principal components (eigenvector) analysis of market forward curves/planes is used to explain the dynamics of the forward price curve/plane. Here we are effectively calibrating a model to the market data. The changes and shapes of the forward curves within markets can be expressed in terms of the most important volatility components. Numerical techniques therefore become essential when pricing derivative instruments.

Forward prices can be derived from the spot price models, or contrastingly, the spot models can be made to be consistent with market forward prices.

Forward prices in energies are not, in general, equal to the expected future spot price. This explicable anomaly occurs in other markets too but is enhanced here with the effects of convenience yield, rather than just simple dividends in other stock markets. A forward curve should capture the expectations of future supply and demand for the spot commodity, adjusted for the differences in characteristics between paper and physical markets.

Convenience Yield

Defined in commodity markets, convenience yield represents the return on a commodity earned through holding an inventory of that commodity. It is relatively much more important in energy markets than financial markets. A similar definition was proposed by Ghosh and Ramesh [20] who define it as something which is unique to commodities held for consumption purposes. Convenience yield can be expressed as the difference between the benefits and costs of holding an underlying asset (whenever either of the two attributes are actually relevant). It is analogous to a dividend yield in capital markets and is thus treated in the same way. Unfortunately, with electricity, the cost of carry can be infinite – or at least very large relative to the value of the electricity itself due to its non-storability. It is therefore an exception and cannot be treated in such a rudimentary way as dividend-yields. This argument explains the existence of many other modelling approaches that have been developed for electricity prices. Convenience yield is also an important variable underlying the energy forward curve.

An implied convenience yield represents the relative advantage/disadvantage of holding the underlying spot asset as opposed to a forward position in the asset. It can be positive or negative and in the short-term represents a storage problem, in the long term a fuel extraction problem. It is the resultant differential between short and long term prices net of any other explained pricing differences. It is often implied through discrepancies between forward prices and spot prices rather than expressed as an explicit value. It is the rate that balances the current spot price with the forward prices after allowing for:

- real growth in the asset value.
- storage, insurance and obsolescence costs.
- non-systematic risk.
- the risk free rate.

The greater the possibility that there will be shortages of the asset in the future, the higher the convenience yield. If users of the commodity have a high inventory and the chances of shortages are slim, the convenience yield tends to be low.

Cost-of-carry The following is a general formula relating the spot price to the futures price when part of the difference between the two can be attributed to a convenience yield:

$$F = Se^{(c-\delta)T}$$

where

$S =$	the current spot price,
$c =$	cost of holding the asset i.e. the convenience yield,
$\delta =$	continuous yield generated by the asset,
$T =$	maturity date of the contract.

Multi-factor forward curve model An example of a model which is used to model the forward price at time t for maturity at T is:

$$\frac{dF(t,T)}{F(t,T)} = \sum_{i=1}^{n} \sigma_i(t,T)dz_i(t)$$

where

n	=	number of independent sources of uncertainty (usually 1,2 or 3),
$\sigma_i(t,T)$	=	the associated volatility functions determining the size and direction of the shifts in the curve due to factor i,
$dz_i(t)$	=	independent source of risk due to factor i.

Many other models for forward curves are dealt with in some detail by Pilipović [41] and Clewlow and Strickland [10].

2.5 Electricity Derivatives

The study of electricity derivatives is largely a sub-study of energy derivatives, which in turn falls under derivative studies in general. The special features of the underlying spot price in the case of electricity (including the characteristics described in Section 2.4, ensures that techniques will be drawn from the most specialised research in the field.

In this section, the issues surrounding electricity derivatives are introduced, followed by some points outlining the challenges presented. Following the introduction and outline is a detailed classification of the types of derivative instruments found in the most developed electricity markets. Some of the methods used for pricing derivatives are briefly described, and some notes on their uses and risk management are also given.

2.5.1 Introduction

Traditionally, markets existed through the undertaking of agreements between parties that would benefit through an achievable hedging arrangement. The traditional agreements (between say customers, utilities and power producers) are quickly being replaced by derivative instruments with the intention of standardisation for trading. The outcome will be a reduction in transaction costs and the increase in prevalence of a range of hedging tools for both buyers and sellers. Traditional contracts in the old markets were generally of a long-term nature, with regimented tariff structure as dictated by the appropriate regulating authority. Non-derivative instruments/contracts for physical delivery (Power Purchase Agreements) and the capacity-based long-term type contracts of the past have given way to energy-based, short-term contracts and spot-market trade.

New contracts for spot market trade have not only been designed to replace the old overpriced ones, but also to be used in conjunction with them, and while meeting the commitments of the old contracts.

Exotic contracts are of little use without standardisation and the ability to trade in a liquid market. The arrangements may meet the hedging requirements, but the market may be too 'thin' to make the participation worthwhile.

Very often, electricity derivatives will be of the Asian (average price type) in order to accommodate the need to hedge against extreme price fluctuations over particular periods of time (say even in the prices over a particular day).

Many papers deal with the development of options markets for power trading in a market setup, giving due consideration to power system planning and operational constraints and requirements e.g. [20] which deals specifically with options markets for bulk power trading.

Real Options

In the 'real options' environment we attempt to value optionality in the following types of strategic financial situations: choice of technology; production decisions; investment timing decisions; options to temporarily/permanently shut down plant; other similar decisions with respect to real and/or physical assets. Denton et al. [15] published a paper on the management of market risk which is measured with the use of option pricing methodology (using closed-form solutions and trinomial tree/forest methods). The application is done with reference to participants in electrical energy markets. Results can then be used to schedule production and for asset portfolio optimisation.

An approach using real options is also given in [14] where real options-based valuation formulae are derived for generation and transmission assets. The formulae in turn are based on valuation formulae derived for spark and spread options on electricity futures. The authors therefore propose a way of valuing generation (and transmission) assets using options valuation methodology. Like many other authors, they derive their formulae under assumptions of both GBM and mean reversion for the futures prices of electricity. Comparison of historical values with the theoretical ones reveals that the methods are more accurate than simple discounted cash flow techniques. Further development in the field could progress through the inclusion of operating optionality of the generator, which would thus attempt to incorporate the presence of system technical constraints. Refer also to [38] for an example on the use and valuation of real options.

2.5.2 The Challenges

Some of the challenges defined and explored in the arena of electricity derivatives relate to:

- Valuation.
- Extreme short-term volatility of prices and **volatility smiles** (see Glossary).
- Modelling of mean reversion, seasonality and jumps in spot prices.
- Non-storability of the asset and the associated convenience yield necessitate futures-based replication of the electricity derivative when valuing electricity derivatives. The methodology relies on being able to make a portfolio consisting of an electricity futures instrument and a risk-free asset. Deng et al. [14] derive valuation formulae for spark and spread options using portfolio-replication methods.
- Differences to financial markets and differences of electricity to other commodities.

- Cross correlation of energy commodities which each have their own stochastic volatility and multidimensional conditional covariance.
- Using a fundamental or technical approach for analysing prices.
- Integration with power system concepts [20].

2.5.3 Classification of Financial Instruments

It is important to note that any list of types of instruments traded will be far from exhaustive. Optionality has always existed in agreements between parties and had evolved before the derivatives markets were formally established. Thus, we now have huge complexities within the contracts that need to be evaluated accordingly.

1. Firstly, derivatives may be classified in terms of who the counterparties are to the agreement. Instruments traded between two independent parties are termed 'Over-the-counter' (OTC) and those traded through an intermediary are termed 'exchange traded'. The incidence of credit risk will demand a more thorough scrutiny with OTC instruments. In a new and emerging derivative market such as energy, OTC will by far outnumber exchange-traded instruments per volume traded.
2. Any derivative may also be classified according to its perceived complexity. Simple instruments e.g traditional calls or puts, or any other well-understood instrument that is frequently traded (including those traded OTC), are termed 'vanilla'. Instruments with a more complex or less understood structure are termed 'exotic' or sometimes 'second generation'. Most derivatives traded in energy markets will currently be of the OTC, exotic sort. The simple types of calls and puts are seldom traded in energy markets because of the exotic nature of most price risks that need to be hedged. Contract-types termed 'exotic' in conventional markets are often considered 'vanilla' in energy markets. Some practitioners may also equate exotic options to path-dependent options, rather than simply treating the latter as a subset of the former.

A detailed classification of the types of derivatives now follows.

Futures and Forward Contracts

Futures and forwards are agreements to exchange assets at a future date with the former being standardised and exchange-traded (and therefore subject to substantially lower levels of credit risk), the latter being a more direct agreement between two parties (with an appropriately greater level of credit risk). Such agreements are priced using a cost-of-carry relationship that allows for the differential between financing costs and the yield on the asset i.e. convenience yield. Pricing deviates from this standard in energies as quite often there is further optionality built into the contract (e.g. with respect to location of delivery). When contracts have built-in optionality with respect to the quantity or volume of the energy that is agreed to be bought or sold, we value this optionality through the specification of a 'swing option'.

Forwards may form the basic unit of trade in an energy derivatives market, starting from a simple contract for hourly electricity, to few hour blocks for peak and off-peak trade. Aggregating the daily units, we get weekly, then four-weekly and seasonal to more long term contracts.

Swaps

Swaps (also known as Contracts-for-Differences or **CFD's**) are used to lock into a series of prices for the purchase of a predetermined quantity of underlying. Types include vanilla, differential (also termed margin or crack swaps), participation, double-up, extendible, and variable volume swaps. They are generally valued as functions of forward prices.

Simple Vanilla swaps involve a simple exchange of fixed prices for the floating (underlying) price going at each of the agreed payment times. They effectively comprise a series of forward deals.

Variable Volume swaps have a 'swing' option in that the quantity or volume of the underlying to be traded is not known in advance.

Differential swaps are similar to vanilla swaps except that the difference between two floating prices is exchanged for a fixed amount at each agreed payment time. They are thus used for hedging basis risk. A particular example is a margin or crack swap, where the price difference is between a raw commodity and its refined product (e.g. the difference between the coal price and the electricity price).

Participation swaps are a specialised type of vanilla swap that entitle the holder to a portion of the benefits arising from upside gains as a result of favourable price movements. The gains would have been lost under a vanilla swap agreement. A participation swap is equivalent to simultaneously taking out a vanilla swap with a long position in a floor option, which in turn has a strike equal to the amount of the fixed payment.

Double-up swaps allow participation in favourable price movements (which would be lost under a vanilla swap), often in exchange for an option to double the volume of asset traded.

Extendible swaps are double-up swaps with an option to extend the swap period for a predetermined period.

Bunn and Day [9] give a description of the most common forward agreements traded between electricity market participants. Many generating firms often sign contracts for large proportions of their output with regional electricity companies and large industrial users. Such contracts enable them to hedge their exposure to volatile pool prices and take the form of simple vanilla swaps. A generator will sign a contract to trade a volume

g_t at a fixed strike price f_t for hour t. When hour t arrives, f_t is compared to the SMP for the hour, S_t. There are two possible outcomes:

$f_t > S_t$: the buyer pays the seller an amount equal to $(f_t - S_t) \cdot g_t$

$f_t < S_t$: the seller pays the buyer an amount equal to $(S_t - f_t) \cdot g_t$

The net effect in an agreement between a Genco and a consumer is that the generator receives (pays) an amount $(f_t - S_t) \cdot g_t$ from (to) the consumer if it is positive (negative). The arrangement ensures that the Genco receives the strike price for g_t MWh of electricity regardless of what the market price is; They are protected from low prices when $f_t > S_t$, but also miss out on the extra income they could have received when $f_t < S_t$. Note that the Genco is still exposed to volume risk here, as the capacity agreed in the contract, g_t, may not be the actual volume ultimately traded for the hour.

Options

1. Options are first classified according to the type of transaction action they entitle the holder to:
   (a) A **call option** gives the holder the right, but not the obligation, to purchase an underlying asset according to prespecified conditions of time, volume, date, and price averaging which are all specified in the agreement.
   (b) Contrastingly a **put option** gives the holder the right, but not the obligation, to sell an underlying asset according to the prespecified conditions.
2. All options will be one of two types.
   (a) **European options** that may only be exercised at the specified maturity date.
   (b) **American options** that may be exercised at any time, or on one of a series of specified dates, up to and including the maturity date. American options are often simply referred to as 'early exercise' options.

Non-path dependent options

1. Caps, floors and collars (they are sometimes known as CFD's, though it is more common to refer to swaps as CFD's)

   Cap – a series of call options priced as a single contract.

   Floor – a series of put options priced as a single contract.

   Collar – a combination of a long position in a cap and a short position in a floor.

2. Swaptions – options on swaps.

   Payer swaptions – a call option on a swap

Receiver option – a put option on a swap

3. Compound options – options on options.

   Standard – calls or puts on simple calls or puts.

   Captions – a call option on a cap.

   Floption – a call option on a floor.

4. Spread options – are written on the difference between two prices.

   Calendar Spreads – options on the difference between two futures prices on the same underlying asset but with different maturities.

   Crack spreads – the futures contracts underlying the option are based on different commodities. A particular type of crack spread is a spark spread which is based on the difference between the electricity price and the price of the fuel used for generating the electricity. Other types of spreads encountered in electricity markets are location spreads, which have payoffs determined by the differences in location-specific electricity prices (otherwise known as LMP's).

5. Exchange options – are written on the relative performance of two futures prices.

   Out-performance exchanges – payoff is determined on the better of the relative performances of the futures prices on two different commodities.

   Percentage out-performance exchanges – payoff is determined on the percentage by which a futures price on one commodity out-performs that of another commodity.

Path-dependent options

Types include Asian, barrier, lookback and swing options.

Asian options have a final payoff that is based on an average (arithmetic or otherwise) of prices, rather than on the simple difference between the spot and strike prices.

   Average Price – payoff is based on the difference between the strike price and the average spot price over a period of the option's life. They are also known as 'fixed-strike Asians'.

   Average Strike – payoff is based on the difference between the average of a series of strike prices and the spot price over a period of the option's life. Also known as 'floating-strike Asians'.

Barrier options may commence existence or expire when a specific price level is reached by the underlying asset's spot price.

   Knock-out – cease to exist when a specific barrier level is crossed/reached. They may be of the 'down-and-out' or 'up-and-out' type.

Knock-in – come into existence when a specific barrier level is crossed/reached. They may also be of the 'down-and-out' or 'up-and-out' type.

Lookback options have a payoff dependent on the highest or lowest price attained over a period of the life of the option.

Fixed Strike – Payoff is calculated on the difference between the maximum or minimum spot price over the period and a fixed strike price.

Floating Strike – Payoff is calculated on the difference between the maximum or minimum of a series of strike values over the period and the spot price at the date of expiry of the option.

Ladder – Discrete level version of a lookback option and may be of fixed strike or floating strike type. If the spot price crosses a specific level during its life, a minimum payoff is locked into.

Cliquet – Discrete time version of a lookback option and may be of fixed-strike or floating-strike type. If the spot price has crossed a specific level at each of the snapshot dates, a minimum payoff is locked into.

Swing options as described above, may be classified according to the types of counterparties to the contracts in which they are embedded. Swing options have arisen due to the increasing uncertainty with respect to demand (being the quantity ultimately consumed by the end users), and the fact that one needs to hedge this volume risk. The optimal decision on the quantity of energy to buy or sell depends on the energy price as well as the quantity already bought or sold to date, so they are treated as path-dependent American-style options where the volume is the path-dependent variable.

1. 'Price-driven swing options' occur when the counterparties can both buy and sell the underlying energy in the market place, allowing the holder of the option to maximise the swing value of the contract. Varying quantities of the energy commodity can be delivered according to the terms of the contract which may specify particular maxima and minima. In addition, a base-volume (greater than or equal to zero) may be set which specifies the value around which the quantity delivered or withheld may swing (zero would imply an option to take no delivery at all). The number of times the swing from the base-volume value may occur may also be specified in a contract of the 'swing' sort.

   Pricing of swing instruments is carried out by means of a no-arbitrage assumption in conjunction with a numerical tree method.

2. If only one of the parties can take or withhold from delivery of the energy commodity, then we have a 'demand-driven swing option'. The contract is usually between dealers and the retail sector of the marketplace, though industrial users may also enter into demand-driven swing option contracts. An example would be a contract between a supplier of electricity and the residential users, of whom the latter may take delivery of the commodity though may not participate in the electricity market themselves.

Pricing is more complicated in under such circumstances as we need to account for the functional relationship between prices and quantity demanded.

In summary, we have the following types of derivative currently traded in developed tertiary markets for the electricity commodity:

- Futures and forwards.
- Swaps.
- Options: Asian, path-dependent, and other exotics (Swing, Look-back, Barrier, Ladder).
- Real options.

2.5.4 Methods of Valuation

Valuation methods reflect the complexity of the behaviour of the underlying spot asset, and thus tend to be complex in their own right. A broad outline of methods is discussed in this subsection. Traditionally, methods for valuing derivatives range from the following main approaches:

- Valuing equivalent portfolios which *replicate* the position in the derivative using combinations of positions in the underlying asset and a risk-free asset.
- Using a futures-based approach where the underlying asset is a forward contract in the underlying asset, rather than a position in the asset itself.
- Analytical formulae and closed form solutions.
- Numerical trees which map out the possible price paths of the derivative or the asset itself.
- Simulation and Monte Carlo methods.
- Distribution analysis.

In this section attention is drawn to the more popular methods of valuation in advanced tertiary markets for energy commodities, namely trees, Monte Carlo simulation and analytical formulae.

Closed form solutions

Black-Scholes-Merton approach: A method based on the principles of no-arbitrage, risk-neutral valuation. We construct a replicating portfolio in the underlying asset and calculate the expected discounted payoff using a simplified assumption about the behaviour of the price of the underlying asset. Model parameters can be simulated or estimated from historical data, or implied, or based on a mixture of the approaches.

Relaxing some of the assumptions leads to variations on closed-form theme; we can modify the underlying parameters (e.g. in the case of the volatility smile) or use the basic form of the formula and numerically integrate to arrive at results for the individual parameters.

Closed-form solution techniques can also be incorporated within the framework of other valuation techniques (simulation and trees) and vice-versa. Integration of techniques may happen when we wish to value American-style options or path-dependent options. The method of pricing is easy and tractable but unrealistic and oversimplified, especially for complex instruments. The technique can accommodate these complexities to an extent through the application of approximations to the general pricing formula (see for example [41]). The reader is referred to the Appendix (page 179) for details of some of the common closed-form solution formulae.

Numerical techniques

The general methods and main disadvantages of trees and Monte Carlo simulation are now discussed.

1. Trees

Method: Trinomial trees are more common than binomial trees for valuing electricity derivatives. They involve the discretisation of the price modelling process and the construction of trees of possible price evolution with *three* possible movements at each branch. The probability of each movement are calculated using arbitrage arguments. Dynamic programming or recursive techniques are used to calculate price trees and numerically value the options using the possible prices at each point in time. The expected present value of the instrument is then calculated. The technique is useful for American options and optimal exercise strategies. It provides a good framework for the risk management strategy as well because we can incorporate the volatility term structure.

We discretise the price process over a small time period Δt such that the change in the asset price over this period is Δx. Then we define p_u, p_m, and p_d to be the respective probabilities that the price increases, remains the same, or decreases over Δt. The space step cannot be chosen independently of the time step, and it has been shown that a good choice for Δx is $\sigma\sqrt{3\Delta t}$. Equating the first 2 statistical moments of the price change over ΔT and using the constraint,

$$p_u + p_m + p_d = 1$$

we can solve for the values of p_u, p_m, and p_d. Next we transform the price process back to an asset price tree depending on the type of price process used.

Let i denote the number of the time step and j the level of the asset price relative to its initial value. Then if $C_{i,j}$ represents the option value at node (i, j) then the option value at maturity is

$$C_{N,j} = \max[0, S_{N,j} - K]; \quad j = -N, \ldots, N$$

Using the assumption of risk neutrality we can excursively calculate each $C_{i,j}$ via backward induction,

$$C_{i,j} = e^{-r\Delta t}(p_u C_{i+1,j+1} + p_m C_{i+1,j} + p_d C_{i+1,j-1})$$

or if the option is American style,

$$C_{i,j} = \max\left[e^{-r\Delta t}(p_u C_{i+1,j+1} + p_m C_{i+1,j} + p_d C_{i+1,j-1}), S_{i,j} - K\right]$$

The current option value is given by $C_{0,0}$.

Drawbacks: Problems arise with complex path-dependent options where we end up with some very complicated forests.

2. Monte Carlo Simulation

Method: Once again, we discretise the price process then simulate possible outcomes using random numbers until convergence is obtained. We thus obtain a probability distribution of outcomes. The Monte Carlo technique is useful in that it can be used to price a wide variety of path-dependent options. It is fairly easy to implement and is increasingly used in many other wide-ranging applications because of its versatility.

The basic procedure is outlined as follows:

Let $C_{T,j}$ be the j'th simulated option value $= \max[0, S_{T,j} - K]$, then

$$C_{0,j} = C_{T,j} \exp\left(-\int_0^T r_u du\right)$$

which simplifies to $P(0,T)C_{T,j}$ if r_u is constant or deterministic.

After M simulations, we estimate the mean and standard deviation (SD) of the simulated distribution of option values:

$$\begin{aligned}
\hat{C}_0 &= \frac{1}{M}\sum_{j=1}^{m} C_{0,j} \\
\text{Standard Error}(\hat{C}_0) &= SD(\hat{C}_0)/\sqrt{M} \\
\text{where } SD(\hat{C}_0) &= \sqrt{\frac{1}{M-1}\sum_{j=1}^{M}(C_{0,j} - \hat{C}_0)^2}
\end{aligned}$$

Drawbacks: The method can be computationally expensive and may therefore require substantial time to get an accurate answer, especially when the underlying price process and/or the derivative has a complicated payoff structure. The computational expense can be solved to an extent by using variance reduction techniques. Another consideration is the valuation of American options where the simulation must be done in conjunction with a tree method.

Combined and other methods

To add to the increasing complexity of the markets, the valuation techniques have experienced unsurpassed growth in complexity. The result of the complexity is that many methods now draw on mixed techniques in the quest for viable alternatives to existing pricing approaches.

An approach to valuing American-style options with Monte Carlo simulation using a dynamic programming argument which is relatively computationally efficient is discussed in [22]. It is traditionally thought that Monte Carlo methods break down here when early exercise is a possibility, though it may be more of a fear of computational complexity, than an inability to value the instrument.

Volatility is important for both valuation and risk management such as VaR methods. Traditionally, volatility can be defined as the annualised standard deviation of price returns. There is a tendency for volatility to behave very differently over the life of the instrument. Time series models are useful in evaluating long term volatility levels e.g. ARCH and GARCH models. Volatilities may be related across time periods and also between commodities through a price correlation structure. In general volatility is an important area for the application of statistical wares such as time series, least squares and maximum likelihood). Efficacy of these techniques can be tested and benchmarked via the appropriate goodness-of-fit tests.

Most models are extensively parameterised, so various techniques have been employed to estimate these parameters. Examples include time series, market-implied estimation, simulation (including historical), maximum likelihood, least squares and regression.

2.5.5 Uses of Derivative Instruments

Since almost everything is being traded nowadays, the need for derivatives to hedge exposures to retail prices and for speculation has increased dramatically. Examples include the recent introduction of bandwidth and emissions commodities (the latter being a key issue facing northern European countries recently where emissions are an important factor in the determination of generating strategies). Technological advances and the development of 'greener' forms of electricity (wind, solar, hydro, etc) may have an important effect, with the added uncertainty with respect to the time frame with which change can occur.

In the adaptation to the market environment, the risks associated with both price and quantity have necessitated the introduction of the types of contracts described in the classification earlier in this section.

For example, spark spread and a location spread options have arisen due to the differences between the electricity price and the fuel price used for generating it, and due to differences in location-specific electricity prices (respectively) [14]. The development of spread options is an important realisation of the fact that there is a significant element of basis risk in energies. Basis risk can be defined as the risk resulting from the difference in price between the same product (or between a product and its spot value) in different markets.

There is an increasing prevalence of Asian-type options due to high volatility and spikes in the price of electricity, such that the average price of electricity (received by) Genco's and (paid by) consumers can be hedged.

There is also an increasing in the use of weather derivatives for hedging risks in electricity markets (see for example, reference [48] for a thorough exploration on the subject of weather derivatives). Derivatives are also used to value real options and therefore for obtaining generation and transmission asset values. Such options are also useful for comparing observed instrument or asset values to their theoretical ones.

2.5.6 Risk Management of Electricity Derivatives

This subsection deals with management of price risk for institutions which trade in energy derivatives, and are then faced with the management of risks of those derivative positions.

The main risks facing a company trading in an energy tertiary market are: geographic; market segmentation; pricing and contractual; credit; and transmission procurement. Alternatively these risks could be classified as market, commodity and human risks. Deregulation has certainly resulted in substantial price uncertainty in modern power trade. The risk associated with price uncertainty can lead to significant pricing inconsistencies, a worrying factor when price is the fundamental input to a derivative pricing and risk management framework.

Risk management is also a young arena in the field of energy derivatives. The portfolios containing the risk-hedging products need to be immunised and readjusted within the dynamic framework. Electricity companies such as Genco's need to set up portfolios of positions in both sales of their electricity and their purchases of primary energy, as well as derivative positions in these underlying commodities. The arrangements must be made in such a way that their portfolio is immunised against undesirable changes in the values of the variables. The key to immunisation lies in sensitivity analysis. Consistency between pricing and risk management is a highly desirable feature in model selection.

Various sensitivity metrics can be used for quantifying risk exposures and then adjusting the portfolio composition. The metrics are summarised as follows (the first five of these are generically referred to as the 'Greeks'):

Delta: sensitivity to price change — The most important of the first-order hedging sensitivities. It is used to immunise a portfolio or instrument within a portfolio against changes in the price of the underlying. It tells us how many units of the underlying asset we need to buy or sell in order to protect against impending price changes.

Gamma: sensitivity to changes in Delta — Gamma is also very important. It is a second-order sensitivity with which we immunise the portfolio against changes in the change in price of the underlying. It tells us how frequently (with reference to absolute price change) we need to apply Delta-hedging to remain Delta-neutral. Cross-Gamma risk occurs when instruments and/or assets in the portfolio are correlated, and it therefore represents an additional secondary effect that we need to hedge. A simple example would be an electricity producer who is naturally long in electricity but short in the generation fuel and is aiming to be delta-neutral in both when the prices of the electricity and the fuel may be correlated.

Vega: sensitivity to volatility change — Vega represents a first-order hedge against changes in the volatility of the underlying.

Theta: sensitivity to time — Theta is not something we are able to hedge, but something we ought to be aware of. It is the change in the value of the instrument with respect to time e.g. options generally decay with time as there is less time for them to realise gains, as their effective optionality is lower.

Rho: sensitivity to changes in interest rates — The first order exposure to interest rates is of little importance in energy markets as other factors tend to outweigh the effects of uncertainty in interest rates.

Factor hedging of exposure to possible changes in the structure of the forward curve (its shape determined by the factors in the multi-factor forward curve). First and second order interactions between factors need to be considered if appropriate.

(Monte Carlo) Simulation is useful tool for assessing the effectiveness of the hedging strategy adopted.

VaR — Value at risk is a confidence interval for the potential changes in a portfolio value in a given time horizon. Various industry standards are available and though their use in energy markets is questionable, they have been widely imposed across all risk management fields. Effects are once again exacerbated by the generally extreme nature of energy price behaviour. We are assuming an underlying probability distribution of portfolio returns at the time horizon. Four approaches are available: Delta, Delta-Gamma, Historical and Monte Carlo simulation. Techniques are laid out in the *Riskmetrics* documents of *J.P. Morgan*. Again, we include all the price-modelling and parameter estimation paradigms of valuation in a manner that is consistent between risk management and valuation strategies. Versatility at the valuation stage will make the risk management task easier, as we will already have the inputs to perform the calculations.

Credit Risk deals with the part of the risk of the portfolio not related to pricing fundamentals, but more to the changes in the credit rating of the counterparties to the agreements held in the portfolio. In the worst case the counterparty may default completely on their obligations and we are then concerned with the recoverable value of the portfolio with respect to that party. *Creditmetrics* (also a product of *J.P. Morgan*) provides an industry-wide mechanism for calculating and managing credit risk. When examining the overall exposure we need to take into account the correlations between the market players to which we are exposed across industries or sectors. Statistical techniques prove useful in the latter case, and distribution theory may also be used to model items such as recovery amounts and the occurrence of defaults. Testing of credit risk models via scenario analysis as well as stress testing provide further enhancements to the credit risk strategies.

Portfolio Analysis: using minimum-variance techniques to determine optimal hedging strategies. At present, this branch of investment analysis appears to be of minimal importance in young energy markets where the primary concerns are liquidity and pricing. However, it is necessary to be aware of it should markets evolve as expected, and techniques must be updated accordingly.

In energy markets it has been widely accepted that simple VaR methods (using the 'Greek' sensitivities above) do not provide sufficient accuracy, and the more sophisticated methods of historical and Monte Carlo simulation and will provide more accurate risk analyses.

2.6 Overview

This chapter has given a very broad overview of the types of research topics currently prevailing in the realm of modern electricity markets. A great deal of terminology has been introduced and the important aspects of electricity economics have been highlighted with a brief coverage of strategic decision making in Section 2.2. The notion of system-wide modelling was also mentioned in this section and is important for providing an ultimate goal for the development of a progressive model of electricity trade. The issues of that section will be expanded upon in more detail in the following chapter.

A history of power market development, processes of deregulation, and the type of market structures found internationally were described in the first section. Of particular importance are the types of pools and contracts, the various possibilities for auction arrangements and some economic terminology regarding oligopolies, price-takers and price-setters. The experiences of other markets provide useful lessons to markets currently undergoing transformation, although quite often the needs for strategic decision-making will be highly circumstantial and specific to the structure of the market question, and also to particular participants in that market.

The area of risk management was discussed in some detail in Section 2.3, and though not dealt with in an explicit manner in the remainder of this thesis, it serves as a guide to the types of concerns raised in any strategic simulation activity. It is conjectured that the model of this thesis may ultimately be adapted to the type of risk assessment and risk management strategies of that section. The section also highlighted the types of risks facing modern power companies and proposed some (often complex) methodologies for solving a variety of risk management problems. The complex methods will serve as a benchmark for the approach adopted later in this thesis, and have value with regard to both justification for, and a critique of the model. Also of value in Section 2.3 is the idea of correlated variable stochasticity in the study by Otero-Novas et al. [39]. The importance of this notion will become apparent in the analyses of Chapter 6.

The study of pricing models in Section 2.4 is useful for comparative purposes for the much simpler model of the electricity price variable which will developed in the formulation of Chapter 5. While emphasising the characteristics of electricity prices in deregulated markets, one is reminded of the ease with which model deficiencies become apparent when attempting to capture the important characteristics of the SMP variable. An awareness is therefore created with respect to modelling of SMP's in this section, and the technical characteristics that were described will become important given the prospect of practically implementing the model of this thesis.

Markets currently lagging in development (e.g. in South Africa) will not, in general, have progressed sufficiently to justify any detailed inclusion of the techniques mentioned in Section 2.5 in the models developed for the market in question (e.g. with regard to electricity derivatives and their associated risk management). Underdeveloped markets do not have a sufficiently high level of competition or liquidity of trade to enable efficient pricing, trading and risk management of complex instruments such as weather derivatives or real options. However, the techniques may be useful in the provision of guidelines for the valuation of particular OTC contracts currently traded in (say) the EPP. For the model of Chapter 5 there is at most scope for inclusion of the simple forward contracts in the model, in the form described on page 50. In the case of the EPP, it would be justified by virtue of the current hedging arrangements that are in place between the Genco's of the pool and the Generation Production and Sales division (see Chapter 4).

This chapter has also provided a comprehensive coverage of the range of mathematical techniques that have been used to facilitate risk management, derivative valuation, SMP (and other variable modelling), parameter estimation techniques, and strategic decision-making in general. The chapter which now follows focuses on the application of these types of tools to the challenges presented by generator trading strategies.

Chapter 3

Generator Trading Strategies

The subject of generator trading strategies has been tackled at length by researchers in both a direct and an indirect manner. The previous chapter discussed some of the more general research areas in power system economics, often incorporating the trading strategies of generators indirectly. The focus was on how the strategies are incorporated in a wider modelling sense. This chapter aims to review a range of techniques used to model these trading strategies, drawing on research papers that have dealt with the subject directly and, where relevant, drawing on sections from the broader papers and extracting the treatment of trading strategies for inclusion in this survey.

The chapter will therefore be divided into five sections. The first section will highlight some of the modelling work that has been done, justifying the study of trading strategies, and summarising references for the types of research problems identified in the literature. The second section will examine the various treatments of price-formation and the types of strategic behaviour adopted by participants in electricity pools. In the third section, electricity supply functions are defined and various approaches to modelling these functions will be elaborated upon. Section 3.4 examines various techniques for obtaining the optimal bidding strategy.[1] Finally, Section 3.5 will summarise the aspects of generator trading strategies that have been examined in the models alongside those aspects that have not been tackled in the various analyses.

3.1 Modelling Activities in Electricity Markets

The types of modelling activities that have so far taken place in respect of modern power markets will be described below. The nature of the subject has meant that most researchers, while attempting to solve problems in isolation, have been forced to examine aspects that they had not intended to, but did so in order to achieve their main goal. The result is that many of the themes below have been dealt with by researchers,

[1] Strictly speaking 'bidding strategy' should refer to the actions of a consumer who bids for electricity, however the term is used interchangeably with 'offering strategy' which is the more correct version for generators 'offering' their energy to the market.

without them having expressly intended to do so. Quite often, the research areas have transcended many themes and many cross-overs become apparent.

Optimal offering strategy

Optimal offering strategies are tackled explicitly in references [4, 11, 21, 25, 42, 52, 53, 54]

With the advent of a competitive market for electrical power comes the desire of participating Genco's to maximise their profits in respect of power sales. In addition, regulators will seek methods of modelling how participants will behave under competition and with various market designs in place. **SO's** will also need to know how participants are likely to bid so that they can ensure the grid operates safely and reliably. Generators will select the appropriate offering strategy after allowing for the effects of variation in system demand, unit commitment, costs, and other influences.

The researcher of the optimal strategy sought by generators must consider a vast array of factors. Such factors range from:

- the type of market.
- rival behaviour.
- uncertainties (such as the probability of offers being accepted).
- price-setting ability.
- type of supply function.
- risk profile of the Genco.
- treatment of system variables (such as price and demand forecasting).
- effects of outages, network conditions and system locational/nodal constraints.
- Volumetric (quantity) and market (price) risks that the Genco may be exposed to.

Obviously taking all these factors into account is a large task, and the modeller will not be able to tackle them all. A more prudent approach — vindicated in most of the research — is to examine a few of the aspects (whichever are the most important for the aims of the model and the type of market) and make some simplifying assumptions for those that are deemed less important for the purposes of the analysis (such as ignore them). In most cases the researchers attempt to identify any deficiencies in their models as a result of their simplifications, and mention the possibility of upgrading their models in future work.

Conditions for optimality

Some authors [11, 37] have investigated the conditions under which the supply functions offered to the market give the optimal response to a range of demand outcomes, and derive bounds on revenue lost when approximating their supply functions and those of their competitors. Their analyses may also consider the existence of supply function equilibria.

Neame et al. [37] determine the optimal offer stack from the perspective of a price-taker, while [40] does the same for the situation of a price-setting Genco. The price-setting ability of a Genco is an important aspect distinguishing two unique treatments of price-formation in electricity pools.

Oligopoly versus perfect competition

See references [13, 17, 42, 51] for modelling of both system-wide and supplier-specific offers assuming all of the suppliers are price-takers (i.e. a perfectly competitive market) [51], or none of them, or some of them [13]. The latter two cases represent the instance of an oligopoly.

Market Design

Rajaraman and Alvarado [42] examine the impact of design rules on the bidding strategies and profits of Genco's while He et al. [25] look more generally at the impact of liberalisation. The latter study concludes that without the presence of demand-side bidding, the newly liberalised market will suffer a reduction in social welfare with increased costs to consumers. Other models have been developed for markets that permit revision of bids one or more times prior to the time of actual production. Researchers also aim to measure the extent of market power under varying conditions of market design, e.g. with respect to the type of clearing mechanism in place.

System-wide models

Studies have been done on entire systems of Genco's, or even entire power systems. These model prices, demand levels and production levels based on current and historical values [39]. Modelling tools have been developed and explored for analysing market structures and offering strategies for the benefit of regulators and system operators. These tools contrast with the ones developed solely for the benefit of individual generators. Ferrero and Shahidehpour [17], Rajaraman and Alvarado [42] show that the pool optimal schedule is *not equivalent* to that of an individual participant who must maximise his own benefits. The nonequivalence poses the philosophical question of whether pools and competition are a viable means of power trade, and asks whether the ISO should allocate any benefits arising from pool-type markets, or whether participants should merely be allowed to seek their own benefits. Furthermore, which of these two ideologies results in the greatest overall benefits to consumers and producers?

Some models are of two or three suppliers and are usually not extendible to the more general case of n suppliers.

Longer term analyses

Keppo [31] examines the long-term optimality of a multireservoir hydropower scheme, including the use of weather derivatives to hedge rainfall uncertainties, and other derivatives for hedging price uncertainties. Other authors have also attempted to extend their models to examine longer term strategies, thus moving away from the single period (hourly or daily) problem in general.

Derivative markets

Models of the more advanced markets in developed countries must incorporate the effects of derivative arrangements on the trading strategies (when these are used as a means of hedging market risks), or even decide on the optimal utilisation of such contracts. Choosing the optimal strategy is directly related to deciding on an optimal portfolio of sales and purchase contracts for a given level of risk preferences [7, 35, 43]. It is therefore necessary to examine the relationship between contract profitability, bidding strategies, risks and availability of information. Keppo [31] conducts a study in this realm where weather derivatives are included in the portfolio.

Other issues

Authors have attempted to develop self-scheduling mechanisms for suppliers in an auction-type market for electricity [24, 30]. Others have tried to capture aspects of adaptation and evolution of bidding strategies.

The following sections examine some more detailed aspects of the above topics, drawing on the specifics of the most common themes and providing a reference for some of the model development that takes place in Chapters 5 and 6.

3.2 Price-Formation and Strategic Behaviour in Electricity Pools

Two approaches prevail in the methodology of modelling electricity prices, and usually the approach depends on the purpose of the modelling. When aiming to find an appropriate bidding strategy, and the scale of the model is too small to capture the full range of deterministic influences, it would be more appropriate to treat price exogenously i.e. as in external variable with its own fundamental economic drivers. If on the other hand, price was the measure of appropriateness of regulatory strategy, the level of competition or price-setting ability of market players in a wider market sense, the price would be an explicit output of the modelling process.

Broadly, two approaches can therefore be identified. Firstly, there are methods which treat the electricity price as an exogenous variable governed by some probabilistic process. Examples of price models include the jump diffusion and mean reverting models described in Section 2.4, neural networks, techniques based on Fourier and Hartley transforms, and time series analysis. These models produce forecasts for prices (often the SMP's) that relate actual prices to demands and past prices, assuming the outcome for each hour is a random variable conditioned on the price history [11].

The second possible treatment of price is through modelling the competitive behaviour of all Genco's in the market (and possibly the large consumer companies as well [53]). In such cases, the SMP is treated as an endogenous output of the modelling scheme such as the one described in [9], and the concern is with analysing strategic behaviour rather than proposing a tool to develop offering strategies.

3.2.1 A model of price formation in the England and Wales Pool

A detailed exercise in modelling price-formation in the E&W electricity pool is carried out in [9] for the ten year period from 1990 to 2000. In this study, the methodology of computational learning and gaming is used and recommended as an approach for modelling competitive markets. The model is simultaneously used to identify situations of market misconduct or deficiencies in market structure. Characterising the E&W market is a small number of generators with large amounts of information in common, a situation that lends itself well to this type of modelling.

The authors of the paper maintain that market power persists, despite the amount of research and regulatory intervention in the restructuring process. The persistence of market power has resulted in widespread accusations against generators within many pools that market power has been abused. Concerns have also arisen surrounding the philosophy of electricity liberalisation itself. The approach used to analyse market conduct in this paper permits discontinuous supply functions, asymmetric markets (with respect to competitor size) and includes forward contracts, the latter having a significant impact on most modern spot markets.

The methodology is validated in the situation where analytical results can actually be computed and it is shown that a conjecture of fully optimised best response is inferior to bounded rationality coupled with incremental goal-seeking.

The model proposed by the authors is one of the entire E&W pool with the aim of determining the key determinants of the price outcomes over the period from 1990 to 2000. The process that they adopt enables the isolation of the effects of structural changes, relating to costs and regulatory intervention, from the continuous evolution of learning and gaming (without convergence to particular equilibria).

The approach is one of computational modelling inspired by evolutionary economics and is a viable representation of reality. The contribution of this model is two-fold:

1. From a theoretical standpoint it provides a model for competitive electricity markets.
2. In an applied sense it provides a basis for identifying whether high market prices can be attributed to faults of market structure (unsatisfactory regulation) or market conduct (exercising market power through collusion of generating firms).

Demand inelasticity is relevant to this discussion as it enables market power to be exercised at low levels of supplier concentration.

The computational approach provides a benchmark against which to assess generator conduct, therefore providing a baseline for diagnosing (separately) both market structure and generator conduct when actual prices are observed to be greater than the marginal costs of production.

The model of the supply functions is an evolutionary one, meaning that the progression of daily profit-maximising behaviour is simulated rather than solving for equilibrium conditions. The profit-maximising behaviour reflects the ability of Genco's to form conjectures about their opponents' actions, and maximise their own profits according to these conjectures. The methodology is based on the fact that a market with only a few Genco's, who repeatedly partake in daily auctions, and where there is a large amount of common information, will result in a "continuous evolution of learning and gaming...". As a result the methodology permits freedom in the type of function being used, namely discontinuous supply curves with asymmetric firm-sizes. In addition, financial contracting is incorporated into the model, as it is clearly an aspect of the markets that has a substantial effect on the overall pricing in the spot market.

The experimental characteristics show the presence of 'price-cycling' in the supply function modelling, suggesting agents cut prices to enter the market, followed by increasing them once they have attained sufficient market share, all the while constrained by capacity. Such activity is prevalent when supply functions are allowed to be discontinuous. The severity of the cycling is dependent on the degree of concentration in the market.

The authors use a satisficing mode of bounded rationality[1] to represent real decision-making with a level of pragmatism. The method is a reasonable alternative to the unrealistic scenario of fully optimised best response to competitors' actions. At lower demand levels the level of cycling is reduced since altering the supply function has little effect on profits at these lower levels. When limiting the extent of the optimisation, the supply functions become stable. A partial best response model does seem to capture the cycling and hence the dynamic character of the real market. Independent Power Producers (IPP's) are treated as price-takers who are unable to act strategically — their supply functions are effectively constant in terms of the model.

The problem of estimating short-run marginal costs (MC's) is discussed. In the past they have been based on efficiency and fuel cost data, which is less appropriate in modern times because of privatisation and improved efficiency, so instead, efficiency is estimated from data of fuel consumed and the quantities of electricity produced by each firm (say

[1] i.e. choosing what is 'good enough' rather than what is best under limited capacity for choosing what is 'best'.

from compulsory environmental reports). A third more obvious way is to simply examine the firms' reports on marginal costs — if the reports are available!

With regard to the assumptions on demand, three scenarios ranging from inelastic to more elastic linear demand curves are explored and the results compared. Contract-cover presents a difficulty from a data perspective, so two scenarios of relatively high cover are explored, giving six scenarios in total. One outcome of this analysis is that with higher contract cover, we have lower prices indicated by the supply function, in fact they are close to MC if nearly all sales were contract-covered.

Overall, the modelled supply functions are above MC, but less than the observed system supply function. Hence the modelled functions indicate that the existing market structure is a profit-maximising oligopoly (as indicated by the former), and that there is evidence of collusion (indicated by the latter).

A further observation is that in low demand periods, pricing could even be under MC, probably indicating that firms are avoiding shut-down costs. An alternative explanation is that MC's could have been overestimated for these periods.

It is noted that the differences between observed and modelled supply functions are wider at greater levels of contract cover. Also, higher demand elasticity meant lower prices (except where contract cover approaches 100% and begins to dominate the influence of demand elasticity).

In conclusion, this paper develops a detailed model of price formation and offers a model that is a good reflection of reality. It has normative qualities in the sense of providing the evolutionary approach to modelling price-formation, and is also of descriptive value in identifying problems of market structure and conduct, and such problems can be identified through the prices that emerge from the simulations. The observed periodicity of the pricing cycles was dependent on the degree to which agents adopted an optimising behaviour. A highly bounded rationality and limited goal-seeking attitude was identified — a plausible result given the complexities of a daily auction process and associated uncertainties.

The paper was also valuable from a policy-making perspective, providing methods for unravelling collusion or conduct problems, and structural problems where regulatory action would be required.

Deficiencies of the model are a lack of reliable information on contracting levels, and uncertainty with regard to how firms recover their fixed costs. In trying to cover the latter, firms may bid substantially above MC, especially if they are including long-run profit margins in their mark-ups and/or looking at the expected prices or forward curves in their decision process. Finally it has been recently observed that after voluntary divestiture of some generation assets, system prices did in fact decrease. An obvious question to be asked is why this paper does not accommodate any of the physical, or system constraints as they may quite readily affect pool-price formation.

3.2.2 Simulation of a wholesale market

The authors of [39] present a simulation model of a wholesale electricity market. The outputs of the model are expected bid prices and quantities, system hourly prices and generation schedules. The model takes into account bidding strategies of generators and market structure, and reflects the profit-maximising behaviour of the market agents. Their model is termed *COSMEE* and it is used to simulate a real wholesale market.

Three types of price formation in markets for electrical energy are described, each dependent on the type of market:

Wholesale price: a unit commitment or economic dispatch program is used to determine the wholesale price via some kind of least cost optimisation algorithm. Least-cost approaches are common in the studies of regulated markets.

Spot Price: variable costs of the marginal unit plus an allowance for recouping of allocated start-up costs (start-up costs therefore treated externally to the bid). The results of such pricing rules (as implemented in Argentina and E&W) are different depending whether production costs rather than consumer costs are minimised. In the past the rules have led to stability and fairness problems when many near optimal solutions are present. Such difficulties also motivate the need for type of model proposed in Chapter 5.

Auction: clearing price is determined where the quantity willingly supplied by the aggregate supplier entity equals the required demand for a particular hour. It is therefore required that the suppliers internalise their strategies, technical constraints and start-up costs in their offers. Recent trends in markets such as those of Norway and Australia have lead to auction-type processes for clearing the market.

The advent of auction-type markets — especially when the national market is such that it integrates all three of the above market types — has resulted in simulation models having become the necessary tools for defining the strategies of the generators and analysing the potential effects of regulatory or risk management decisions. A simple chronological simulation tool with embedded optimisation of total system costs will not account for the effects of bidding strategies (since in reality bids will not necessarily reflect costs only). Previous attempts to model strategic aspects of supplier behaviour have included:

1. Game theory for examining the influences of market power and the effects of contracts or capacity payments.
2. Cournot models of oligopoly. In a Cournot model, each supplier assumes that the quantities produced by rival firms will remain unchanged in response to their own output, and will tend to lower the price of the commodity. Cournot competitors are defined as those who are able to modify prices whereas marginal competitors submit offers close to their marginal costs.

Such models failed to account for technical constraints, unit commitment and intertemporal links (hence the gap which this paper attempts to fill) in addition to an advancement on total cost chronological simulation.

Primary uses for the simulation model envisaged in this paper are:

1. Describing generator strategies and their effects on price formation.
2. Analysing the effects of potential regulatory decisions.
3. Risk management.

The authors use the model to simulate the market under two different strategy assumptions:

Perfect competition (uncoordinated simulation) where each competitor is essentially an independent price-taker.

Oligopoly (coordinated simulation) where groups of units belong to firms who try to maximise profits.

In so doing, this model can help analyse the effect of each of the bidding strategies, therefore aiding regulatory decision-making and identifying the effects of the strategies on the behaviour of other market agents.

Model type: An iterative mixed model based on generalised Cournot and Bertrand[1] equilibria, with refinable beliefs (about competitors' behaviour) at each iteration is designed. Simulations are run on the two types of market, taking into account intertemporal links and technical constraints into the offering strategies.

The following assumptions are made:

1. Market clearing is based on simple bids.
2. Demand is inelastic (i.e. non-responsive to price) and divided into hourly blocks for each day.
3. Both a thermal and hydro generation plants are considered with the appropriate constraints for the type of unit, such as minimum/maximum outputs, ramp rates and cost structure.
4. The particular characteristics of the Spanish market are utilised for the purposes of a case study implementation of the model under realistic assumptions.

The outputs include estimates of expected bid prices and quantities, system hourly prices and generation schedules.

[1]In contrast to Cournot models in which suppliers assume output remains unchanged, Bertrand competition occurs when suppliers assume that their rivals will fix their prices. This assumption will tend to drive prices down toward MC.

Simulation algorithm: The algorithm consists of five modules:

1. **Initial offer** — must be high as only decrements in the bid price are allowed at each revision. Includes no-load, start-up and variable costs, with start-up initially allocated to every hour and thereafter reduced depending on the actual dispatch. For a hydro plant, the initial offer is the same as the highest thermal plant offer.

2. **Clearing module** — computes the spot clearing price, the highest price at which all demand is met. Technical constraints are internalised by generators and therefore not explicitly allowed for.

3. **Optimal strategic decisions** — offers are chosen taking into account competitors' offers. This module will be different for the coordinated and uncoordinated simulations. First quantities, then prices are modified based on information from the previous clearing process. Costs determine the lowest bound for the price bid.

4. **Convergence** — determines whether profits can be improved through modification.

5. **Results** — marginal prices, profits and scheduled productions are computed.

The algorithm iteratively improves the profits of the generating units subject to their technical constraints until convergence is attained. At each iteration quantities are determined/modified through an optimisation routine after which prices can be modified through a fixed decrement if necessary. The results obtained at convergence reflect the optimal strategy for maximising profits subject to the technical constraints. Dynamic iterations represent updates of information received by participants. The resultant spot price for each hour is equal to the most expensive bid accepted among all the bids. Iterations are separate from the time frame of the model which is hourly in nature.

The type of supply function used is described in Section 3.3, and the construction of optimal offers in Section 3.4 thereafter.

An example is presented including 67 thermal units and 19 hydro units. The uncoordinated simulation (assumption of perfect competition) converged much faster than the coordinated (assumption of imperfect competition). The results of the example are different for price-taking and price-setting environments with regard to prices, profits and final dispatch. The price-setting environment leads to higher prices, especially for peak hours. In the price-setting environment, firms do reduce their production to avoid reductions in price, but end up with increased profits because the SMP escalates as a consequence of these actions. Differences are exacerbated in peak hours. During valley periods, competition is in fact greater, as units push prices down to avoid shut-downs, though prices still remain higher than for the corresponding coordinated simulation. Overall, firm profits are also greater in the coordinated simulation.

A comparison is also shown between hydro units, which act as price-setters, and those units which offer at cost. The difference here is as noticeable in peak hours as it is in valleys, the hydro units simply meet "run-of-the-river" production.

Conclusions: *COSMEE* is a useful tool developed by the authors for analysing wholesale market behaviour when bids are simple with costs and constraints internalised. It demonstrates the effects of different strategies and goes beyond traditional production costing/unit commitment algorithms. Other strategies are in fact possible in reality and results for February 1998 show that real prices were equivalent to somewhere between coordinated and uncoordinated strategies, though closer to coordinated. Possible modifications include an extension to the model for a year's horizon with the associated strategy decisions. In terms of modelling objectives, the model is highly descriptive: it aims to determine the type of strategy adopted by participants given generator cost structures and internalised constraints and offer strategies. In so doing it also aims to capture the market structure and any conditions which may lead to pricing away from MC. In the case of the Spanish market, the simulation achieved values close to the historical outcomes.

It is unclear from the paper whether it is market design or competitor strategy that is being compared, though it seems, at face-value, to imply that two different industry structure scenarios are being compared, with the price-setting structure giving rise to higher SMP's.

3.2.3 System-wide participant behaviour

Authors Wen and David [53] argue that deregulated markets are more akin to oligopoly, where participants can improve their profits through strategic bidding at the expense of social welfare, than to perfect competition. In this particular reference they present a method for building offering and bidding strategies for suppliers and large consumers in a pool-type market. They assume linear supply and demand functions are submitted by each participant and determine the coefficients in these functions to maximise benefits, given their expectations of how rivals will bid. Though deriving the optimal strategy for an individual Genco, the approach has the objective of identifying the potential for abuse of market power, and therefore the loopholes which may exist in the market structure. A brief overview (including criticism) of the literature on the strategic bidding problem is provided in this reference. This is one of few papers that integrates demand-side bidding into the market clearing process. Demand-side integration is made possible by allowing the large consumers to choose an appropriate (linear) demand function prior to the market being cleared.

The following assumptions are made in this system-wide research in the field of participant behaviour:

1. The market is a day-ahead one where 24 auctions are conducted and cleared simultaneously and separately, one for each hour. In this paper, only a one-period auction (e.g. for a single hour) is considered.

2. The structure of the California electricity market including a single-part bid structure with a single energy price bid is assumed. All costs such as no-load, start-up, shut-down, and others are internalised within the offer.

3. Intertemporal constraints such as minimum up and down-times, maximum numbers of start-ups and shut-downs are not included in the study. Transmission constraints are also ignored.

4. The effects of reserves are not examined as the reserves are served by a separate market in California anyway.

The following formulation is described:

1. n independent power suppliers and an elastic demand consisting of m large consumers (in addition to an aggregate body of small consumers) who participate in demand-side bidding.

2. Each participant in the market offers a linear supply/demand function of the form described in Section 3.3

3. It is implied in the formulation that each participant in the market has an influence on the price, and there are no price-takers.

An optimal bidding strategy is derived for each supplier and large consumer as described in Section 3.4 and based on the supply/demand functions described in Section 3.3. The strategy used optimises the coefficients in the bidding functions given each participant's personal mathematical conjectures of rivals' behaviour.

Once the SO has received all the supply and demand functions from all participants, it determines the clearing price (which is an analytical function of the bidding coefficients, system load and demand elasticity — if the latter is present), and then determines the set of allocated outputs and demands. Those participants with allocation below the minimum are removed from the system. Those with allocations above their maximum are allocated this maximum, however their supply/demand functions are then ignored as a constraint in the SO's allocation problem, since they are no longer a marginal generator/consumer. Presumably these changes will affect the SMP and the allocations, though the authors do not elaborate on the associated consequences. If the bidding coefficients of these 'marginal' participants are ignored, they could be construed as being price-takers or baseload generators, and perhaps explains how the authors could (indirectly) be allowing for price-taking in the market, though no obvious explanation is provided.

Price-setting ability (for the Genco's) may be implicitly dependent on the (quadratic) cost functions assumed by each Genco, their estimation of rival supply coefficients and possible interaction with the estimates of the bids of the large consumers'. All the information about price-setting ability is therefore contained in the interaction of the participants' various parameterisations, which would in turn lead to a particular price-formation. The tweaking of assumptions in the model (such as the symmetry of information) appears to be the scenario generator for examining the effects of market design and analysing participant behaviour.

3.2.4 The residual demand curve

The ability to affect price and the presence of rival uncertainty are once again the main challenges in building the optimal offer strategy in a paper by Baillo et al. [4]. The type of market considered consists of 24 hourly uniform-price multiunit double auctions with sealed-bids. Transmission constraints are assumed to be not significant to simplify the analysis and the term 'double', 'multi-unit', 'uniform price' and 'sealed-bid' were all defined in Section 2.1 [p. 18]. The model uses the idea of a 'residual demand curve' and considers longer-term strategic decisions as well as spot market strategies and forward contracts. The uncertainty arising from the spot market is represented by a probabilistic residual demand curve based on historical behaviour of the other participants, and the price arises from an expected value derived from historical outcomes. Reserves are not considered. The approach is normative: it aims to reach a trade off between effort dedicated to the spot market trade and the company's portfolio of longer term contracts. It also has prescriptive qualities in providing a tool for optimal offers given a probability distribution for the behaviour of other participants. Overall the model is comprehensive in its attention to detail on the operation of a particular Genco. A potential problem with the modelling of price-formation lies in their assumption of sufficient historical data detailing the behaviour of *all* participants. Obtaining sufficient data seems infeasible given the very recent introduction of competition in most markets, and the potential for the existence of pending and past changes in structure that have to be taken into account.

3.2.5 Other treatments of the SMP

The approach to price modelling in reference [11] is to treat the SMP, λ_t, as a random variable that is approximately lognormally distributed. The authors derive a confidence interval for λ_t using Normal tables at the desired level of confidence with the parameters of the lognormal distribution being determined from a time series forecasting procedure. The data used for the time series are the historical values up to and including the period 24 hours before the hour for which the forecast is required, however the type of time series model is not specified. Importantly, for comparison to other methods of price-forecasting, the price forecasts are *conditioned* on the historical time series of prices which are used to derive the parameters for the confidence interval. The price is used as the crucial input for a probabilistic self-scheduling profit-maximisation problem, which can be solved to provide a simple yet informed bidding rule. Such models have been developed to tackle the high price uncertainty faced by pool-market Genco's. This particular model is concerned with the instance of a price-taker (costs are formulated via a non-linear, non-convex function and a related set of operating constraints). More details on the supply function and optimal bidding strategy adopted by these authors are given in the next two sections.

An optimisation routine matching supply and demand and minimising the total revealed cost of power delivery is used to determine the clearing price in [3]. Clearing may take place at locational nodes if they exist and must take into account transmission constraints.

There are also the various exogenous treatments of price that were detailed in Section 2.4 of Chapter 2.

3.2.6 Summary

This section has examined some of the ways in which prices are formed in pools as the outputs of various modelling approaches, or as independent entities for which unique modelling techniques are sought. In the case of the former, various levels of detail can be incorporated into the modelling, depending on the express intentions of the modeller and the type of market they have chosen to model. Most of the models which are of descriptive value, treat the formation of the SMP in pool-type markets as a measure of the impact of market design rules (hence the type of supply function), or of the effects of system constraints and alternative cost scenarios, or even of the effects of derivatives such as forward contracts. The more normative models will use the SMP in a model of price formation to determine an appropriate probability distribution upon which the participants can develop optimal strategies, though such models will be of descriptive value to individual participants who wish to behave rationally in a market.

Some models include exceptional levels of detail with regard to the effects of financial contracts and derivatives, demand elasticity, technical constraints, intertemporal links and length of time horizon. Others do not attempt to capture every characteristic of the market, but tend to focus on certain issues in isolation, effectively ignoring the other factors' effects.

There is a great tendency to use price formation as an indicator of the effectiveness of a competitive environment, as well as for examining differences between perfectly competitive and oligopoly-type markets. Approaches to price formation are classified as being either equilibrium-based, or non-equilibrium-based in nature.

3.3 The Electricity Supply Function

A supply function for offering capacity into a power pool is defined by the quantity(ies) of energy offered and their associated set of prices. In most markets the offers consist of a number of discrete blocks of energy which form a step function, sometimes also known as the *offer stacks* or *tranches* for a particular supplier. These price-quantity pairs are represented by supply functions that can be used by market participants for offering generation into electricity markets, or as a theoretical basis for examining system-wide behaviour of suppliers.

In a power pool, the supply functions of all the participants can be aggregated to form a market supply function which is matched to the system demand function for a particular period. An appropriate representation of each generating unit's supply function is therefore crucial, both for the determination of the resultant pool price by the SO, and for the supplier in deciding on the optimal profit that it can achieve. The problem facing most generators is constructing a supply curve that maximises its profit for a time period given certain conditions (e.g. risk preferences, capacity limits and technical constraints), exposure to price variability (through the presence of otherwise of two-way CFD's) and uncertainties (e.g. of demand and competitor behaviour).

An important aspect that needs to be considered when deciding on an appropriate representation of a company's supply function is the price-setting ability of the company. A price-taker is a company that cannot readily offer enough power into the market to substantially affect the price and can be a small supplier in any market or a *normal* supplier in a perfectly competitive market. Conversely a price-setter is a company that can offer enough power into the market in order to play a significant role in the setting of the market price, and is either a *normal* supplier in an oligopoly or a relatively large supplier in a competitive market. Moreover, a company can be considered a price-setter if it operates marginal units (such as a peaking-type plant in periods of planned or unplanned surges in system demand), or if it is a baseload plant under a normal demand situation. The important thing to note here is that we are concerned with optimising the generator's profit function with respect to a price variable. From a modelling perspective, the price variable in the profit function of a price-setter will be endogenous to the supply function, whereas the price-taker will treat it as purely exogenous.

The following subsections give examples of the types of supply functions that have been used by researchers to represent the offer curves of suppliers. Each supply function will have a corresponding objective profit function that will need to be optimised, depending on the aim of the model — which may be to aggregate the pool supply (e.g. by a SO) or maximise the profit of an individual supplier. Some of the unique functions will be discussed in detail, and others will be included for completeness.

3.3.1 Single Offers

Single offers are not supply 'curves' in the true sense. They represent the simplest type of offer that can be submitted for an auction in a single hour. They are characterised by a single price for a fixed volume of power much the same as the simplification adopted in the model-formulation in Chapter 5. Simple offers have been used in cases where the type of supply function is of minimal importance to the analysis. They are likely to be used for representing the supply functions of price-takers who offer on behalf of a single generating unit, and are able to internalise operating costs.

3.3.2 Smooth supply functions

A parameterised continuous supply *function* for the offer curve of the form

$$\vec{s} = \{((p(t), q(t)), 0 \leq t \leq T\}$$

where the price and quantity — $p(t)$ and $q(t)$ respectively — are non-decreasing functions of t (the parameter defining the curve) is proposed and analysed by Anderson and Philpott [3]. The associated *supply function* here is $S(p)$ if $q(t)$ is equal to 0 for some value of t and $p(\cdot)$ is strictly increasing.

The type of supply *curve* described is a set of offer stacks/tranches and therefore not continuous, though the individual components, $p(t)$ and $q(t)$, are continuous. In the research article it is claimed that previous authors have proved that when assuming continuous supply functions in markets where offer curves are in fact step functions, there is an effect on the nature of the analysis. It is also demonstrated that if all players offer continuous curves, then a finite set of price-quantity pairs can be constructed to approximate the optimal strategy. The payoff from the discontinuous approximation is close to the one from the optimal continuous curve. The relevance to the existence of a supply-function equilibrium in a symmetric oligopoly and general convex costs is demonstrated.

The aim is to find an optimal strategy in a market where competitor behaviour can be predicted using supply functions which are insensitive to system demand, and derive conditions when the optimality is in fact possible. Potential losses from approximating competitor supply functions can be estimated. The methodology is not able to solve the optimal supply function in the face of uncertain demand.

3.3.3 Offer stacks

A stack of prices for quantities is specified and the price component of the price-quantity pair is chosen depending on an historically derived probability distribution.

3.3.4 Piece-wise linear functions

Bunn and Day [9], Day and Bunn [13] conjecture a piece-wise linear supply function for each equal-size bin i for a particular half-hour period in the following day,

$$p = \frac{up_i - lp_i}{c_i} \cdot q + \left(lp_i - \frac{up_i - lp_i}{c_i} \cdot sc_i \right)$$

for prices ranging from lp_i to up_i, a capacity of c_i allocated to the bin and a starting capacity for the bin of sc_i. The capacity and price ranges of this supply function are thus assumed to be discrete. While this assumption is realistic for capacity (e.g. for a generator who has several units which may be offered to the market), the price is in fact a continuous variable and discretisation is a modelling simplification that enables a discrete optimisation routine to be performed.

The price, p is a function of the quantity q in each of the $i = 1, \ldots, N$ bins for this particular supplier. It is possible that bins do have zero capacity allocated to them, such that we have a vertical line (jump) extended over a particular bin's price range at a single point on the capacity axis. In this model it has been assumed that each firm in the pool has the same discretised price range, such that the offer of supply functions to the pool simply implies an allocation of generating quantities to the bins by each bidder.

From the above it can be seen that pricing takes the form of allocating sets of generation to the desired price bins such that c_i is allocated to each (equally-sized) price bin i. Moreover, different generators are assumed to have the same equal size. The more sets of capacity allocated to each bin, the flatter the linear slope of the section of the supply curve in a particular bin will be. With fewer sets, the curve becomes steeper until the case

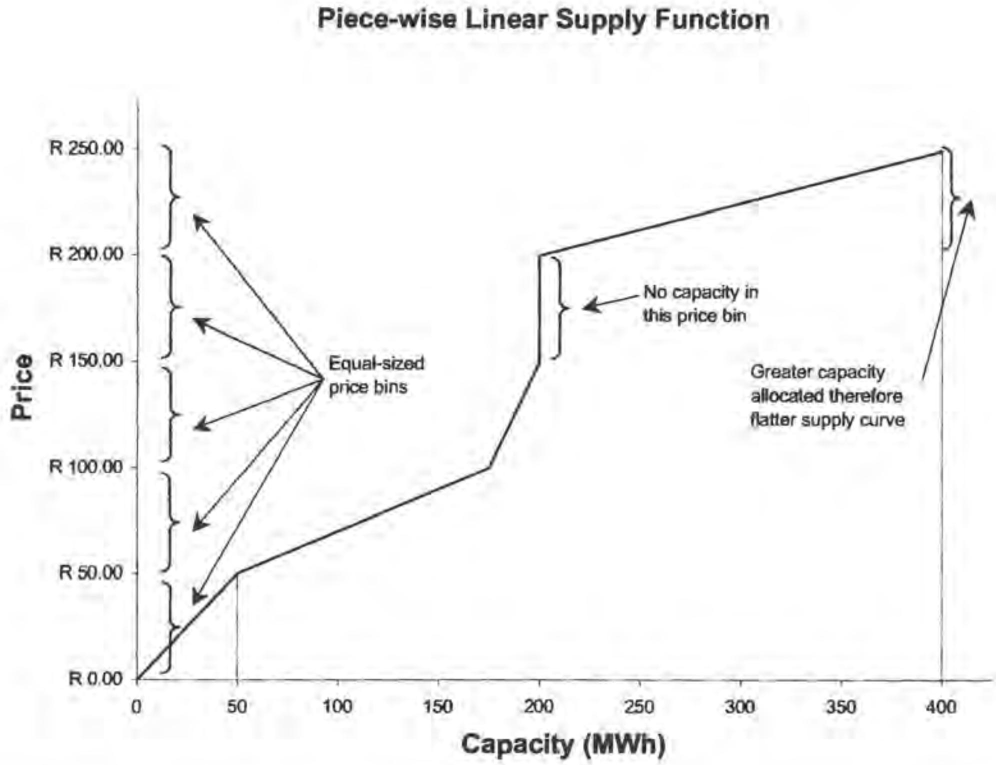


Figure 3.1: A piece-wise linear supply function for a particular period in the day

of zero sets where we have a jump in the supply function over that bin. The graphical representation of such a supply function model is a curve as shown in Figure 3.1.

A day-ahead notification to the operator of (effectively) the number of capacity sets the company wishes to allocate to each of the fixed price bins takes place. This supply curve, together with a downward-sloping (possibly *linear*) demand curve — indicating a potential allowance for demand-side response to prices — allows the evaluation of system price, where the aggregated supply of M suppliers intersects this demand curve. In the model the evaluation involves a search for the marginal price bin, allocating the proportion of that bin's capacity to the relevant offering Gencos, and allocating the full remaining capacity of the lower bins to all suppliers who offered capacity in these ranges.

The choice of supply function by each Genco does not represent an equilibrium approach, but rather one of forming conjectures of opponents actions and optimising their profits as a response. The task is made easier when the form of the supply function is less restrictive (with regard to symmetry of firm-size and in being a continuous function). Profit from the pool is added to the income from the hedging contracts or financial swap arrangements, and this function is optimised over the 48 half-hour periods of the auction:

Mathematically, for company k, we optimise:

$$\sum_{t=1}^{48} gc_{k,t} \cdot MCP_t - C(gc_{k,t}) - MCP_t \cdot x_{k,t}$$

where the final term represents the *variable* part of the net income from a CFD/swap agreement and.

MCP_t	=	Market clearing price at time t
$gc_{k,t}$	=	Total generating capacity for company k in time t
$C(gc_{k,t})$	=	Total cost of generating $gc_{k,t}$
$x_{k,t}$	=	Contract volume for company k at time t

(The term $fp_{k,t}x_{k,t}$, represents the fixed income received from the forward contract, where $fp_{k,t}$ is the price received per unit contract volume, according to the forward agreement for company k at time t. It would have formed part of the original profit equation, but has been excluded as it is a constant in the optimisation routine.)

The routine involves an exhaustive search of at most $N \cdot (N-1)$ choices for the best bin in which to allocate the capacity at each iteration, in effect choosing to move each capacity set from its existing bin to the one which produces the biggest increase in profit. Though this routine appears to optimise the above objective function with respect to the $gc_{k,t}$'s, it is actually modelling competition among the firms as sets are moved between bins. There is no strategic selection of quantity — only price is important. Also, we have a single auction rather than a repeated game. The result of the routine gives a baseline benchmark for competition assessment without looking at collusion.

3.3.5 Linear supply functions

An example of the use of a linear supply function for a supplier's (j's) marginal supply price is proposed in reference [53]. The general model is essentially descriptive of participant behaviour, as the authors have stressed the importance of market structure and achieving fair competition in pool-type markets.

The attempt at describing participant behaviour however, necessitated the establishment of a Monte Carlo method for solving the optimal offer/bid strategy for Genco's and large consumers. Consequently, the stochastic optimisation model is claimed to have normative qualities. The reality however, is that the model is probably more valuable in a descriptive sense by virtue of its over-parameterisation. A system-wide model (with multiple parameters) does not appear to transfer well into the solution of an individual participant's optimal strategy, as the goals are conflicting and many parameters are required to model the behaviour of rival firms. Perhaps the goals would conflict less, and the number of parameters would be justifiable, in a system with only a couple of large Genco's and consumers. In a simpler system, the descriptive and normative qualities would both be more valuable. The model of the supply function used is illustrated here and the Monte Carlo optimisation described in Section 3.4. The paper is valuable for its inclusion of demand-side bidding and demonstrating the impact of unsymmetrical information.

Their linear supply function is of the form

$$G_j(P_j) = \alpha_j + \beta_j Pj$$

where P_j is the active power output, and (α_j, β_j) are the bidding coefficients for the j'th supplier which may follow some distribution e.g. [1]

$$(\alpha_j, \beta_j) \sim N\left(\mu_j^{(\alpha)}, \mu_j^{(\beta)}, \sigma_j^{(\alpha)}, \sigma_j^{(\beta)}, \rho_j\right)$$

The demand function (if required) for large consumer (l) is analogously defined, though it has a negative slope. The marginal demand price equals

$$L_l(W_l) = \phi_l - \varphi_l W_l$$

where W_l is the active power load, and (ϕ_l, φ_l) are the bidding coefficients which may follow some prespecified distribution. The remaining demand is treated as an aggregate load that may be assumed to be either elastic or inelastic to the resultant SMP.

The clearing mechanism is such that the SO allocates values for all the P_j's and W_l's according to:

1. the supply/demand coefficients submitted by each producer/large consumer and,
2. their individual constraints and the total system demand.

Transmission constraints are not considered in this analysis. The resultant SMP is the price that clears all demand under the formulation. The solution of the problem can be examined from the two viewpoints:

1. from that of the SO, who allocates load to market participants based on received bidding coefficients and,
2. from that of a particular supplier/large consumer trying to maximise their profits by simulating the behaviour of all the other participants, choosing their own profit-maximising bidding coefficients, and thereby determining *their* expected SMP's and load allocations.

It is worth noting here that none of the participants are *explicitly* treated as price-takers or price-setters. The resultant system clearing price the benefit measure under various scenarios of market structure. The actual price-formation for this research paper was described in Section 3.2 [p. 72].

The same authors extend their supply function analysis in a later paper [54] to allow bids for an entire 24 hour day. They use the same supply function described above with the

[1] The authors say that these coefficients are non-negative contradicting the use of a Normal distribution which implies that negative values are possible. Perhaps a lognormal distribution would have been more appropriate (although the approximation is adequate if the mean is more than three standard deviations above 0).

addition of an index for time, so that in effect, 24 linear supply functions are offered in the day-ahead market. The SMP will obviously now differ for each hour and will depend on the clearing process for the relevant hour. No demand functions are considered in the formulation, and loads are forecast for each hour by the SO and made known to all suppliers. The single-part linear supply function that is submitted for each hour internalises all of the unit start-up, no-load and other fixed or variable costs (including energy costs), and represents the *tranches* of energy offered for each price. As in the first paper, the authors demonstrate the methods by which the SO clears the market using the bidding coefficients of all the suppliers, as well as the methods by which individual suppliers should choose their optimal bidding coefficients.

It is worth emphasising that a system-wide model of this kind has large array of parameters, and scepticism is appropriate when relying too heavily on the meaning of the actual outputs. Examples include the parameterisations of the distributions that are required both for and by each supplier. The number of parameters is substantial and leaves room for compounded errors of estimation in a model which aims to be complete. Using this model as a tool for assessing the appropriateness of a market design would be an onerous task especially from a computational perspective. Nevertheless it could be useful in a small market with similar structure to the California day-ahead market that is assumed in the paper.

3.3.6 Offers based on cost functions

In reference [25], offers submitted by generators are based on the coefficients of their individual quadratic cost functions. The resultant profit function is equal to

$$\max f(S,\lambda) = \lambda S - (CS^2 + BS + A)$$

where S is the scheduled output of the generator, C, B, A are the cost coefficients, λ is the spot price and S and λ are explicit functions of K, S and λ determined by optimal power flow methods. K is the generator's optimal bid chosen for C while keeping A and B constant. Given a set of K's, each determined for a particular generator, an optimal bid for the generator under analysis is then derived from the above equation using first and second-order conditions. The purpose of this model is detailed later in this chapter [p. 84].

3.3.7 Two-tranche offers

The type of supply function used in the *COSMEE* model of [39] is a two block offer, the first block being the minimum stable load, and the second being the controllable load from this lower value to the maximum possible power output. The price associated with the minimum stable load has no lower bound, as units may wish to operate at a loss in order to avoid start-up, assuming their potential loss is less than the cost of start-up. Thermal units may be dispatched throughout the day, or only for peak periods, with the two different strategies resulting in different cost allocations. Thus units that operate the whole day have a lower bound equal to variable cost plus no-load cost, and units that operate in peak hours have their lower bound equal to variable cost plus start-up cost. Start-up costs are allocated to dispatch hours (though other allocations are possible). Prices may decrease with each model iteration until the lower bound (which depends on cost data).

A different consideration of the two-tranche function is demonstrated in [11] (see p. 73). Quantities are first chosen to maximise expected profits given the technical constraints of the production unit and the company's conjectures for the probability distribution of SMP's. In a separate routine, quantities are divided into the appropriate blocks and offers attached to these blocks using a confidence interval, resulting in the optimal bidding rule for the company in the day-ahead market. The type of hourly supply function is thus a two-tranche function with prices at either the lower or upper confidence intervals for the SMP forecast. The allocation of quantities to the two price bins depends on the optimal schedule of the generating company, which is in turn dependent on the price forecast distribution, the operational constraints, and the cost function. The construction of this supply function is described in more detail in Section 3.4.

3.3.8 Summary

In this section, the electricity supply function has been defined and a range of curve-types have been shown to be used and implemented by various researchers. A few of the selected implementations have been described in detail. The type of offer curve will depend on the type of market and the associated rules. Certain curves have been specifically designed by researchers to model trading strategies; they have been designed according to each model's goals (e.g. determining the extent of market power or analysing Genco behaviour and quantifying pool benefits (or costs), or determining optimal offers).

The actual construction of supply functions ranges from simple price offers for a fixed quantity of production, to linear functions with slope and intercepts determined for optimal strategy, to continuous functions (which simplify reality), to realistic but intractable step/tranche functions, and to piece-wise linear functions for particular auction-types. Some of these functions have been adapted to similar demand functions in order to include demand-side bidding in a system-wide model.

The type of supply functions directly influence the way in which prices are formed in power pools and auction markets. They can be used by researchers to investigate market equilibria, to determine optimal offer strategies for individual Genco's, or for quantifying pool benefits. Supply functions summarise the type of market design, so altering their form in a model of electricity markets can be of descriptive use, such that the impact of alternative scenarios of market designs can be assessed. Descriptive exploration has been accomplished with varying degrees of detail or simplicity, and with varying degrees of success.

3.4 Optimal Bidding Strategy

Many methods for addressing the strategic bidding problem have been reported on in the literature. Examples include dynamic programming, analytical formulation, heuristics, simple bidding models, and game theoretic/equilibrium approaches. Further methods include ordinal optimisation, Lagrangian relaxation, stochastic optimisation with Monte Carlo simulation and Markov decision processes. Evolutionary and artificial intelligence techniques such as genetic algorithms, genetic programming and finite state automata are all relevant in the framework of multi-round auction markets which are not very common.

3.4.1 Considerations for an optimal strategy and an MCDM method

He and Song [24] provide a good summary of the important factors that ought to be considered when deciding on an optimal offering strategy. The question of how generators can produce optimal offers is considered, taking into account cost-recovery, physical constraints, and market price fluctuation (i.e. competitor behaviour). Once again the special characteristics of the energy commodity are highlighted, namely:

- Non-storability.
- Constraints — on the generator, system or network, as well as regulatory and commercial constraints.

The consequence of these characteristics motivates the need for a sophisticated electricity auction market. Again, differences in the type of auction are documented between various countries and markets (see Section 2.1 in Chapter 2).

Regardless of the type of pricing mechanism, effective bidding strategies must consider:

1. Generator's physical, financial and commercial constraints.
2. Fluctuating market prices.
3. Competitor bidding decisions and potential coalitions.

The actual decision-support system for offers which is proposed in this paper consists of three modules:

1. A (LMP) simulator that creates LMP's on estimates of competitors' bids, forecasted demands and congestion information supplied by the SO. The LMP's feed into the second module.
2. A self-scheduling unit commitment model. Here optimal offers are produced based on forecasts of spot prices, loads, transmission, and any other information posted by the SO, together with the generation units' specific operational constraints. The result is an aggregated offer curve submitted by each Genco on behalf of its units.

3. The multiple-criteria decision-making (MCDM) system. The MCDM model is actually a bicriteria system with the two criteria being the payoff from production and the percentage of market share relative to the entire system's forecasted load. The latter criterion is necessary since a greater percentage market share held by the Genco means that it is endowed with more market power in the market.

A single-round bid with discriminatory pricing is assumed. The model allows individual Genco's to produce optimal day-ahead offers taking into account physical constraints and competitor offers, but not commercial constraints or coalitions. Demand-side bidding is not included but can be should the type of market necessitate it.

The model has the following key features:

1. The optimal offers take into account all costs, including start-up, shutdown and no-load, and the aggregated offer strategy of the competitors (other Genco's are effectively treated as a single competing firm in the model). Commercial constraints and potential coalitions are therefore not considered.

2. A LMP simulator taking into account competitor behaviour and network security constraints.

3. A MCDM method for finding the global optimal decision.

The final decision process is as follows:

1. Consider various scenarios of the competitors' offering strategies;

2. Obtain the best decision with respect to each scenario i.e. generate basic loads for the time period in question, obtain j perturbations of these loads, then apply the LMP simulator at each node, taking note of the node of our generator (k). Run the unit commitment module to get outputs and scheduling decisions for each set of LMP's and generation demands, then build the aggregated generation offer curve for each time period;

3. Calculate the payoff and market share with respect to each decision and;

4. Use MCDM to determine the best decision from all those derived.

Results of a numerical example show that higher market share does not always mean higher payoff, confirming the need to keep it as separate criterion from profit. The priority for the two criteria will depend on the experience of the Genco, as well as its preferences. Simulated LMP's with associated probabilities reflect the system security constraint costs as well as rivals' offer strategies. The inclusion of MCDM techniques is a contribution of this paper to bidding decision methodology. Areas for further research are the inclusion of both commercial constraints and coalitions among Gencos' in the unit commitment model.

3.4.2 Bid (Offer) Sensitivity

In reference [25], a strategy for deriving the optimal offer for an individual generator in the auction market is derived. The strategy is based on the concept of bid sensitivities which can be defined as the first-order derivatives of nodal prices, generation outputs, unit profits and transmission line power (with respect to each unit's offer). The derived offers are optimal with respect to profit, but also with respect to system constraints. The work here is in keeping with the current ideology in deregulated markets:

> maximising social welfare and minimising loopholes for exploitation of market power by participants through improved market management rules.

The authors identify the following main factors affecting decision-making for bidding strategies of individual generators:

- Forecast system demand.
- Generation variable, start-up, no-load and other costs.
- Other competitors' decisions (which represent the greatest degree of uncertainty) and how these decisions interact.
- Contracts and derivatives.

They then mention a plethora of optimisation techniques that have been employed by other researchers in solving the bidding problem: mixed integer programming, dynamic programming, fuzzy numbers, ordinal optimisation, Benders partition algorithm, closed-form ISO solutions with Lagrangian relaxation, genetic programming, Markov decision processes, intelligent negotiation agents, etc. In contrast to these methods, this paper employs an optimisation approach using bid sensitivities.

Some of the assumptions made are:

- The generator under consideration has *basic knowledge* of other competitors' bids.
- Bidding strategies are based on multi-round bidding process.
- Demand-side bidding is ignored.
- The market is pool-based but with no bilateral contracts.

Four types of bid sensitivities are derived:

1. bid-price sensitivities,
2. bid-output sensitivities,
3. bid-profit sensitivities,

4. and bid-line flow sensitivities.

The above sensitivities are invaluable to individual suppliers for choosing partners for potential coalition, and strategising to impair other rivals' benefits and for the market operator/regulator in preventing gaming among individual suppliers and thus mitigating the impact of their market power.

The bid-sensitivities are used by the individual generator to optimise profit by choosing the optimal cost coefficient. The optimisation algorithm is applied in a multi-round bid, each generator maximising its profit in each round until a Nash Equilibrium is reached (i.e the equilibrium is valid if each competitor has an optimal strategy given other competitors have chosen equilibrium strategies.)

The conclusions of this paper are that a liberalised market in fact reduces social welfare under the given assumptions. Bidding sensitivities have been identified as valuable information. Further work is needed on how to offer when participants engage in gaming and exercise market power (non-rational behaviour). Also the paper only considers a single period market without consideration of intertemporal constraints such as unit commitment.

3.4.3 Optimal strategy through simulation and iterative equilibrium

The type of offer optimisation used by Otero-Novas et al. [39] is different depending on whether units are price-takers (uncoordinated simulation) or price-setters (coordinated simulation):

Price-takers: The quantities are chosen at each iteration are dependent on the SMP at the previous iteration through a mixed integer programming routine in which the total profits over all hours is maximised. The routine differs between thermal and hydro units, the latter opting for a more profitable 'peak-shaving' strategy. Subsequent to determination of quantities, price may be modified by a fixed decrement *if* it is above the SMP from the previous iteration and *if* the reduction does not transgress the lower bound imposed by costs; otherwise no modification of price takes place for the unit. Price-takers will strive for maximum production as they have no effect on the wholesale price.

Price-setters: In an oligopoly, modification of prices is less simple as firms may accept lower production in order to raise the prices they receive. Here quantities are chosen so that the sum of each firm's production units' profits are optimised subject to similar constraints as above, but with the additional caveat that total production is at the optimum generation level (from a first order Cournot equilibrium). Firms who are fully dispatched make no modification to their offer price. Those who are not maintain the same price or reduce their prices, and therefore reduce the profits of other inframarginal competitors. The amount by which profits are adjusted will depend on the amount of dispatched production.

The model is simplified in that competition stranded costs and required national coal consumption are ignored. Nuclear units have to be considered as 'must run' and demand is fixed and inelastic for each hour.

3.4.4 An optimal strategy for a price-taker

An example of a framework for obtaining the optimal bidding strategy for a price-taker producer is described in [11]. The optimal strategy is achieved (in three steps) by specifying a probability density function (pdf) for the next day's hourly SMP's, then formulating a self-scheduling profit maximisation problem and solving it to obtain a simple yet informed bidding rule. A realistic case study is conducted and the results discussed.

The study is conducted with the following contextual assumptions:

1. The Genco under consideration is thermal production unit.
2. The optimal strategy for single price-taking generator is required.
3. A pool-based market which is not necessarily perfectly competitive.
4. Market-clearing takes place one day in advance on an hourly basis.
5. Producers (consumers) submit hourly supply (demand) curves consisting of tranches of energy at their corresponding prices.
6. Generators offer all their power in one or several tranches at increasing prices (chosen through the profit-maximisation routine).
7. An inherently high price-uncertainty — an implemented price-forecasting tool is used by generators for calculating the pdf's of the next-day's hourly SMP's.
8. All generators who offer below or at the SMP receive that price for their energy, and all consumers whose bids are accepted pay this common amount.

Given the lognormal distribution for price described in Section 3.2, the quantities to generate each hour are determined by maximising the expected profits (revenues less costs) subject to the operating constraints (power limits, ramp-rate constraints, minimum up and down-time) and according to the expected SMP in each time period. The crucial assumption implied here is that the quantity chosen has no impact on the price distribution i.e. the generator is a price-taker. The maximisation problem is linear and mixed-integer and solved accordingly. No mention is made of offer prices up to this stage, only the optimum self-scheduling quantities have been chosen. A particular omission is with regard to the presence of any quantities of hedged sales that could influence the production decision. The authors have used the expected values of the λ_t's (defined on p. 73) to avoid the use of a complicated price scenario approach.

The profit achieved under the self-scheduled production for each hour becomes a random variable which is a simple linear transformation of λ_t, namely $B_t = \lambda_t p_t^* - c_t^*$ where

p_t^* and c_t^* are the optimal quantity and cost respectively, for each hour t. The means and variances of the B_t's are thus easily calculated. The variance of the daily profit will therefore be a covariance matrix containing off-diagonal elements that indicate the extent of the correlation between SMP's across various hours of the day. This argument relies on the actual SMP falling within the specified confidence interval.

Using the quantities from the self-scheduling problem, a proposed offering strategy for each hour is derived as follows:

1. If $p_t^* = 0$ then the maximum output, $\bar{P}$, is offered in a single tranche at the upper confidence limit for price. Specifying a level $p_t^* = 0$ guarantees, with the specified level of confidence, that no power is accepted.

2. If $p_t^* = \bar{P}$ then a single tranche of power, $\bar{P}$, is offered at the lower confidence limit for price. The price level then guarantees that all the power accepted with the chosen level of confidence.

3. If p_t^* is at some level between 0 and $\bar{P}$ then two blocks are offered: p_t^* at the lower confidence limit and $\bar{P} - p_t^*$ at the upper limit, guaranteeing that p_t^* is accepted with the desired level of confidence.

The method thus proposes that a supply function is submitted in such a manner that the desired level of output is achieved subject to the conjectures about the probability distribution of the SMP; it implies that we have a maximum of two blocks of energy. Should the market rules require more, the three cases above could be modified, though the authors do not suggest how the modification can be done. A non-convex cost curve is treated in the analysis, though a convex offer curve is required in reality.

An actual case study for a particular trading day is demonstrated in which the above techniques are implemented and compared against the case where one has perfect knowledge of the price outcomes. The difference in profits is negligible for the particular day, and the desired schedule becomes the actual one. Conclusions are therefore favourable for this case. No mention however, is made of the potential influence of hedging arrangements or their effect on the company's strategy, albeit an important consideration in modern markets. No mention of any extension to the medium term is mentioned or considered. Although the authors derive the standard deviations of the prospective profits, they make no mention of the potential of these values to be integrated into a wider risk management strategy.

3.4.5 A Monte Carlo approach

In reference [53] a method is shown whereby the Genco can solve their stochastic profit-maximising problem using a Monte Carlo approach. In this approach, the bidding co-efficients of the other participants are treated as random variables from distributions determined through the statistical analysis of historical data. The result of the optimisation problem will give the coefficients of the linear supply function that the participant should submit in order to maximise profits. The profit function that must be maximised for the j'th supplier is

$$F(\alpha_j, \beta_j) = RP_j - C_j P_j$$

where R is the SMP for the particular hour and C_j is the production cost coefficient. An analogous function is maximised if the participant is a large consumer,

$$H(\phi_l, \varphi_l) = B_l(W_l) - RW_l$$

where $B_l(W_l)$ is the benefit function of the consumer.

The optimisation algorithm is carried out by fixing the first coefficient (e.g. α_j) and searching for the optimal value of the second coefficient (say β_j) using the golden section search method and subject to the sampled values of the other participants' coefficients and all constraints (except transmission). This process is repeated for each iteration. The final value for the second coefficient is the average of the optimal values from each iteration. Similarly one could fix the second coefficient and search for the optimal value of the first. It is important to note that any chosen value for the second coefficient must be chosen within the scope imposed by the cost function to avoid offering a function that will result in a loss. The authors circumvent this issue in their numerical example by searching for the second coefficient within a range determined with reference to the cost function coefficients. No explicit treatment for a general cost function is described in this formulation, other than the fact that the parameters for the pdf's of α_j and β_j are chosen to reflect the underlying cost exposure. In the example, the cost function is quadratic, hence its first derivative is linear and can be compared with the linear supply function when obtaining the appropriate bounds for the coefficients.

A numerical example with six generators and two large consumers with quadratic production cost and demand benefit functions is given. Two experiments are performed:

1. **Symmetrical information.** Since there is insufficient historical data to parameterise the pdf's of the bidding coefficients, parameters are chosen with reference to the quadratic cost function such that offers are submitted at 20% above the marginal cost function (i.e. 20% above the derivative of the quadratic cost functions), and such that four standard deviations above and below the μ_j's is equivalent to 15% above and below the MC. The correlation coefficient, ρ_j [see p. 79] is chosen to be slightly negative to reflect that a supplier's decision of increasing one of the bidding coefficients will lead to their reducing the other coefficient (in a mature market). A similar choice of parameters is performed for the pdf's of the large consumers. It is a system-wide simulation, so each participant determines their optimal supply/demand function through simulating their (randomly sampled) rivals' supply/demand functions. The outputs are each participants optimal bid coefficients. When given the coeffiecients, the SO determines the outputs for each supplier, demands for each consumer (including the aggregate one), and the resultant SMP which clears the market.
2. **Asymmetrical information.** In this case, the experiment is conducted such that some participants make better estimates than others. Such a scenario is imitated by assuming that the second supplier overestimates his rivals' parameters. The

results show that their share of the market — and the resultant profit — decreases, and the SMP increases when compared to the scenario of symmetrical information. The large consumers' benefits are also reduced owing to the increased SMP.

The above research therefore proves useful for providing a method for market participants to optimise their bids in an auction-type market, assuming they all submit linear supply/demand functions. It also demonstrates the effect of a participant having less accurate information on the benefits they can achieve and also on the social welfare of the system (i.e. the SMP). What has not been considered however, is the effect of derivatives markets on the bidding strategies. A further drawback of this exercise is that modelling the entire system from the point of view of each participant as well as that of the SO, is in reality a very complex and unwieldy task. The methods employed necessarily imply that levels of information are very high and that the market is mature. The methods do not propose strategies for small suppliers/large consumers who have no influence on the market; no explicit formulation is provided for the inclusion of price-takers in the market. The SMP is directly determined from the bidding coefficients of all the participants and has an analytical solution.

3.4.6 Day-ahead markets and marginal units

Two different bidding schemes are suggested for each hour's offer in [54] and an overall offering strategy is then developed based on these two schemes. The two strategies are described using stochastic optimisation models and a genetic-algorithm-based method is described for developing an overall offer strategy for the day-ahead market.

Maximum hourly benefit is the strategy used for offering in each of the 24 hours of the daily schedule. The coefficients $\alpha_i^{(t)}$ and $\beta_i^{(t)}$ [p. 79] are chosen to maximise Genco profits based on their expected outputs and the SMP (both are determined with an allowance for competitor behaviour) for each hour, as well as the cost function (which also depends on their expected output for the hour). The constraints are that expected outputs must be within the Genco's output limits.

Minimum stable output is the alternative strategy used in the hours when the unit cannot be dispatched as recommended by maximum hourly benefit strategy above. In this strategy, a loss results and the coefficients are chosen such that the expected output will be as close as possible, or equal to, the minimum output for the hour.

As in a previous paper [53], suppliers submit coefficients of their linear supply function, although in this case, one set for each hour of the day ahead is submitted, subject to expectations about how rivals will bid. Unlike in their previous paper, suppliers are now additionally required to make decisions on unit commitment before choosing their supply function coefficients. The problem is therefore two-fold and a genetic algorithm solves the unit's commitment/decommitment status in each hour and the offering strategies for those hours that the unit is in operation.

In solving for the optimal bidding coefficients, the maximum-hourly-benefit strategy is employed, and for all those hours in which no production is scheduled using this method, the minimum-stable-output method must be employed. Since it is a single-part-bid market, the suppliers themselves must decide on unit commitment. The authors suggests a genetic algorithm for modelling this decision. The genetic algorithm takes into account the minimum up and down time, and the possibilities of 'banking' a unit (i.e. keeping it running without generating), or allowing it to cool down and then incurring associated start-up costs.

A numerical example similar to the one in [53] is presented though falls short of doing the example with asymmetrical information.

3.4.7 Unknown demand

A study of strategies for offering generation in a pool-type market when demand is unknown has been proposed in [3]. The optimal policy for a generator is derived hence giving insights into the type of behaviour that may be observed in an electricity market. A fundamental difference in the approach is that no probability distribution for demand is needed. The authors show that in the situation of uncertain but inelastic demand (e.g. in the short term in most markets), the optimal supply function response exists when:

1. Marginal costs are non-decreasing for all generators.

2. The combined offers of all the generators are log-concave when price is a function of quantity offered.

The cost/supply functions need not be smooth. The key specifications of the analysis are:

- A pool market with a central dispatch and pricing mechanism (as opposed to a decentralised, bilateral market such as the California one).

- Two-way CFD's (defined on p. 49) are used to hedge exposure to the SMP, with the contracts being separate from the market mechanism.

- Supply curves consists of (possibly discontinuous) non-decreasing offer tranches.

- SMP is determined so as to satisfy demand at least possible cost (at the appropriate locational nodes if necessary) and taking into account transmission constraints. The SMP is thus determined to minimise the total revealed cost of power delivery.

- An oligopoly market situation — in particular the authors consider a duopoly though they indicate one of the two players could be an amalgam representing the remaining contingent of market participants.

Assuming smooth supply functions, conditions are derived for when a single supply function represents the optimal response to offers by other participants over a range of demands. In practice, deriving the conditions would entail approximating the supply functions of the competitors.

Bounds are derived for the revenue lost (relative to the case of exact supply functions) when the Genco uses approximations for both their own and their competitor's supply functions. The existence of symmetric supply function equilibria is also demonstrated.

3.4.8 A marginal cost strategy

Very often, a firm's minimum offer will be equal to its marginal cost, and in some cases it may be the most profitable. The idea is considered in the case of a price-taker in reference [43] where the supplier must maximise his expected profit, $E(\Pi)$ where

$$E(\Pi) = \phi(\rho P_g - C_g(P_g)) + (1-\phi)(-C_0)$$

and

$$\begin{aligned} P_g &= \text{generation level} \\ C_g(P_g) &= \text{cost of generation} \\ C_0 &= \text{cost of restarting the unit after an unanticipated outage} \\ \phi &= \text{probability of selling output after bid acceptance} \\ \rho &= \text{market price} \\ \Pi &= \text{profit} \end{aligned}$$

Taking the first derivative of the above profit equation with respect to P_g and solving for ρ permits an analysis of whether offers are set above or below marginal costs (depending on the probability of actually being available to supply the market). The goals of this paper are to stress the importance of knowledge of MC's for developing an offer strategy. The same idea is implicit in many of the other approaches above.

3.4.9 Summary

It has been demonstrated that there are few treatments of the optimal offer strategy that are common among various researchers. Tools have been implemented from all but a few of the operations researcher's wares. Though appearing to tackle the question of how to achieve the optimal supply in a competitive market, much of the work actually uses the optimal strategy as a means of predicting Genco behaviour in response to competition from rival firms. Techniques used include advanced stochastic optimisation routines, Monte Carlo simulation, equilibrium models, consideration of multiple criteria, mathematical analyses of algebraic supply functions, and genetic algorithms among others.

The purposes of the optimisation are in accordance with those mentioned in Sections 3.2 and 3.3 above. In title, many of the papers aim to solve the optimal offer strategy for

Genco's in pool-type markets, however the implication is often more subtle. There are two interrelated analyses that often characterise research of this nature. In most cases the descriptive and normative models (most of the formulations exhibit qualities of both) lead to one or other prescriptive analysis. A brief description of the uses of normative and descriptive models follows.

Normative models for market participants

Normative models aim to solve the optimal offer strategy for a Genco under various market conditions, degrees of uncertainty, market designs and/or information scenarios. The models will aim to capture the uncertainties, and the cost scenario of the competitors together with their price-taking or price-setting ability. The outputs of such models will include one or more of the following, and may or may not include measures of robustness to scenarios that define the uncertainties:

- optimal schedules for production.
- offer prices and/or quantities.
- quantities of futures contracts to be purchased.
- optimal portfolios of energy contracts.
- distributions of profit outcomes.

Descriptive models of participant behaviour

Descriptive models formulate optimal strategies in order to mimic the behaviour of participants acting in a profit-maximising manner, however the effects of their actions on price formation will be target items of interest. Such formulations may also be of normative value to individual participants, who wish to understand their market power and devise their strategies for trade and risk management accordingly.

3.5 Concluding remarks

This chapter has concentrated on that part of power system economics which relates directly to the trading strategies adopted by Genco's. In so doing, it has identified the three interrelated concepts of price formation, supply functions and optimal strategy. Nearly all of the literature that was sourced for this dissertation, and which analysed trading strategies (whatever the motivation for the analyses and the types of market were), dealt in some manner with these three concepts. The scope for additional consolidation of the research is somewhat limited due to the wealth of variety between market designs, research aims and techniques for analysis.

Most researchers have engaged at least some coverage of system and technical constraints in their analyses of strategies, drawing on knowledge of systems previously researched in the 'least-cost' era of electricity production. However, they have had to drastically modify these approaches for the new market conditions. The main problem seems to be that information is no longer fully disclosed or available, and the Genco's are exposed to additional uncertainties and a greater diversity of risks, which were not previously encountered. Such uncertainties relate to:

- System demand (and the fact that it may now be elastic) and the presence (or otherwise) of demand-side bidding.
- Competitor behaviour and the ability of the rival firms to influence prices in concentrated markets. Competition is related to study of price uncertainty itself.
- The existence (or otherwise) of derivatives and bilateral contracts and the additional uncertainties that accompany them. In the case of derivatives, the related strategic trading analyses are relatively young, and have mostly dealt with the simpler, fixed-volume swap contracts/CFD's for hedging price.
- A dynamic regulatory environment that is constantly under the watchful eye of national regulators and the researchers themselves, with frequent and drastic alterations in design always looming.
- The relationships between risk and bidding strategies and between contract evaluation and scheduling of physical resources.
- The vast array of modelling techniques have demonstrated the more subtle risk of excluding too much detail (e.g. by ignoring the effects of one or more of the four uncertainties above in the model assumptions), or incorporating too much detail at the expense of model simplicity, and attempting to 'over-model'.

One of the problems encountered lies in the lack of consistency between approaches, and there appears to be no uniformly unique approach to systems thinking for electricity trade. Therefore while models have attempted to solve complex problems (e.g finding an optimal strategy), they seem to get bogged down in the intricacies of the market design and as a whole they demonstrate a lack of conviction in choosing from a wide range of mathematical tools. The result is a general lack of consensus on the most appropriate tools for modelling competitive electricity markets. An additional point is that models which appear to be solving the offer strategy problem, are often tools for analysing market power and comparing oligopolies with perfectly competitive markets. In their favour, they have succeeded in modelling price formation when comparing the historical realisations to the modelled ones, and developed the technique of supply function analysis and its links to other techniques. A direct simulation approach appears to be the most adept at handling adaptive and evolutionary learning though care should be taken not to try and model too much detail.

In summary, the research in this chapter has proven useful for identifying the key characteristics that ought to be considered when developing a model of generator behaviour. As far as possible, they are the characteristics that will be considered for the development of the simulation model (and for the analyses that follow it) in the remainder of this dissertation.

Chapter 4

The Eskom Trading Environment

4.1 Introduction

This chapter briefly summarises the type of environment that exists in the context of the South African electricity market. Some of the history of the development of the market was obtained from publications of the National Energy Regulator (NER), though the summary of the workings of the Eskom Power Pool was obtained from days spent interacting with a trader and observing his actions on behalf of the Peaking cluster of Eskom's generator pool. Further information and a limited amount of data for one of the production units were provided by management of the cluster and by a corporate consultant who represents the Eskom Generation Production and Sales division.

The current state of deregulation in South Africa and the Eskom Power Pool is described in order to provide a foundation for the model construction that commences in the next chapter. At the time of writing, and far as could be ascertained, there has been little to no research conducted which gives particular attention to the South African power market, although a wealth of such research could be sourced for other national markets. Examples include England and Wales, California, Scandinavia, Spanish and New Zealand among others. Though some of the research has a focus that is unique to a particular national electricity sector, the areas of enquiry and methods of investigation are universal, save for the specifics of market design, auction-type and level of deregulation.

Firstly, the current state of restructuring of the South African power market is described, as well as the reasons for the changes (which echoes the motivation for changes in other countries). For political reasons the liberalisation has failed to gather as much momentum as it has in more developed countries and some reasons for the delays are described in the next section. As a result, much of the development that has taken place in the developed markets with regard to energy derivatives trading has not yet emerged in South Africa, though the initial steps toward commoditisation of electricity have taken place. An illustration of this fact is that although there is some internal trading of CFD's, the trades of actual electricity derivatives are so far largely OTC. Moreover, as a developing country which is exempt from the Kyoto Protocol, South African thermal generators are not yet as concerned with emissions trading arrangements. Preoccupation with emissions restrictions indicates a foremost concern in many developed countries. The model formulation described in Chapter 5 does not therefore reflect such developments, though a model is envisaged that is amenable to such adaptation should the restructure that has been outlined by the NER progress as planned.

In the third section, the Eskom Power Pool (EPP), its constituents, its structure and the current prevailing trading arrangements are described, and finally, a motivation for the choice of the market entity to be modelled is outlined in section 4.4.

4.2 Restructuring of the South African Power Market

The needs for restructuring of the South African electricity sector were outlined in the government's Energy White Paper released in December 1998. The motivations, broadly speaking, were as follows:

- To introduce competition and therefore improve the efficiency and effectiveness of the electricity supply.
- Increased access by potential consumers to affordable energy services and improved energy governance.
- Attraction of foreign investment in the form of Independent Power Producers (IPP's) and stimulation of economic development.
- Management of energy-related environmental impacts and securing of energy supplies through diversity of primary energy sources.
- Facilitation of black economic empowerment and strategic equity participation.

The following ideas have characterised the changes undergone in the sector since Eskom's initial move away from its status as a fully state-owned enterprise:

- The government policy was ultimately to establish a fully privatised electricity enterprise (amid a pronounced and current opposition to this ideology outlined below).
- To date, corporatisation of Eskom has taken place with the formation of separate transmission, distribution and generation entities. The formation of the three entities is representative of the classic unbundling that has characterised most of the world's power markets.
- Hierarchical unbundling has also taken place leading to the formation of independent generating companies.
- Privatisation of generators is also going ahead.
- Up to now, indiscriminate access to the transmission grid continues. The grid remains a state-owned entity subject to operation by a separate company, the National Transmission Company (NTC).

- During the years 1996 to 1997 the Electricity Distribution Industry (EDI) was the focus of restructure with the formation of six new Regional Electricity Distributors (RED's).
- The NER controls and regulates the supply industry and licenses the generators.
- The establishment of the Southern African Power Pool (SAPP) has facilitated trading with other African countries.
- As far as types of trading are concerned, there has been a pursuit of a combined wholesale and retail market for electricity.
- Toward the end of 1999, Eskom commenced the changes by splitting its business into regulated (Eskom Holdings Limited) and non-regulated (Eskom Enterprises) business; the latter being responsible for business activities within and outside South Africa and the former converted to a public company with effect from July, 2002.
- Generation will continue to be part of Eskom for the present, but could be split into a number of subsidiaries with a holding company and privatisation partners could be brought on board. In 2003, power stations in Generation were paired together into seven clusters to prepare this sector for exposure to competition; flexibility was maintained in the arrangements to accommodate the various options in a changing supply industry.
- Transmission takes responsibility for the grid (worldwide this is more often than not the case) and is regulated such that all players have access to it even if the electricity is purchased from IPP's or the SADC (South African Development Community) pool.
- Distribution is to undergo the most radical change. The EDI is to be separated from Eskom and merged with the electricity departments of more than 400 municipalities to form the RED's. These RED's will be subsidiaries of the holding company until they can become independent. Their responsibility is the distribution of electricity and the collection of revenue.
- Eskom Enterprises is responsible for managing and developing all future Eskom subsidiaries whose business activities fall outside the three regulated activities. They will also be responsible for developing markets in the rest of Africa where Eskom will be able to sell its power utility expertise.

Plans are therefore in place for the complete restructuring and liberalisation of the SA electricity industry. The deadline set by the Minister of Public Enterprises for completion of the restructuring programme was originally set to 2004. As of September, 2004 these plans were under revision, the government's program to sell off Eskom assets has not gained sufficient momentum. In addition Eskom is currently building new generating plant to meet the ever-growing demand. The opposing ideology in response to the original plans argued that:

- The plans are socially infeasible as the goals of privatisation conflict with the government's (currently incomplete) plan of electricity provision to all rural and impoverished areas in the country. There will also be detrimental effects to the environment if full-scale privatisation takes place while coal is still the cheapest and most readily available fuel in the country. New independent power producers will have no incentive to utilise 'cleaner' forms of generating fuels.

- Eskom currently has excess generating capacity (so-called "sunken assets") that are an obstacle to the implementation of a completely free market commoditisation of electricity. The counter-argument to this point is that existing plant is currently ageing, and the excess capacity is a form of contingency for that. In depth market research would be required to assess whether the excess capacity is more of a long term feature in the market. Even with this excess capacity, there are fears of imminent shortages in the years ahead as a result of the current rapid growth in demand.

- Municipalities would potentially lose out on important revenue previously generated by electricity sales.

- Economic instability and the tight monetary policy of the government will not attract the investment money of foreign IPP's.

- The current nation-wide brain drain through the emigration of skilled professionals presents a lack of human resources to effectively control and manage the transition toward and the operation of a liberalised market.

Figure 4.1 shows the structure of the South African Electricity Market since unbundling.

4.3 The Eskom Power Pool

In Figure 4.2 the structure of the South African Power Market is outlined. The EPP is the market in which the generating clusters currently participate. Of the total electricity generation in South Africa, Eskom generates 95.9%, Local Government 1% and the private sector 3.1%. Some 87.3% of national generation is coal-fired , 5.1% is nuclear, 1.8% is hydro-electric, 4.7% pumped storage, with the remaining 1.1% coming from gas turbines (approximate figures for the 2003 calendar year).

Most of the national power trading happens in the above market. Each of the seven generation clusters submit offers for production of electricity on behalf of their individual generating units to the EPP. A generating unit refers to an individual power plant, and in the South African context refers to one of the following power plants (percentages based on output projection for 2001). The first two represent the so-called base-load generators:

- Nine Coal-fired Power Stations — roughly 92.4% of the national output.

- One Nuclear Power Station (Koeberg) — 6.4% of total output.

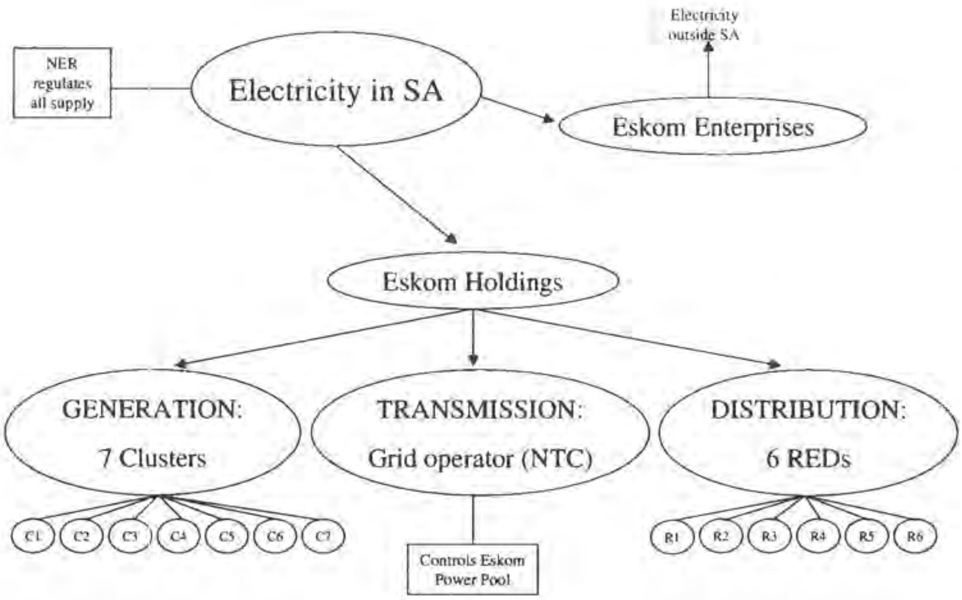


Figure 4.1: The structure of the South African electricity sector

- Hydro-electric — 0.4% of output
- Pumped Storage Schemes — 0.8% of output

The latter two represent the 'peaking' power stations. Also included in the peaking 'mix' are the gas-fired (fuel oil) generating units that were lumped with the coal-fired figure.

Each of the clusters' activities in the market are governed by a trading mandate and the trading goals are determined with reference to performance contracts. The contracts do not only reflect the profit-making ability of the relevant cluster, but include other items such as adherence to maintenance scheduling (for the purpose of achieving plant longevity).

Daily offers in the form of piece-wise-horizontal supply tranches (see Section 3.3) which give the price per MWh across possible ranges of output, and are offered on behalf of each generating unit by its parent cluster. Twenty-four of these (one for each hour) are submitted via an electronic system (known as *POWI*) by the deadline of 10:00 a.m. each day for the day's production hours commencing one day hence. These 'supply' functions are determined by traders acting on behalf of their cluster and take into account (broadly):

- the unit's marginal cost.
- the system-wide hourly demand/load forecast for the period.
- objectives arising from the performance contracts.

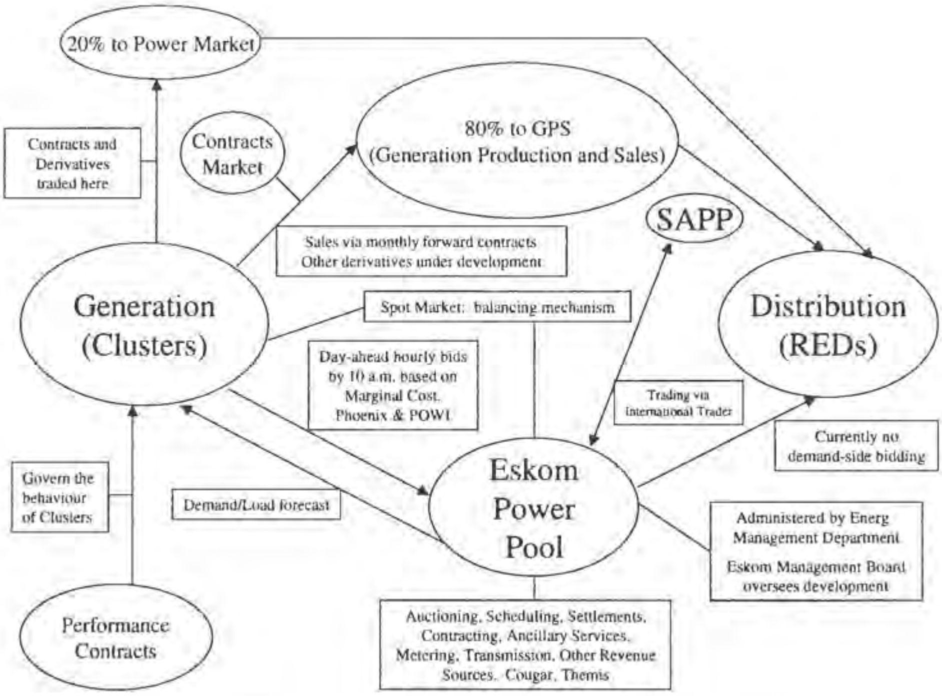


Figure 4.2: The South African Electricity Market

- an anticipation of competitor behaviour.

100% of the power produced by the clusters is traded through the EPP, and the daily sales effectively balance the pre-purchase hedging mechanism that is in place with Generation Production and Sales who are still the effective owners of the generation assets. This situation represents a stage in the transition to fully privatised generation markets. The hedging mechanism is achieved through the sales of monthly forward contracts (specifically in the form of two way contracts-for-differences). The formulation of this type of contract was described in Chapter 2, though it is worth noting here that these are in fact forward contracts as opposed to futures contracts. The reason for the distinction is that the instruments are currently traded within the same company and no margins — in the form of collateral — are therefore required.

The daily trading process has a diagrammatic representation shown in Figure 4.3.

From the point of view of an individual cluster's trading activities, it is important to elaborate upon the following three essential items as they will govern the choices made by the active trader:

Gross Margin: Sales minus Cost of Sales. Margin requirements are determined with reference to historic market performance, historic market prices, accurate forecasts of future market prices, long-term hedging practises, historic sales volumes and

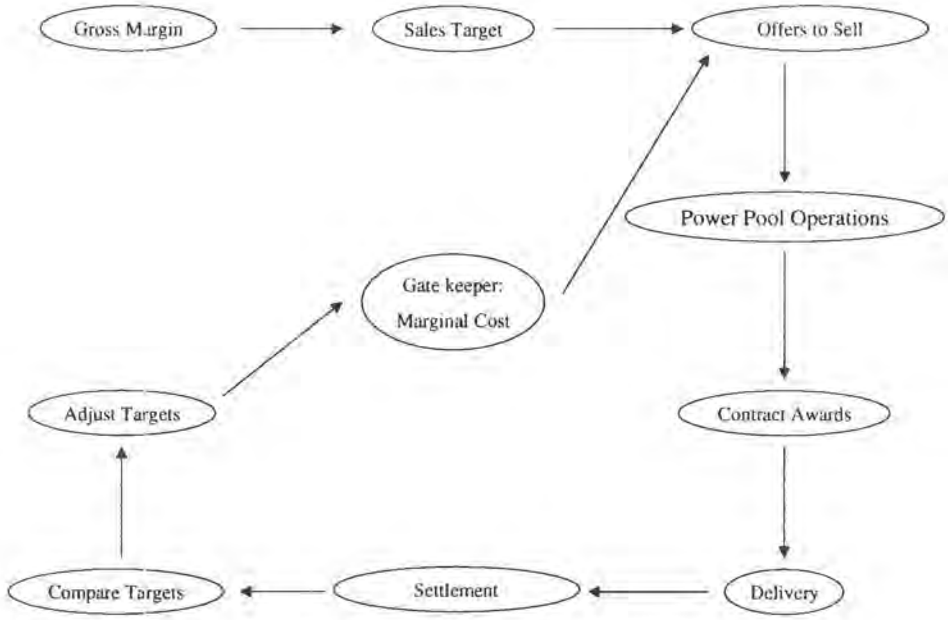


Figure 4.3: The Trading Process

revenue requirements. By the last point a percentage return on assets, as specified by performance contracts, is implied.

SMP forecasts: Prices are forecast (as advised by the holding company) using the following base and phase shift Fourier model with $\varepsilon \sim N(0, \sigma^2)$:

$$SMP_t = \mu + \alpha_1 \cdot \sin(\omega_1 t + \beta_1) + \alpha_2 \cdot \sin(\omega_2 t + \beta_2) + \varepsilon.$$

A possible extension to the above model allows for random shocks in the form of *Poisson*-distributed random variables.

From the model, the Genco derives the hourly sales targets as well as daily, monthly and annual gross margins that it expects to achieve. In order to enhance their performance. traders often conduct their own internal forecast based on any additional information at their disposal. Such information would include knowledge of the system, expected rival behaviour and historical SMP's. In practice, great emphasis is also placed on the outcome of the previous day's trade when selecting a strategy for the forthcoming hourly trades.

Marginal Cost refers to the cost of purchasing the primary energy (e.g. coal, pumping costs, etc.) It also makes an allowance for the amount of potential (stored) energy in the form of inventories of primary and potential energy. Models (e.g. *PMAC* for pumped storage) are used to determine the value of the marginal costs which in turn affect potential generation capacity and minimum selling price. It is notably a very important for determining the generator's position in the market.

Settlement

On receipt of all the offers for production of electricity, the Power Pool Operator (PPO) — on an hour-by-hour basis — aggregates all the supply tranches received for each generating unit in the system, and calculates the price that clears the total estimated hourly demand. The resultant market clearing price for each hour is known as the SMP. All generating units with offers at or below the SMP for each hour are contracted to produce the quantity offered for the particular hour and receive the SMP for each MWh that they produce. The clearing process determines the system's constrained schedule. Obviously the forecast demand for each hour is rarely equal to the actual load for that hour and a settlement mechanism operates within the pool to make up for any differences between forecast and actual output, as well as second-by-second system load regulation. This mechanism, in turn determines the unconstrained schedule. Other factors which arise from transmission system constraints and unexpected events (e.g. unplanned generator outages) will also affect the unconstrained schedule. In addition to its scheduling task, the PPO is also responsible for coordinating ancillary services, ensuring correct metering of output, and for transmission arrangements. At the time of discussion with the Eskom trader there was no demand-side bidding in the Eskom Power Pool that would have an affect on the settlement mechanism in the Pool.

The successfully awarded contracts are made known to the Genco's electronically at 14:00 on the day prior to trade and include information on the hourly volumes to produce, ancillary products and required reserves. The reserves markets comprise instantaneous, black-start, regulating, 10-minute and emergency reserves.

Performance Assessment

The delivery performance of each unit is assessed by the PPO with reference to the following items:

- generator status — actual versus forecast (including load losses and generator trips).
- behavioural characteristics of the generator (mill changes, ramping, etc.)
- hourly adherence to load volumes.
- second-by-second regulation.

Post-Delivery

In post-delivery, the PPO actions the following:

- Metering of availability, regulation and governance
- Reconciliation of amounts over/under
- Events and performance indicators
- Daily settlements — governed by EPP rules, disputes resolved through an electronic system (*Themis*)
- Monthly billing

After the delivery period, traders are able to compare their actual gross margin against their targets, offers for the following period are revised with respect to previous performance.

4.4 Study Specialisation

The section justifies the choice of Peaking as an appropriate application, followed by a brief description of the workings of a pumped-storage scheme, and some remarks on how this specialisation fits into the greater scheme of the thesis.

Justification

The subject for this thesis was chosen to be the "Peaking" cluster of the Generation sector. Preliminary discussions with a representative from the Generation division of Eskom's head office were what motivated the need for research into the area of financial risk management within the division as a whole, and indeed within a South African context. For the purposes of a masters dissertation, examining the whole of Generation was deemed too large a task. It was therefore agreed that research would be confined to one of the seven generation clusters. Peaking was an obvious choice for the following reasons:

1. Wider research interest due to variations in plant type. For example the types of generating plant which they operate are not only, say coal-fired or thermal units.
2. The risk profile of peaking-type plants is more varied, and would, for example, be concerned with items such as weather variables. The model of a market participant is therefore endowed with a generality that would hopefully permit a reasonable adaptation to the study of a base-load generator.
3. The proximity of the Peaking office and the current existence of managerial contacts at that office, would allow the researcher to spend time in the trading environment there. In so doing, some insights could be gained as to the type of concerns faced by a trader in a market for electricity generation. There was also scope for the provision of hourly historical data by the cluster in respect of one of its generating units. The data was provided for research purposes.

In this thesis, we therefore proceed by focusing on the Peaking cluster while preserving as much generality as possible with regard to the model definitions. In so doing we envisage a representation which captures the main characteristics of any type of participant in a market for electricity generation. The profile would be one that could ultimately be specialised for the particular characteristics of other market participants, and perhaps even serve to highlight important differences between the participants. Given the nature of existing research on system-wide modelling, it is hoped that by keeping the model for a single participant as general as possible, a formulation can be developed for many such participants (each with their own specific characteristics), and that each of these can be refined and amalgamated into a representation of a system describing the market as a whole.

Pumped-Storage Generators

Pumped-storage hydro is essentially a form of energy storage. When the scheme is not generating, it is either pumping water from the lower reservoir to the higher one, or simply standing idle until its energy is needed by the grid or pool. It has low running costs and quick start-up time, which makes it ideal for peaking-type production. When pumping, it may be responsible for increasing the capacity factor of the base-load units in the grid during off-peak periods or simply be viewed as a consumer along with other users of electricity. The unit essentially converts energy produced in periods of low system loads to (a reduced amount of energy) available for high period loads. The turbines are reversible in the sense that the same unit is used for pumping and for generating. Generating simply means allowing water from the higher reservoir through the turbine to the lower one.

In summary, a pumped storage scheme is a generator of electricity in periods of peak demand or grid production deficit, and a consumer who purchases power at off-peak periods of low demand. The fact that it serves both as an instantaneous provider of power in demand surges or failure of other generators, and as a bulk user of power when output of baseload generation is pushed to its minimum in off-peak periods, makes the pumped storage generator a socially important entity in the power system. Although pumped storage is only responsible for only 0.8% of the national production of electricity, it plays a key role in stabilising the grid and avoiding power outages. Pumped storage generators have great leverage in the determination of the SMP's in peak periods.

The Palmiet scheme additionally provides an ancillary service to the Department of Water Affairs, where water from their reservoirs is diverted between river systems during pumping or generation.

The marginal costs of the scheme depend almost wholly on the cost of pumping the water from the lower reservoir to the higher one, together the efficiency of the turbine in pumping the water relative to the generation capacity of the pumped water. The treatment of costs in the simulation model of this thesis is described in more detail toward the end of the next chapter. Timing of production and pumping is of the utmost importance in the profitability of these types of units. However, the aim of the pending model is not to examine the optimal scheduling for the unit in isolation, but rather to study how it copes with the operational and market uncertainties in the new environment of uncertain market conditions, energy prices and demands. As mentioned before, the specialisation is undertaken with a view to developing a generic model for all types of generating plant.

4.5 Final Remarks

This chapter has provided details of the local conditions (and context) for the development of the simulation model in the forthcoming chapter and the subsequent experimentation in Chapter 6. The scientific importance of the specialisation has also been justified through the choice of a Eskom 'Peaking' unit. There are far-reaching social consequences of understanding such units, owing to the vital role they play in the market (notwithstanding their extensive market power during peak demand) and in ensuring stability of the national grid.

What follows in the next chapters is the development of a representation of a Peaking-like unit — in particular a pumped storage scheme — as a single market participant exposed to exogenous system demands, prices and costs, and which acts in the market so as to maximise its potential profits from generating electricity and selling it via an auction mechanism into the Eskom Power Pool. The analysis will be simulation-based (as observed in many of the research papers to date) though it will soon become apparent that the approach is somewhat different to those adopted in Chapter 3 and has many of its own unique merits. A further characteristic of the approach is that it is exploration-based and adaptable, the latter being a desirable model characteristic for systems as dynamic as modern power markets.

Chapter 5

Generic representation of an Eskom-like system

The aim of this chapter is to develop an investigative simulation model for describing the reality of the Eskom trading environment, using the tools of systems thinking. In the light of the topics discussed in Chapters 2 and 3, a unique model is developed describing the particular strategic environment of a company trading in the Eskom Power Pool.

A versatile model form is chosen in order to maintain sufficient generality and potential to ultimately tackle at least some of the vast range of issues discussed in those chapters. Rather than proposing an express goal for the model, it will be developed as a tool for adaptive learning, and where possible, modifications will be suggested that will enable a more practical implementation in order to achieve more specific goals, such as deciding on the optimal bidding strategy for the trader. This idea of 'learning through modelling' is indeed characteristic of many of the approaches adopted by other researchers.

Rather than moving straight toward the proposition of a decision support system for a market participant, a model is developed to mimic the actions of a trading Genco. The model will enable a discovery of the environment in which the Genco operates and highlight the relative importance of both environmental (exogenous) and internal (endogenous) factors, as well as any significant interactions present among these factors.

Firstly, the most important state variables in a market for electricity generation will be defined in a general sense, thus comprising the initial step away from reality and toward a generic model representation of a system. The actual trading environment is therefore described in terms of the state variables, classified as deterministic or stochastic, and endogenous or exogenous. A general simulation algorithm describing the participant's actions will then be described and will provide a platform for the next section. By this stage, a single participant in the generation market will have been represented in the most general sense.

In Section 5.2 the next step toward the development of the model is taken and parametric definitions of the simulation variables are given. This step, in turn, is followed by an explanation of how the available data were incorporated into the model to represent the 'actual' values of some of the simulation variables.

The penultimate Section 5.3 suggests some initial, simplified trading rules representing the trading decisions of a Genco, then concludes with the final devised simulation algorithm together with explanations and assumptions. The final model incorporates all of the defined variables, parameters and trading rules. Some initial parameter values are also suggested and motivated. Section 5.4 provides a short summary of the chapter.

5.1 The Actual Trading Environment

5.1.1 State variables in a market for electricity generation

The following definitions apply to the subsidiary of a single generating company, generically known as a Genco. They therefore refer to the variables which the Genco — on behalf of its subsidiary unit — explicitly considers in its endeavour to undertake its daily operations and trading activities. From a trader's point of view, they are the variables most commonly considered as important in the literature. There are many other variables in the realm of unit commitment, scheduling and system constraints that have not been examined in the formulation of the model in this thesis. It is felt that these variables were more relevant for research into the power systems of the former monopoly industries. Rather than giving them explicit treatment (as many other researchers have attempted to do), this modelling approach opts for an implicit treatment of these concepts that will become apparent in the formulation which follows, and in the analyses of Chapter 6. Unless otherwise stated, the following state variables take on values at each hour of a particular trading day.

Actual Demand is the actual amount of electricity consumed by the system in a particular hour, and is only known once the hour is complete and system measurements have been recorded.

Forecasted Demand usually comes from a system operator and is often made known publicly. The forecast is based on historical demand with possible inclusion of items such as expected weather events, and varies according to long term trends and/or cycles, season, day of the week, time of the day (all of which drive the actual demand) and random fluctuation. Genco's may conduct their own internal forecast of demand in addition to that provided by the System Operator (SO).

Actual System Marginal Price (SMP) is determined via a clearing mechanism. In the clearing mechanism, the total of all aggregated volume offers from the Genco's which submit before the deadline, is set equal to the aggregate forecasted demand for the particular hour. The SMP is the minimal price at which the aggregate supply volume equals the aggregate demand volume.

Forecasted SMP is based on an historical time series model supplied by the generation holding company (Eskom Generation Production and Sales in the South African context), though it could be calculated internally by a Genco, based on the expected outcome of a stochastic process. Refer to Chapters 2 and 3 for examples of these models.

Marginal cost (MC) (of primary energy) incorporating start-up and running costs and inventories of fuels e.g. coal, fuel oil (diesel), gas or uranium reserves for a thermal generator and; reservoir levels, river flow, damn levels for hydro/pumped storage generators. The MC is calculated for a particular generating hour via an internal forecast that will depend on exogenous factors such as fossil fuel prices, rainfall, evaporation, and wind speed (for a wind farm). When calculating their marginal costs, generators will also have to take into account their efficiency: the *heat rate* in the case of a thermal generator and *pumping efficiency* in the case of a pumped storage scheme.

Fixed costs are the fixed running costs of the plant. They are costs incurred regardless of whether any generation takes place, for example capital costs, plant maintenance and labour costs. An important element of the so-called fixed costs are those of maintaining the plant and are quite often known in advance from the maintenance schedule, however costs of restoration after an unplanned outages or plant failure will also have to be factored into the long term fixed cost. Generators quite often build their recovery of fixed costs into the return they aim for above their variable costs. As they are largely fixed items, we could still treat them as hourly variables by dividing the total costs incurred over a year by the number of hours in the year. A perhaps better approach would be to treat all profits as contributions to the fixed running costs of a plant.

Profit Margin is the amount determined at the end of each generating hour, or in practice after the market's final settlement mechanism has been completed, and after the net revenues or losses from the hedging positions have been taken into account. Traditionally,

$$\text{Profit} = \text{Total Revenue} - \text{Total Cost}$$

The effect of interest earned on cash flows is ignored for the purposes of this dissertation.

Offer curve is the set of price-quantity pairs. It is the crucial decision variable in the trading process and is determined with reference to profit requirements (e.g. via performance contracts), availability, previous day's bidding strategy and expected competitor behaviour. The trader decides how much to offer and at what price level. This decision depend on his expectations of SMP's, MC's, system demand and competitor behaviour. The trader's decision comprises both unit commitment and strategic bidding. It is common for a unit to have fixed batches of volume available per hour (depending of course on the type of unit we are dealing with). Thus the decision will consist of a two-part process:

1. The "When" of the decision: Is it profitable to generate at all in a particular hour? If so,
2. The "How much" element: At what prices should the batches of power be made available?

More details on optimal bids are given in Section 3.4

Other Genco offers (bids) are effectively imposed on a particular Genco via the SMP market-clearing mechanism (unless the company concerned can knowingly influence the SMP outcome through its own actions in the market). Other companies' bids are only known in retrospect, though a Genco would wish to have advance insights into how their competitors will offer before they submit their own bids. They could 'guess' competitor offers from past behaviour and expected deviations, or simply treat forecasted SMP as a single exogenous variable summarising the aggregate actions of all competitors. The interpretation of competitors' offers will depend on the price-taking (or price-setting) capability of the company. A more in-depth discussion of supply functions is given in Section 3.3.

Production unit status is the actual state of the units at the end of the previous generating hour. It may be "generating", "not generating" or "unavailable" (owing to planned or unplanned outages). If "generating", then at what output? Planned outages make the unit unavailable; unplanned outages may follow some parametric distribution, and can effectively occur at any time in the pending hour. With most thermal units, this status will influence the amount of start-up/shut-down costs to be incurred in the following hour if the company decides to commit/decommit their unit for the hour and if their offer is then accepted/declined.

Hedged positions may be in place where contracts for generation have been pre-sold for a fixed price. There may also be existing positions in derivatives contracts to which the unit may be a party for the particular hour. Such positions will also affect the trading decision for that hour. It may be that a decision ought to be taken to initiate derivative contracts for future periods.

Having defined the eleven key state variables of a realistic market from the perspective of a single Genco, the specifics of the stochastic simulation model can now be defined along with the relevant simulation parameters.

5.1.2 Time structure

Firstly, we need to define the time-step for the simulation and the time-frame for the investigation.

Increment

An hourly increment is the most appropriate for a short to medium term investigation horizon. In the EPP, offers for all 24 hours of the following day are submitted prior to a predetermined cut-off time (unlike the 48 half-hourly periods in the E&W market). Moreover, all of the major measurements for demand (in MWh) , SMP (in units of currency per MWh) and MC (per MWh) are calculated hourly. The hour is therefore the obvious choice for the lowest-level, indivisible, discrete time increment.

Endogenous	Exogenous
Forecasted SMP	Actual SMP
Forecasted Demand	Actual Demand
Forecasted MC	Actual MC
Offer Curve	Other Genco Offer Curves
Fixed Costs	
Production Unit status	
Profit Margin	

Table 5.1: Endogenous and exogenous state variables

Horizon

The time-frame for an initial investigation is initially chosen as one year, so that we could for example have an investigation horizon of $T = 365 \times 24 = 8760$ individual production periods. At the outset of the investigation, this choice is clearly arbitrary and can easily be amended according to the purpose of the simulation. The intended approach will be to measure the performance of a trader over a specified period (such as a month or year) under various scenarios rather than adopting the single period (hourly or daily) analyses of many researchers as noted in Chapter 3.

5.1.3 Classification

Now that the temporal context of the simulation has been stated, we can now classify the state variables for a generic Genco in the EPP system.

Endogenous and Exogenous variables

Endogenous state variables, in context of the formulation, are those which depend on the activities of the Genco under study. To an extent they are 'controllable' by the company. In contrast the exogenous state variables are those externally imposed on the Genco, having their own fundamental drivers that determine their outcomes. Through the actions of the Genco in the market, personal perceptions of the exogenous variables are created, resulting in some of the endogenous variables. The classification in this regard is given in Table 5.1 In some cases the classification is not well defined e.g. "production unit status" could be exogenous in the case of a peaking-type plant where a sudden commitment of plant may be required, or an active unit shut down.

Deterministic and Stochastic variables

From a generation cluster's perspective, state variables may be viewed as either deterministic or stochastic. Some of the stochastic variables may be truly deterministic (e.g. if we were studying the entire system of Genco's and knew what offers they had submitted we would know exactly what the SMP would be), however from the perspective

Deterministic	Stochastic
Forecasted SMP	Actual SMP
Forecasted Demand	Actual Demand
Forecasted MC	Actual MC
Offer Curve	Other Genco Offer Curves
Fixed Costs	
Production Unit status	
Profit Margin	

Table 5.2: Deterministic and stochastic state variables

of an individual generator they are imposed as stochastic variables. In simpler terms, in this context stochastic simply means unknown to the Genco at the time of decision-making (e.g. Actual SMP is endogenous to the system as a whole and stochastic from the perspective of a price-taking Genco). See Table 5.2 for the classification.

5.1.4 Trading Algorithm

A generic hourly trading process is enumerated in the steps below which provide a broad overview of the actual hourly trading process. The corresponding simulation algorithm will be given in Section 5.3.

1. Read forecast values of demand (from SO), SMP's (from internal forecasts), marginal cost (estimates) and unit availability.

2. Estimate rival Genco offers and take into account the Genco-of-interest's required profit margins (if unit is available) while evaluating the previous day's performance for the corresponding hour. Examine the current hedged position and any other derivative positions that are affected by our actions, or take out hedging arrangements if possible and if deemed necessary.

3. Calculate the offer price(s) and associated capacity(ies) that maximise expected profits allowing for these conjectures and submit offers to the SO.

4. SO determines the SMP by aggregating all the offers from the Genco's to form a system supply function, and recording the price at which the total demand forecast for the hour intersects this supply function. Contracts for generation for each hour are then allocated to the winning Genco's which have offers lower than (or at) the SMP. The allocation is the mechanism through which the market is cleared.

5. Genco generates the amount contracted for the hour (if any).

6. Calculate actual profits or losses from quantity generated, SMP and actual MC incurred. Accumulate profits made or losses incurred to the end of the investigation period then evaluate and assess performance.

Note:

- We shall, for the purposes of the simulation, assume that the trades and clearing mechanism for each hour occur immediately prior to the real-time period. In practice, a day-ahead market exists where trades for each of the 24 hours occur in advance and all at once on the preceding day. The formulation above therefore implies an initial simplification.

- The above algorithm specifically ignores the effects of ancillary serves and reserves markets (both of which are often subject to a separate treatment from that of the main market anyway).

- The algorithm could be modified to incorporate the employment of simple hedging contracts and their effects on the decisions and profit margins. Such contracts could effectively lock into a fixed price for generation prior to the clearing process, though the quantities and other terms of such contracts would have to be specified.

The above has shown the general context for systems thinking for a generation market such as the EPP. The context may be refined in many ways to achieve a desired representation. The actual formulation that now follows represents a particular instance of such a refinement. It was necessary to define the general context above as a basis for future model development or as part of a possible proposal for a commercial implementation.

5.2 Variable Definitions and Model Parameterisation

In this section we describe a particular formulation of the model to simulate the operations of the trading environment described above. There are many simplifications and choices that will be made, and they will be governed by the limitations on the level of detail provided by the managers of the Eskom Peaking Cluster as described in Chapter 4. The simplifications and choices will be explained during the course of the formulation that follows.

5.2.1 Variable definitions:

N	The number of simulation iterations.
t	Hour of generation, $t = 0, 1, 2, \ldots, T$. Here, T is the investigation horizon which we can arbitrarily choose as one year.[1]
D_a	the natural logarithm (log) of actual system demand which is the total power load required by consumers from the pool for each hour.
D_f	log(Forecasted system demand) $= D_a +$ forecasting error.
C_a	log(Actual variable MC (Marginal Cost)); incurred per MWh of generation.
C_f	log(Forecasted variable MC) $= C_a +$ forecasting error.
S_a	log(SMP); determined by the SO after the offer deadline.
S_f	log(Forecasted SMP) $= S_a +$ forecasting error.
F	the fixed cost incurred by a generator, regardless of whether or not the unit is contracted (as described earlier, they will henceforth be assumed to be zero, and the profits treated as contributions to fixed costs).
y	the marginal offer price that the trader calculates with reference to his conjectures/forecasts. For a unit that has more than one bin of capacity, y is a vector of cumulative offer prices.
g	the capacity associated with each price offered. It indicates the maximum (or fixed) quantity the unit is willing to generate at each price. For a unit that offers a set of cumulative prices, g is a vector of associated cumulative volumes per hour.
P	the actual profit made in each time period

Therefore

$$P = \begin{cases} g \times \exp(S_a) - g \times \exp(C_a) & \text{if offer accepted} \\ 0 & \text{if no offer made or offer not accepted} \end{cases}$$

5.2.2 Parametric definitions of variables

<u>**The Actuals:**</u>

Actual system demand: The logarithm of demand, $D_a(t)$, is modelled as follows:

$$D_a(t) = \mu_t^D + \gamma_t^D$$

where

$$\begin{aligned} \mu_t^D &= \mu^D + d_j^D + h_k^D + m_l^D \\ \gamma_t^D &= \rho\gamma_{t-1}^D + (1-\rho)\delta_t \end{aligned}$$

so that actual demand is given by $\exp(D_a(t))$. In this formulation,

[1]All variables from D_a down are explicit functions of t though the functionality has been dropped for ease of presentation.

$\mu^D =$	annual mean log demand	
$d_j^D =$	effect on log demand attributed to the day of the week	$j = 1, \ldots, 7$
$h_k^D =$	effect on log demand attributed to hourly variation	$k = 1, \ldots, 24$
$m_l^D =$	effect on log demand attributed to inter-month variation (seasonal effect)	$l = 1, \ldots, 12$
$\delta_t \sim$	$N(0, \sigma_\gamma^2)$.	

The indexes j, k and l refer to the day, hour and month implied by t and,

$$\sum_{j=1}^{7} d_j^D = \sum_{k=1}^{24} h_k^D = \sum_{l=1}^{12} d_l^D = 0.$$

It can be seen that the actual demand consists of a deterministic component represented by μ_t^D's, and a stochastic component, denoted by the γ_t^D's.

μ_t^D is an explicit function of time, allowing for trends, cycles and seasons — though an actual history of hourly values, read from a database could be used instead. In the case of the latter, one is assuming that the data capture all the temporal characteristics of the demand variable's behaviour. However, for the remainder of the model development, we shall be confined to the use of the additive effects model described above.

The form of γ_t^D, which models the unexplained bumps and shocks that occur in reality, is initially chosen to be an autoregressive time series process. A simpler alternative would be to assume that the γ_t^D's are zero and the Actuals therefore have no stochasticity (i.e. utilising an historical record of realised values). Such a deterministic model would deliver little insight into the relationships between the parameters of interest. The stochasticity is an essential part of the modelling process. Assuming an autoregressive process of order 1, a smoothing parameter, ρ and process variance σ_γ^2 results in the exponential smoothing process for the stochastic errors represented by γ_t^D.

Actual SMP: The logarithm of hourly system prices is modelled in exactly the same manner as system demand:

$$S_a(t) = \mu_t^S + \gamma_t^S$$

where

$$\begin{aligned} \mu_t^S &= \mu^S + d_j^S + h_k^S + m_l^S \\ \gamma_t^S &= \rho\gamma_{t-1}^S + (1-\rho)\delta_t \end{aligned}$$

so that actual SMP is given by $\exp(S_a(t))$. In this formulation

$\mu^S =$ annual mean SMP

$d_j^S =$ effect on SMP attributed to the day of the week $\quad j = 1, \ldots, 7$

$h_k^S =$ effect on SMP attributed to hourly variation $\quad k = 1, \ldots, 24$

$m_l^S =$ effect on SMP attributed to between-month variation (seasonal effect) $\quad l = 1, \ldots, 12$

$\delta_t \sim N(0, \sigma_\gamma^2)$ (independently of those of γ_t^D).

Once again we have

$$\sum_{j=1}^{7} d_j^S = \sum_{k=1}^{24} h_k^S = \sum_{l=1}^{12} d_l^S = 0.$$

Actual Marginal Cost: for a generic generator, the model for $C_a(t)$ will depend on the particular costing model used by the generator, which depends on the type of generating unit.

For a thermal generator whose MC depends directly on the price of the primary energy commodity, we could model the logarithm of the hourly cost in a manner analogous to SMP and Demand. In the case of a fuel or coal-fired generator, the cost would be modelled as a function of the underlying diesel or coal acquisition prices resulting in a similarly structured parameterisation as that of μ_t^D and μ_t^S and with:

$$C_a(t) = \mu_t^C + \gamma_t^C$$

However, in the specialisation that follows, the model is directed toward a pumped storage scheme. The underlying costs will therefore be a function of the SMP values in the hours when the trader chooses to pump to the upper reservoir (effectively supplying the potential for generation in later periods). This functionality will depend on the pumping efficiency of the scheme and the commitment decision for the number of hours for pumping and for production. The reasons for the specialisation were described in Chapter 4.

The treatment of the cost variable is very important and leads us into the realm of cost function analysis. The particular treatment used in the simulation will be detailed in the simulation algorithm in the next section.

Trader conjectures

In contrast to the above parameterisations for the Actuals, we simulate the trader's conjectures as follows:

$$\begin{aligned} D_f(t) &= D_a(t) + \varepsilon_D \quad \text{where} \quad \varepsilon_D \sim N(\xi_D, \sigma_D^2) \\ S_f(t) &= S_a(t) + \varepsilon_S \quad \text{where} \quad \varepsilon_S \sim N(\xi_S, \sigma_S^2) \end{aligned}$$

and for a thermal generator,

$$C_f(t) = C_a(t) + \varepsilon_C \quad \text{where} \quad \varepsilon_C \sim N(\xi_C, \sigma_C^2)$$

(The actual treatment of $C_f(t)$ is different for a pumped storage scheme and attention is drawn to the simulation algorithm of the next section for the treatment of $C_f(t)$ and $C_a(t)$.)

The above conjectures imply that the trader can estimate the true values of the system variables with levels of bias and precision that indicate his proficiency and knowledge of the system, and the quality and quantity of the information at his disposal. By choosing values for ξ_D and ξ_S other than zero, we are saying the trader has a biased forecast of the system variables. Similarly we can control his 'forecasting precision' by setting various levels for σ_D and σ_S.

5.2.3 The Data

Eskom Peaking Cluster were able to supply some representative data for one of their pumped storage units. Included in the spreadsheet were the variable values for each hour in 2003. i.e. hourly SMP, National Load, Quantity Bid for Pumping, Actual Quantity Pumped, Actual Generation, Dam Level and MC. From these figures it could be ascertained that the efficiency of the scheme was approximately 76%. Efficiency is calculated by dividing the total power generated for the year by the total power used for pumping. Unfortunately they were unable to supply a record of their offers made. A record of the historical offers would have enabled a quantitative discovery of the offering strategy which they employed over the year, over and above the somewhat incomplete qualitative explanation that was given in Chapter 4

The fixed effects models were fitted for Demand and SMP using (natural logarithms of) the true hourly values for 2003 to obtain the seasonality factors defined earlier on. The factors are shown in Tables 5.3 and 5.4 and were calculated using a *Visual Basic* routine in *Microsoft Excel*.

Table 5.3 gives the factors for the model,

$$\mu_t^D = \mu^D + h_j^D + d_k^D + m_l^D,$$

while Table 5.4 shows the factors for the model,

$$\mu_t^S = \mu^S + h_j^S + d_k^S + m_l^S.$$

It can be seen even from these crude models that the effects are as we expect them to be for hours of the day, days of the week and months of the year, and with a reasonable amount of similarity in sign and size between demand and SMP effects. As expected, the loads and prices are greater in winter months. There are morning/evening peaks and the load is greater on weekdays than weekends (when other factors considered equal).

With regard to MC's, the data are representative of a pumped storage scheme, and a glance over the figures suggests that pumping generally takes place in the six lowest

Hourly Effects			Daily Effects			Monthly Effects		
Hour	j	h_j^D	Day	k	d_k^D	Month	l	m_l^D
00:00	1	-0.104	Monday	1	0.007	January	1	-0.066
01:00	2	-0.139	Tuesday	2	0.032	February	2	-0.030
02:00	3	-0.156	Wednesday	3	0.032	March	3	-0.032
03:00	4	-0.165	Thursday	4	0.030	April	4	-0.046
04:00	5	-0.164	Friday	5	0.021	May	5	0.002
05:00	6	-0.145	Saturday	6	-0.036	June	6	0.042
06:00	7	-0.084	Sunday	7	-0.086	July	7	0.055
07:00	8	0.004				August	8	0.032
08:00	9	0.053				September	9	0.010
09:00	10	0.085				October	10	0.032
10:00	11	0.084				November	11	0.026
11:00	12	0.084				December	12	-0.024
12:00	13	0.076						
13:00	14	0.063						
14:00	15	0.042						
15:00	16	0.030						
16:00	17	0.029						
17:00	18	0.033						
18:00	19	0.060						
19:00	20	0.110						
20:00	21	0.130						
21:00	22	0.097						
22:00	23	0.025						
23:00	24	-0.046						
Total:		0.000			0.000			0.000

μ^D was calculated to be 10.095, equating to an overall average hourly demand of $\exp(10.095) = 24,222MWh$.

Table 5.3: Fixed effects factors for log system demand

SMP hours of the day, usually from around 23:00 to 05:00 in order to keep their pumping costs as low as possible. Once again, had we been dealing with another type of plant, the modelling strategy would be to obtain price (and volume) data on the energy commodity consumed by a particular plant and information on its *heat rate* (or energy conversion efficiency). C_a and C_f are specified as being different. For other types of generator, the MC's may be known (and fixed) in advance of the trading hour. For example, a thermal generator may have hedged their purchase of primary energy or simply know the energy value of their inventory.

The stochastic terms for the Actuals (i.e. the γ_t's) will be added to the fitted deterministic values during the simulation routine.

Hourly Effects			Daily Effects			Monthly Effects		
Hour	j	h_j^S	Day	k	d_k^S	Month	l	m_l^S
00:00	1	-0.557	Monday	1	0.026	January	1	0.021
01:00	2	-0.614	Tuesday	2	0.095	February	2	0.277
02:00	3	-0.651	Wednesday	3	0.080	March	3	0.303
03:00	4	-0.665	Thursday	4	0.078	April	4	0.061
04:00	5	-0.595	Friday	5	0.085	May	5	-0.079
05:00	6	-0.289	Saturday	6	-0.090	June	6	-0.214
06:00	7	0.102	Sunday	7	-0.272	July	7	-0.300
07:00	8	0.191				August	8	-0.175
08:00	9	0.408				September	9	-0.165
09:00	10	0.288				October	10	0.072
10:00	11	0.387				November	11	0.229
11:00	12	0.493				December	12	-0.031
12:00	13	0.326						
13:00	14	0.121						
14:00	15	0.022						
15:00	16	0.027						
16:00	17	0.007						
17:00	18	-0.028						
18:00	19	0.675						
19:00	20	0.789						
20:00	21	0.370						
21:00	22	-0.057						
22:00	23	-0.277						
23:00	24	-0.473						
Total:		0.000			0.000			0.000

μ^S was calculated to be 4.364, equating to an overall average hourly pool price of $\exp(4.364) = R78.57$.

Table 5.4: Fixed effects factors for log SMP

5.3 The Simulation Model

This section explains the trading rules used in the simulation and defines the parameters of a detailed algorithm for the case of a Genco which is able to exert a specified amount of influence on the realised SMP for each hour. The simulated decision process reflects reality where there is a daily, rather than hourly decision period, allowing the Genco to schedule their offers for the entire day in advance of the clearing mechanism. At the time of market clearing, once all Genco's have submitted their offers, the true values of the actual system variables become known.

5.3.1 Decision rules

The next important component of the simulation is the *decision rule* of the trader. In this instance we construct a two-fold rule, defining

1. when to trade: this essentially governs the unit commitment question.
2. what quantities and associated price levels are to be offered in the periods when a commitment is made: in essence this is the supply function we submit to the SO.

Clearly both of these elements will be functionally dependent on the trader's conjectures as modelled above.

Note: Two important simplifications will be made with regard to the supply function from this point on.

- The supply function,y is a scalar and there is no decision to be made on quantity. Only one price is offered for a single block of output i.e. g is fixed. We are assuming the generating unit has a fixed capacity available and when contracted generates this full capacity. This assumption is reasonable for the single production unit in this model since tranches/blocks are more representative of a cluster of units that wish to offer their owned units at cumulative rates. In the latter case y would have been be a vector of prices.
- Further justification for a fixed capacity is that price is a variable which is functionally dependent on quantity (e.g. it may be linear and a choice of quantity would be associated with a particular price.) This approach is vindicated by references in Chapter 3 which postulate that even when there is a more complex supply function, the choice of supply function is simply a choice of either price *or* quantity, but not both. A fixed capacity has been assumed here. Furthermore, in reality not all of the capacity agreed in the trade will actually be generated owing to real-time fluctuations in demand and system constraints, and some capacity may be contracted in other markets such as reserves and ancillary services. A more detailed discussion on this matter has been given in Section 3.3.

The following trading rules are thus proposed:

1. An two-part simple, initial rule governing *when* to trade would be a combination of:

   (a)

   $$D_f(t) > d$$

   where d is a constant with a value in the range of possible demand values and,

(b)

$$S_f(t) > f \times C_f(t)$$

where f is a constant between, say 0 and 2.

It is clearly possible to increase the complexity of this rule, but it is a reasonable one in the early stages of the modelling process. We can justify this assumption in the context of a Peaking unit that only comes into the market when it is felt that reasonable profits can be made at the margins of peak demand, AND when expected SMP's are at a sufficient level relative to expected MC. One would expect, for example, to benefit from the higher price levels associated with higher levels of system demand at the 'peaks' without wanting to commit when SMP's are expected to be too low relative to expected MC's.

2. The second stage of the trading rule is deciding on an appropriate price, $y(t)$, at which to offer the unit's capacity, g. For simplicity we currently assume the available output from the generating plant is fixed and contracted in its entirety in the event of a successful bid.

   A flexible initial rule for this variable is to assume an offer of

$$y(t) \in [C_f; S_f]$$

   This rule restricts the offer to being above the expected MC and below the expected SMP. Clearly one could build in greater complexity here by building in a required return on marginal cost, and a possible recovery of fixed and capital costs into our offer, say

$$y(t) = C_f(1+r)$$

   where r is the required return on MC. The formula merely demonstrates a possibility; given the relevance of price-formation it is preferable to propose an offer price which in a modelling context allows us to explore the consequences of offering our capacity at a price close to our expected MC, or at a price closer to our expected SMP. So, in keeping with the logical choices for offer prices, we define the offer price as follows:

$$y(t) = \begin{cases} p \cdot \exp(S_f(t)) + (1-p) \cdot \exp(C_f(t)) & \text{if } S_f(t) \geq C_f(t) \\ 0 & \text{otherwise} \end{cases}$$

   where $p \in [0;1]$ in effect defines the policy to be adopted. A value of p close to 0 indicates a trading policy of making offers near to marginal cost and a value close to 1 indicates a policy of making offers near the conjectured SMP.

   For the pumped storage scheme, C_f is a function of the expected prices in the hours selected by the trader for pumping (such as the average of the six lowest divided by the efficiency, e) and C_a will depend on the realised prices in those hours. It is important to note that the performance of the trader will depend significantly on the selection of pumping and generating hours he/she makes.

Explanations and assumptions

In order to clarify some of the modelling choices, the following points need to be made:

1. The trading operation of a single generating unit is considered, though typically a cluster (or Genco) trades on behalf of each of its subsidiary generators with an objective that is aggregated over all of them.

2. We are examining an hourly trading process in which offers are (theoretically) made at the beginning of each hour. Settlement of transactions and performance assessments are effectively carried out at the end of each hour. In reality, 24 hourly offers are submitted all at once, and a day in advance of the actual trading hours. The settlement and assessment take place at some point after the actual production day is completed.

3. We have simplified the model by restricting the decision process to one of deciding on an appropriate offer price given exogenous system demand, SMP and MC. We are assuming the unit has a fixed capacity specified by g, and when contracted, all of this available capacity is in fact generated. In practice, a set of price-quantity pairs is submitted to the SO, representing generating unit's *supply function*. The latter realistically assumes that the capacity which the unit is prepared to offer into the market is allocated to a set of bins, the prices increasing incrementally with each bin. Also, capacity — as opposed to demand — is the true determinant of price in the supply function sense.

4. By taking the natural logarithms of SMP and Demand we are effectively assuming that any stochasticity that is present is multiplicative, and hence that the errors in the forecasted variables (the 'forecast accuracies') are proportional. Additive errors could be assumed if we were to use the original antilogarithmic values rather than the logarithmic transforms.

5. The forecasted values, S_f and D_f represent the trader's conjectures about what their actual values will be. In the modelling process we can control the extent of accuracy with which we endow the trader. In the definition above, we have proportional errors (ε's) with error biases characterised by their sampling distributions' means (the ξ's) and variances (σ^2's).

6. The incidence and effects of planned or unplanned outages on the generating unit's strategy have been ignored, though it is possible to factor in a schedule of planned outages, and add a *Poisson*-type variable to the market clearing process to allow for unplanned down-times and unscheduled maintenance costs.

7. We have ignored the effect of price-hedging mechanisms (e.g. two-way CFD's) and derivative positions on the offer price decision. This assumption could be amended by adding a hedge term to the profit functions and amending the decision process for y. The effect of the "Production Unit Status" variable on the trading decision has also been ignored. The assumption is therefore a further simplification of reality and essentially a part of the unit commitment problem faced by Genco's in the actual market. In the day-ahead market we thus assume that the unit is

available in any hour and there are no restrictions on length of production period or on numbers of start-ups and shut-downs.

8. The generating unit has thus-far been assumed to be a *price-taker* in the market, i.e. our choice for $y(t)$ has no effect on the realised value of S_a. The 'price-taker' assumption will be modified in the simulation algorithm where we define a modified SMP in hour t,

$$S_a^*(t) = \beta y(t) + (1 - \beta)\exp(S_a(t))$$

   where β then represents the propensity of the Genco to influence price ($\beta = 0$ implies no such influence and $\beta = 1$ would mean that the actual SMP is equal to $y(t)$, their offer price).

9. The stochastic errors (γ_t's) are independently sampled for SMP and demand. They are generated and sampled independently though this independence is not obvious due to the same parametric definition having been used. Moreover, independence has been identified as an area for further exploration in this model, as one could incorporate a correlation structure between the two variables (three if we included costs), resulting in a multivariate autoregressive process for the stochastic errors.

10. Following on from the point above, one notes that the stochastic errors (δ_t's), share a common, though independently sampled, normal distribution, $N(0, {\sigma_\gamma}^2)$. The implied stochastic variability is therefore the same for demand as it is for SMP in the current formulation. An alternative formulation would have either a pair of unique normal variates, or a correlated sampling distribution for the stochastic errors leading to a dependency similar that described in the previous point. For the remainder of the dissertation however, σ_γ will contains all the information on the global stochasticity of the model.

5.3.2 Parameters

The following table summarises the simulation parameters and their basic definitions:

Parameter	Description
N	number of simulation iterations
T	investigation horizon (days)
F	the fixed running costs
g	fixed capacity offered and generated (MWh)
ρ	smoothing parameter for Actuals' stochasticity
σ_γ	standard deviation of stochasticity in Actuals
ξ_D	estimation bias for log demand
ξ_S	estimation bias for log SMP
σ_D	precision for estimate of log demand
σ_S	precision for estimate of log SMP
h	number of hours for pumping and generation
d	demand threshold for offer strategy (MWh)
f	relative proportion of S_f to C_f for offer strategy
p	proportion of $[C_f, S_f]$ above C_f for offer price
e	the efficiency parameter for a pumped-storage scheme
β	The influence parameter for the price-setter simulation

5.3.3 The Price-setter Simulation Algorithm

An abbreviated and simplified simulation algorithm is outlined here in nine generic steps.

1. For a particular simulation, set N, T, ξ_D, ξ_S, σ_S, σ_D, ρ, σ_γ, e, g, d, f, p, e, β and h. The parameters define the exogenous context and decision rules being simulated.
2. Calculate the deterministic components of $D_a(t)$ and $S_a(t)$ for all hours $t = 1$ to $24 \times T$ i.e. determine μ_t^S and μ_t^D for all t.
3. For each iteration, $i = 1, \ldots, N$:
   (a) Set γ_0^D and γ_0^S equal to 0.
   (b) Set $SumP(0)$, $SumO(0)$ and $SumA(0)$ equal to zero where $SumP(d)$, $SumO(d)$ and $SumA(d)$ are the respective accumulated profits, offers made and offers accepted at the end of day d.
4. For each day, $d = 1$ to T in each iteration, call the DAILY TRADING MODULE:
5. DAILY TRADING MODULE:
   (a) **Generate hourly stochastic noise factors**
   For $j = 1$ to 24

$$\gamma^D_{j+24(d-1)} = \rho\gamma^D_{j-1+24(d-1)} + (1-\rho)N(0, {\sigma_\gamma}^2)$$
$$\gamma^S_{j+24(d-1)} = \rho\gamma^S_{j-1+24(d-1)} + (1-\rho)N(0, {\sigma_\gamma}^2)$$

   (Note, the $N(0, {\sigma_\gamma}^2)$'s are independent for D_a and S_a)

(b) **Calculate hourly forecasts of demand and SMP**

$$D_f(j + 24(d-1)) = \mu^D_{j-1+24(d-1)} + \gamma^D_{j-1+24(d-1)} + \varepsilon_D$$
$$S_f(j + 24(d-1)) = \mu^S_{j-1+24(d-1)} + \gamma^D_{j-1+24(d-1)} + \varepsilon_S$$

(c) **Sort the arrays of D_f and S_f by values of S_f from largest to smallest and read in the ordered values**

(d) **Calculate forecasted and actual MC (MC_f and MC_a) by averaging the h smallest values of $\exp(S_f)/e$ and $\exp(S_a)/e$ respectively.**

(e) **Calculate the number of possible offers according to strategy rules:**
For remaining 'non-pumping' hours: If $D_f(j) > d$ and $S_f(j) > f \times MC$ then offer$(j) = 1$
Else: offer$(j) = 0$
countoffer(j) = countoffer$(j-1)$ + offer(j)
Next j

(f) **Submit offers for the relevant hours (up to h):**
For all 'non-pumping' hours: If countoffer$(24) \leq h$ then SUBMIT OFFER when offer$(j) = 1$
Elseif countoffer$(24) > h$ Then set $s =$hth largest of the $(S_f(j))$ and SUBMIT OFFER when $S_f(j) \geq s$
SUBMIT OFFER: $y(j) = MC_f + p(\exp(S_f(j)) - MC_f)$
Next j $SumO(d) = \min[\text{countoffer}(24), h]$

(g) **Calculate "influenced" SMP's taking into account the influence of $y(j)$:**
For all 'non-pumping' hours: When offer$(j) = 1$

$$S^*_a(j) = \beta y(j) + (1-\beta)\exp(S_a(j))$$

Next j

(h) **Market clearing module: If offer accepted, calculate profit and accumulate.**
For all 'non-pumping' hours:
If $y(j) \leq S^*_a(j)$ then acc$(j) = 1$.

$$P(j) = (S^*_a(j) - MC_a) \times g$$

Else acc$(j) = 0$ and $P(j) = 0$
$SumA(j) = SumA(j-1) + \text{acc}(j)$
$SumP(j) = SumP(j-1) + P(j)$
Next j
$SumA(d) = SumA(24)$ and $SumP(d) = SumP(24)$

6. Accumulate the $SumP(d)$'s, $SumO(d)$'s and $SumA(d)$'s to T.

7. After the last time period in each iteration, store the cumulative profits, offers made and offers accepted over the investigation horizon, namely $SumP(T)$, $SumO(T)$ and $SumA(T)$.

8. Calculate maxima, minima, averages and standard deviations of the $SumP(T)$'s, $SumO(T)$'s and $SumA(T)$'s at the end of each experiment.

9. Change ξ_D, ξ_S, σ_S, σ_D, ρ, σ_γ, e, g, d, f, p, e, β and h according to the experimental design and repeat the simulation, summarising the results after each experiment.

A diagram of the trading algorithm is given in Figure 5.1 and the *Visual Basic* code is included in the Appendix.

A note on the output

For each iteration, the values stored are the profits accumulated to the end of the time horizon, the number of offers that were accepted, and the number of offers made for the same horizon. All of these 'response' variables will be kept should an analysis of the number of offers made or accepted be required, or perhaps even an analysis of the nature of the relationship between the responses, given their obvious positive (though imperfect) correlation. The program will output the means, standard deviations, maxima and minima of the three response variables for each simulation experiment that is undertaken.

5.3.4 Summary of Model Formulation

Parameter Values

The following table again summarises the simulation parameters (with shortened definitions) and gives some initial values that were used in some preliminary test runs of the algorithm. The parameters will be classified in more detail before the results and analyses of Chapter 6:

Parameter[1]	Description	Initial Values
N	number of simulation iterations	100
T	investigation horizon (days)	365
F	the fixed running costs	0
g	fixed capacity offered and generated (MWh)	100
ρ	smoothing parameter for Actuals' stochasticity	0.3
σ_Υ	standard deviation of stochasticity in Actuals	0.15
ξ_D	estimation bias for log demand	0
ξ_S	estimation bias for log SMP	0
σ_D	precision for estimate of log demand	0.1
σ_S	precision for estimate of log SMP	0.1
h	number of hours for pumping (and for generation)	10
d	demand threshold for offer strategy (MWh)	20,000
f	relative proportion of S_f to C_f for offer strategy	1
p	proportion of $[C_f, S_f]$ above C_f for offer price	0.5
e	the efficiency parameter for a pumped-storage scheme	0.76
β	the price-influence parameter	0.2

Justification

1. A value for N of 100 was chosen since the frequency distribution of profit outcomes in some test runs appeared sufficiently smooth at this level. Higher values were not justified for the amount of extra processing time required, and lower values tended to lead to more random outcomes across profit bins in the plotted histograms.

2. The horizon, T was set to one year's worth of hours (8,760) in order to capture the deterministic variation of the three Actuals over an entire year (2003 in this instance). Shortening this horizon may have distorted the profit outcomes by biasing the model to a shorter period of the year, though simulation running time is potentially long for a full year horizon.

3. The value for F was kept at zero as explained earlier. For actual implementation, further data would be required from Eskom Peaking Cluster.

4. The notion of fixed capacity ($g = 100MWh$) is an obvious model simplification as explained earlier in this chapter. In practice, it is possible to simultaneously vary (by submitting a step-like supply function) *both* price *and* quantity when offering production for a particular hour. We are therefore now assuming that this unit is only capable of generating a constant 100 Megawatts in an hour, and that when contracted it does in fact generate this amount. The has the potential to be varied. Some of the literature (e.g. [9, 13, 34, 50]) supports such a simplification in the sense that an offer is merely an allocation of capacity to fixed price bins, such that the offer involves the choice of one variable's value (i.e. price *or* quantity) rather than a selection of two (In the case of a linear supply function, it is only required

[1] Values for parameters ρ to β will be varied depending on the run number in the experimental plans in Chapter 6.

to choose one of the coefficients of the linear equation [52, 53]). A further separate model modification would be to permit the amount actually generated to have a random outcome, introducing uncertainty with regard to the amount actually required by the system operator in real time. Such a modification would have to be made without regard to reserves markets and ancillary services which would complicate the model formulation and detract from its current exploratory goals.

5. The smoothing parameter ρ is given an initial value of 0.3 allowing a 'moderately large' amount of smoothing.

6. The stochastic uncertainty, σ_γ is given an initial value of 0.15 ($\approx 0.1/(1-\rho)$) which is equivalent to an error of approximately 20% (see table 6.2 on 137 in Chapter 6).

7. The forecasting biases, ξ_D and ξ_S have been set equal to 0 and could, for example, be varied for an investigation into trader proficiency.

5.3.5 Some Important Issues

Under the headings that follow points that follow, some light is shed on some important attributes of the simulation model, clarifying some of the issues that may not be obvious from the point-by-point algorithm in subsection 5.3.3.

Fixed Costs

Fixed costs, F have been removed from the model; all profits generated can be assumed to be contributions to fixed costs.

Marginal Costs

We could have set $C_f(t) = C_a(t) + \varepsilon_C$ if we wished to include add an additional level of trader uncertainty with respect to the pumping efficiency parameter, e (or any other variations on the theme of cost function analysis). In general, the formulated treatment of costs is by no means a true reflection of reality, though it does provoke insight and has the potential to be modified with further cooperation from Eskom Peaking. Demand-side bidding may (at the time of writing) have already been implemented for the purchase of off-peak pumping power and would in effect alter the formulation substantially were it to be commercially adapted.

Pumping/generating hours

The choice for h in the initial runs the number of pumping hours (and hence the maximum number of generating hours) is somewhat arbitrary. Empirical evidence suggests that the scheme pumps for roughly 40% of the hours of the year and generates for the same proportion (obviously in non-coinciding time periods). The evidence equates to roughly 10 hours of pumping and 10 hours of generating each day. It is rare for the scheme to pump less than 6 hours a day with the bulk of pumping happening in the six lowest demand periods of the day. Further insights could be achieved by treating the parameter h as a daily decision variable whereby the trader may decide each day what the optimal number of hours to generate/pump should be for that day. Indeed the alternative treatment is true of the other decision variables as well. The choice would be functionally dependent on the forecasted values of SMP and Demand as before. Clearly h would be an obvious decision variable in a profit optimality routine, given the values of the exogenous factors.

As an alternative to the above, a more complex optimisation routine could be employed. Such a routine would necessitate specific research on the pumped-storage scheme unit commitment problem which is beyond the scope of this dissertation. Clearly this point opens up debate on the choice of MC as being equal to the average of the pumping costs incurred that day. In reality the MC is not necessarily constant throughout the day, though it could be assumed to be so for trading a day in advance as occurs in practice. Eskom Peaking uses the *'PMAC'* model to determine the potential value of stored energy in the reservoir and hence its marginal cost for generation for the following day. In the simulation it is however assumed the costs are incurred on the same day as production, and based on the SMP forecasts for that day.

Pumping costs incurred on days on which there is less than h hours generation are not carried over to the following period in the form of excess storage — a fact that is also related to unit commitment, production planning and scheduling ideas.

An additional complication which may arise is the (realistic) inclusion of demand-side bidding for the pumping hours. We are presently assuming that the Genco's trader takes a decision to pump for a fixed number of hours, h regardless of what the SMP forecasts are in the lowest hours, i.e. he/she purchases megawatts in the h lowest hours at 'all costs'. A possible modification to the model would be to implement a pumping strategy in a similar vein to that for generating, in which the trader submits a bid to purchase megawatts for pumping if system demand and forecast SMP's are *below* prespecified thresholds. This implementation would, in turn, determine the unit's availability for generating in the remaining hours.

Price influence

The price influence, β, equals 0 if the Genco is a price-taker and 1 if it has complete control over the price level. For 'peaking'-type units which may generate at any time of the day, a more realistic approach would be, for example, to allow β to be a function of $D_a(t)$ such that it may have a greater influence on price when demand is at much higher levels i.e. when it is the marginal production unit. Initially it seems prudent to use a constant low value of β, such as 0.2, and examine the effects on profits and offers accepted by varying this parameter.

We are assuming that when we include a price-influence parameter there is negligible (or no) effect on the underlying deterministic structure of S_a as such an effect would create an illogical loop in the program (see also [51, p. 654]). The purpose of including the model of price-influence as described is to enable exploratory investigation. As such we are able to mimic the propensity of the Genco to sway the SMP in the direction of the price they offer for a particular hour. It must be stressed that we are not attempting to model deliberate action by the Genco to influence the SMP. The price influence model is introduced only to explore sensitivity to this potential effect.

A further avenue of enquiry would be to consider a hybrid of price-taking and price-setting where β takes on a zero value when the Genco is unlikely to be able to affect the price and values close to unity when it has almost complete control. For such a proposition, β would be a function of the actual demand, D_a in the relevant hour. The practical motivation for such a consideration would be that in periods of low demand (ignoring reserves markets), the pumped storage unit is essentially a price-taker (or is fact pumping during those periods). In periods of high demand the Genco would have a greater influence on the price and may even price themselves out of contention.

Demand

In reality, the role of the demand variable may be somewhat more involved than that implied by the decision rule of when to trade. Genco's in real markets are more inclined to consider their potential market share, as well as their competitors' and consumers' responses to their actions in the market, than simply use their forecast of demand as a means for determining a simple threshold for entering the market. For a more realistic integration of the demand variable, it would be necessary to invoke a more in-depth study of local market. The role of demand expounded here is preliminary in nature, however it does make sense for the case of a generic producer of peaking-period electricity.

5.4 Summary

In this chapter, a simulation routine to mimic the trading activities of a pumped storage generator has been developed upon the foundations of a more general Genco entity. The reasons for the specialisation are data-related. The simplifications of reality and all the assumptions have been defined and explained along with some suggestions of possible modifications to the both the general model and the specialised one. The simulation parameters have been outlined and an algorithm described which is a precursor to the experiments and subsequent analyses of the next chapter.

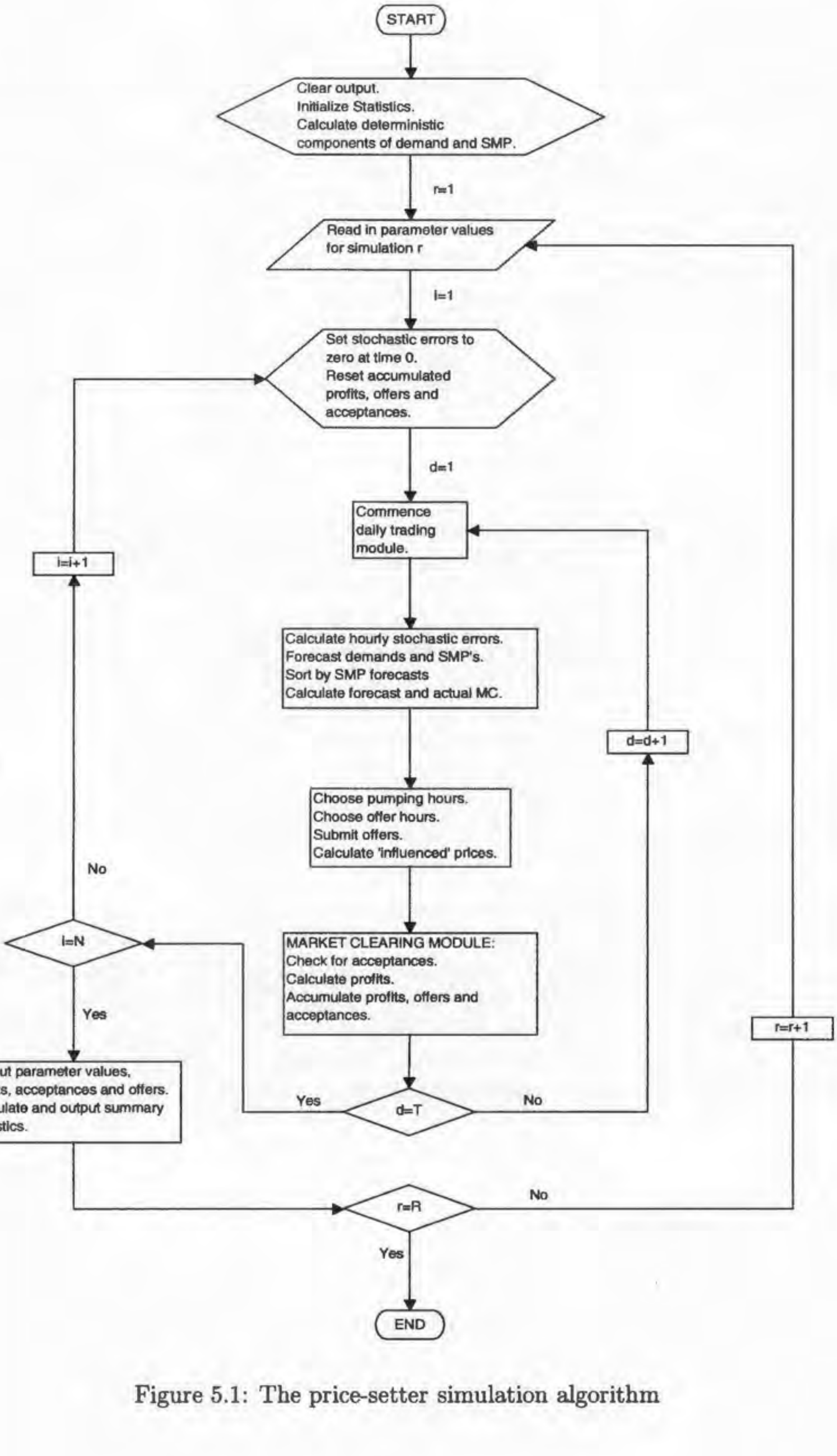


Figure 5.1: The price-setter simulation algorithm

Chapter 6

Results and Observations

The results and analyses of a set of simulation runs based on the model formulation of Chapter 5 are presented in this chapter. Firstly, the definitions and meanings of the model factors (parameters) will be given as a reminder to the reader, along with a classification for them that will enable an interpretation of the outputs of the simulation experiments. In addition, the first part of this chapter will include a discussion of these factors as model inputs (including a table of factor levels), followed by the experimental design for the metasimulation, and ending with the tabular references to the outputs of the metasimulation.

In the second section, we proceed with the analysis of the primary benefit measure, *Mean Profit*, by giving the ANOVA table for first and second order interactions, the mean profits for each of the main factor levels and a discussion of the significant factors and interactions. Section 6.3 proceeds in a similar fashion, by qualifying the results of Section 6.2 with an analysis of the secondary benefit measure, *Mean Acceptances*. A concluding discussion on the results is given at the end of this chapter in Section 6.4.

6.1 The Experimental Design

At this juncture, the reader is reminded that the model of Chapter 5 has been refined in such a way as to illustrate and analyse the strategic behaviour of a generic pumped-storage unit trading in the Eskom Power Pool. The justification for the use of this type of unit was given in the final subsection of Chapter 4 and from hereon it will be treated as a nominal client for the analysis; the adaptability of the formulation to *any* other type of generating plant is once again highlighted as a being plausible for reformulation of the model.

Although some real price and demand data were used for the model's construction, the results themselves have no realistic meaning and are more useful for their interpretative and investigative qualities. The merits of the model as a tool for learning in a competitive market system is the ultimate aim of the exploration. In the terminology of French [18], the type of modelling that has been undertaken is descriptive, and results are analysed using the normative technique of experimental design. The end result is therefore a prescriptive analysis of the behaviour of a trading Genco under various scenarios and strategies. The model is built with the *ultimate* intention of prescribing normative behaviour, such as how to achieve the optimal profit and/or minimise risk exposures. Realistic implementation (in either a descriptive or normative context) may only take place once the model has been demonstrated to a client Genco and revised in the light of their feedback and additional data input. A full implementation is likely to require further model-refinement and adaptation, in conjunction with the extensive cooperation of a particular Genco client.

To illustrate this final point, in reality the Genco would vary their actions on a daily basis, continually reforming their strategies and ideas. The model, on the other hand, assumes a particular configuration of the strategy and the exogenous parameters throughout each investigation horizon. This process is repeated many times, each time with a configuration of strategy and exogenous factors dictated by the experimental design. The prescriptive part of the process arises when we introduce the experimental design, the results of which inform us which strategies are good and/or robust to the external factors, which are represented by the exogenous factors in Table 6.1 below. In this way (and others) the model is a descriptive one. It is also exploratory in a modelling sense, and could lead to refinements of our perceptions about the way both the system and the model behave.

6.1.1 The Parameters

Table 6.1 summarises the parameter definitions and classification for ease of reference throughout this chapter. For more detailed definitions the reader is referred back to Chapter 5.

A particular set of values for the **endogenous** parameters defines the participant's strategy for each simulation run. The **exogenous** parameters give the environmental characteristics for each run: some of which are fixed throughout all runs, some are specific to a participant and others provide a context or scenario under which each experiment takes place.

Endogenous parameters

The endogenous parameters are fixed for the period of each simulation run so as to impose a particular strategy over the investigation horizon. In reality these parameters could be the particular strategy adopted by a trader and could ostensibly be varied for each daily trade. The simulation runs attempt to capture the effects of a particular strategy (combination of factor values) adopted over a length of time, and under various (exogenous scenarios).

Parameter	Description
Endogenous — strategy	
h	number of hours for pumping (and for generation)
d	demand threshold for offer strategy (MWh)
f	relative proportion of S_f to C_f for offer strategy
p	proportion of $[C_f, S_f]$ above C_f for offer price
Exogenous — fixed	
N	number of simulation iterations
T	investigation horizon (days)
g	fixed capacity offered and generated
Exogenous — proficiency	
ξ_D	estimation bias for demand
ξ_S	estimation bias for SMP
σ_D	precision for estimate of demand
σ_S	precision for estimate of SMP
Exogenous — contextual	
β	the price-influence parameter
e	the efficiency parameter for a pumped-storage scheme
ρ	smoothing parameter for Actuals' stochasticity
σ_γ	standard deviation of stochasticity in Actuals

Table 6.1: Summary of parameter classification and definitions

h number of hours for *both* pumping and generation; part of the offer strategy, it specifies the available daily generating capacity (refer to p. 126).

d demand threshold for offer strategy in megawatt hours; used to decide when (i.e in which hours) it is appropriate to submit an offer (p. 118).

f relative proportion of S_f to C_f for offer strategy; used in conjunction with d to decide when (with respect to expected costs and prices) to submit an offer to the pool (p. 118).

p proportion of $[C_f, S_f]$ above C_f for offer price; determines the level at which the trader pitches his offers in relation to his expected costs and the expected system price (p. 119).

From some experimental runs performed before the main metasimulation of this chapter, it was noted that the mean profit decreases monotonically with respect to d, f and p. Parameter h however gave an optimal profit value at a value between 1 and 12, and the value at which this optimum was found depended on the scenario dictated by all of the other factors. Indirectly, d, f and h are essentially factors through which the modeller can control the availability and daily capacity of the generating unit according to the following decision criteria:

1. Parameter d ensures that the Genco only enters the market when the forecast of system demand is above this threshold.

2. The required profit margin is determined by parameter f. Increasing this factor will ensure that offers are only made in periods when the forecast of SMP is a specified proportion greater than the forecast of marginal cost.

3. The daily availability is controlled by h (refer to Section 5.3.5), which essentially places an upper bound on the number of offers made, but also dictates the number of hours for pumping. The criteria for choosing this factor is somewhat complex for a number of reasons. The Genco will select the hours with the lowest expected SMP's for pumping, and the ones with the highest expected SMP's will be for generating. Having offered h hours with the expectation that all the offers will be accepted, the marginal cost estimate is then based on an average of the h lowest forecast SMP hours (divided by the efficiency, e); actual MC's will conversely depend on the average of the h actual SMP's in the hours (also divided by e). The construction of the MC variable is therefore somewhat artificial, but adequate for modelling purposes. The averaging was necessary because realistically the unit's marginal costs will depend on the actual SMP's for a number of hours which is equal to the *accepted* number of generating hours. The variable MC_a, from the simulation algorithm of Chapter 5, is therefore an approximation to the actual marginal cost. As previously mentioned, research into the unit commitment choices of a pumped storage scheme would be necessary for a more realistic representation of the costs, however this model is illustrative and designed to represent a generic generating unit rather than a pumped storage one.

Offer optimality is simplified in this model to choosing an optimal price, rather than both a price and a quantity, or even a *set* of prices and quantities. One of the aims of the model is to determine if there is an optimal value for parameter p that results in an optimal profit. Simultaneous optimisation of all of the endogenous parameters of this model is equivalent to finding the optimal *supply function*, the reason being that parameters d, f and h determine the amount of capacity offered in the daily market. In effect the goal is equivalent to the aims of the (often complex) stochastic optimisation routines described in Chapter 3. Both the approach of this model and those of Chapter 3 essentially amount to the choice of an optimal supply curve for a trading Genco.

Exogenous parameters

(a) Fixed Parameters

N The number of simulation iterations. A value of 100 gives a stable frequency distribution of outcomes without requiring an unreasonable length for run-time. The entire experiment of $2^{10-3} = 128$ runs was completed in approximately six hours on an *Intel Celeron* 1.7Ghz (128MB RAM) and $T = 31$.

T The investigation horizon (days). Ideally, given an entire year's worth of data, a simulation over an equivalent period would be the useful in order to capture the seasonality inherent in the variables. Preliminary runs demonstrated that a full run was infeasible due to the amount of processing time required for a run of one year, and given that the imminent size of the design was large. There was also the desire to avoid confounding preventing the design from being below a particular resolution. It was therefore decided to initially perform the experiment with a horizon of 31 days to mitigate the amount of processing time required.[1]

g Fixed capacity offered and generated in a particular time period. The model is as yet insufficiently complex to incorporate a full-scale investigation of the optimal supply function. Consequently the inclusion of variable quantity offered is a subject for further investigation. A nominal value of 100 is used throughout (no particular units are implied).

(b) Trader Proficiency The trader proficiency parameters are specific to an individual trader acting on behalf of the generating unit. In a modelling sense they can be used to control various scenarios of trader expertise and information availability.

ξ_D the estimation bias for system demand; indicates the tendency of a trader to over or under-estimate the true value of this variable (defined for generality but set to zero in all simulation runs repeated here — variations will be reserved for further future exploration).

ξ_S the estimation bias for the SMP; (same comments as for ξ_D).

σ_D precision for estimate of demand, reflecting the ability of a trader to forecast demand accurately.

σ_S precision for estimate of SMP, reflecting the ability of a trader to forecast SMP accurately.

(c) Contextual The contextual parameters define the context under which the trader operates. Factors ρ and σ_γ (refer to p. 112) describe the inherent variability of the system, the stochasticity of the underlying variables attributed to natural fluctuations

[1]A comparison run with a full year's run ($T = 365$) has subsequently been done and the results were consistent with those of this time horizon with $T = 31$. The presented analyses, however were based on the numerical results of the shorter run.

beyond the control or influence of the Genco. They are essential to the simulation and reflect the extent to which we cannot perfectly mimic reality. They are environmental factors which allow us to impose various scenarios with respect to the levels of uncertainty in a stochastic simulation model. Factors e and β (see pages 119 and 121 respectively) will also be specific to a particular production unit — the former allows a modeller to control the extent to which the unit is responsible for the final price, and the latter is a lumped parameter which permits experimentation with the macro-level attributes of the Genco's cost function for this particular production unit.

β the influence parameter for the price-setter simulation.

ρ the smoothing parameter for Actuals' stochasticity.

σ_γ standard deviation of stochasticity in Actuals.

e the efficiency parameter for a pumped-storage scheme; effectively determines the cost curve of the unit. In practice this parameter is fixed, however in order to investigate the effects of changes in the cost function for the production unit, it was decided to include it in the design. Costs — as defined in the previous chapter — depend on the SMP's in the pumping hours and the pumping efficiency.

6.1.2 Modelling Aims

The initial aim of the simulation model is broadly consistent with many others found in the literature:

> We explore the effects of various scenarios on the benefits accrued to a trading generator and identify those factors (and their combinations) which have a measured effect on the benefits. In so doing we hope to identify:
>
> 1. the most important parameters and the significance of any interactions between them
> 2. the most optimal strategies under various scenarios
> 3. the robustness of strategies to various scenarios
> 4. the suitability of this kind of model to address the issues presented in this thesis

The aims of this model are also exploratory as described earlier in this section.

Initially in Section 6.2 we will define 'benefits' as the overall profit gained over the simulation period. Later it will be worthwhile to investigate the dependency of the other two 'benefit' measures — offers made and offers accepted — on the simulation parameters as such an investigation would help qualify some of the effects on the primary variable of interest, namely profit.

In this dissertation we analyse the qualifying effects of the offers accepted on profit in Section 6.3. An investigation of the qualifying effects of offers made is left for future analysis using the existing results. Additionally, it would be of interest to explore the relationship *between* these benefit measures. For example, we could be achieving equivalent number of offers accepted for two different parameter sets, yet the profit on one set could differ from the other. Such analyses would be useful for investigating the profitability of trades conditional on the offers being successful. Alternatively we can have fewer offers accepted (thus fewer hours spent generating) and suffer little or no reduction in profits. The ideas here present avenues for further experimentation and research (and will actually be undertaken to an extent in Section 6.3 where some interesting insights will be revealed, however the potential for additional analysis using the current set of results is substantial.) Of paramount importance is a critical examination of the suitability of the model to provide a robust method of strategic analysis, including its versatility, simplicity, and ease of implementation. These ideas will be discussed in the concluding chapter of this thesis. Firstly however, the design and results of the main simulation experiment of this dissertation will be presented.

6.1.3 The Simulation Runs

In this subsection we give the particular set of parameter values used in the experimental design and analysis.

Table 6.2 was used to select appropriate values for σ_D, σ_S and σ_γ. The table allows us to choose values for our precision parameters under the lognormal model such that if X is lognormally distributed with median m, and $Y = \ln X$ is normally distributed with mean $\mu = \ln m$ and variance σ^2 then,

$$Z = \frac{Y - \mu}{\sigma} \sim N(0,1)$$

and

$$\begin{aligned} Pr\left[\delta \leq \frac{X}{m} < \frac{1}{\delta}\right] &= Pr\left[\ln \delta \leq Y - \mu \leq -\ln \delta\right] \\ &= Pr\left[\frac{\ln \delta}{\sigma} \leq Z \leq -\frac{\ln \delta}{\sigma}\right]. \end{aligned}$$

The above probability can be set equal to 0.95 to derive values for σ for any desired accuracy, δ. For example, we could choose a forecasting accuracy of 20% (the fifth row of the table) and be 95% sure that our forecast will be between 80% and 125% of the actual value. In the case of stochasticity of the Actuals, σ_γ, we divide the σ-value by $1 - \rho$ to get a correspondingly equivalent measure of stochasticity.

A $2^{(10-3)}$ fractional factorial experiment was designed with the parameter values of Table 6.3. These values were selected intuitively based on plausible values for the system variables, and after having performed several preliminary, trial-and-error 'test' runs. It was intended that these values cover a sufficiently broad range for a 2-level design, and they were selected in such a manner as to facilitate reasonable interpretation and analysis of the results. They are by no means the only possible set of values that could

Table 6.2: Table of precision and volatility values

δ	$1/\delta$	Approximate choice for σ_S or σ_D	Nominal forecasting accuracy
0.99	1.01	0.00	1%
0.95	1.05	0.02	5%
0.90	1.11	0.05	10%
0.85	1.18	0.08	15%
0.80	1.25	0.11	20%
0.75	1.33	0.14	25%
0.70	1.43	0.18	30%
0.60	1.67	0.26	40%
0.50	2.00	0.35	50%
0.40	2.50	0.46	60%
0.30	3.33	0.61	70%
0.10	10	1.17	90%
0.01	100	2.35	99%

have been used. Given extra time for experimentation with alternative parameter sets, the robustness of the results analysed in Sections 6.3 and 6.4 could have been revealed. Additional experimentation of this sort, is left for future experimentation with the model.

Table 6.3: Parameter values for $2^{(10-3)}$ design

Factor	Low Value	High Value
β	0.20	0.80
σ_γ	0.12	0.29
h	6	10
σ_D	0.11	0.26
σ_S	0.11	0.26
d	22000	28000
f	0.9	1.8
p	0.1	0.9
e	0.6	0.9
ρ	0.1	0.3

A fractional design with zero replications was chosen to moderate the amount of processing time required for the metasimulation. The experiment was designed in *STATISTICA*, reducing the full design by a factor of eight to mitigate the amount of processing time. The number of runs required was therefore $2^7 = 128$. The exact configuration of runs was chosen such that each of the two levels of each parameter occurs 64 times, and with each other factor a common number of 32 times. The incomplete block of 128 runs is chosen by invoking a particular set of runs that confines the confounding (aliasing) of factors to terms of higher order than the factors of interest (i.e. to higher than second order). *STATISTICA* was employed to produce a design in which no first order effects were confounded with each other, or with any of the second order or higher effects, and such that no second order effects were confounded with each other or with any higher order effects. In such a design, higher order interactions are presumed to be negligible and the main and second order effects are uniquely estimable. By virtue of having chosen an astute design, the effects are also independent. The resolution of this design is V.

The design and the generators of the fraction alias arrangements are reported in Table A.1 of the appendix while the mean profits, offers and acceptances from each of the 128 experimental runs are given in Table A.2. A discussion and analysis of the results follows in the next section.

6.2 Analysis of Mean Profits

What follows is a factor-by-factor discussion of the first order effects on the mean profit achieved over the investigation horizon. The discussion, in turn, is followed by evidence of some interactive effects and their significance. The ANOVA results for the analysis, with Mean Profit as the dependent variable, are given in Table 6.4. The table was abbreviated to include all ten of the main effects, and only interaction effects that were statistically significant up to a level of 10% (with one greater for illustration). Degrees of freedom (*DF*) for all effects equal 1, so the Sum of Squares equal the Mean Square Errors (MSE's) and have been omitted from the table.

Parameters σ_S, p and ρ were the only main effects not significant at the 1% level. The first eight interaction effects shown in the table were significant at the 1% level with a further two significant at the 5% level. The discussions will therefore only be given for the eight most significant interactions. It is interesting to note at this juncture that although σ_S and p had no significant first-order effect on the mean profit, there were several interactions with these factors that were important.

A note on 'significance'

In a strict statistical sense, there is an issue of multiple comparisons when discussing levels of significance as above. When looking at multiple factors' significance, a much lower statistical significance level would usually be required to render the individual factors significant than if we were only concerned with that individual factor. However, in simulation modelling this is of less importance, because the factors are (in a sense) imaginary, and are unique to the system described by the model. The actual level of significance is therefore less consequential than the magnitude of the factor's parametric effect on the response variable of interest.

Factor	Effect	MSE	F-value	p-value
d	-245439	1.90E+12	333.2	0.00
β	-232287	1.70E+12	298.5	0.00
e	217626	1.50E+12	262	0.00
f	-129004	5.30E+11	92.1	0.00
σ_D	-111273	4.00E+11	68.5	0.00
h	-104427	3.50E+11	60.3	0.00
σ_γ	82891	2.20E+11	38	0.00
ρ	-26506	2.24E+10	3.9	0.05
σ_S	5428	9.43E+08	0.2	0.68
p	-3429	3.76E+08	0.1	0.79
$\beta \times p$	171761	9.40E+11	163.2	0.00
$\beta \times d$	77680	1.90E+11	33.4	0.00
$d \times e$	-71518	1.60E+11	28.3	0.00
$\beta \times e$	-58010	1.10E+11	18.6	0.00
$\sigma_S \times d$	49900	7.97E+10	13.8	0.00
$\beta \times f$	45752	6.70E+10	11.6	0.00
$\sigma_D \times p$	-43388	6.02E+10	10.4	0.00
$\sigma_D \times d$	39800	5.07E+10	8.8	0.00
$d \times f$	33222	3.53E+10	6.1	0.02
$\sigma_\gamma \times h$	-31812	3.23E+10	5.6	0.02
$\sigma_D \times f$	31165	3.10E+10	5.4	0.02
$\beta \times h$	26801	2.30E+10	4	0.05
$\beta \times \sigma_\gamma$	-26203	2.20E+10	3.8	0.05
$\sigma_\gamma \times \rho$	-25741	2.12E+10	3.7	0.06
$\sigma_D \times e$	-24533	1.92E+10	3.3	0.07
$\sigma_\gamma \times f$	-22794	1.67E+10	2.9	0.09
$\sigma_\gamma \times d$	19536	1.22E+10	2.1	0.15
Error		5.78E+9	*DF:*	72

Table 6.4: Abbreviated ANOVA table for analysis of Profits

6.2.1 Main Effects

Table 6.5 shows the means of the main effects (profits) for ten parameters in the design for the low and high value of each of the parameters in turn (non-significant ones have been included for illustrative purposes). The figures in brackets show the standard errors (SE's) of the means.

All of the main effects will be discussed in order of significance, while paying particular attention to the classification and definitions given at the beginning of this chapter. Increasing d and f or reducing h simply means that the trader will submit fewer offers in each trading day, and for the most part, effectively exclude the Genco from possible trades and reduce the numbers of actual transactions. That is not to say that profit will suffer a corresponding decrease in value, since a smaller number of (less profitable)

Factor	Mean Profit		
	Low Value (SE)	High Value (SE)	Change
d	482853 (36642)	237415 (20577)	-51%
β	476277 (35702)	243990 (23266)	-49%
e	251321 (23863)	468947 (36039)	87%
f	424636 (35349)	295632 (29369)	-30%
σ_D	415771 (35577)	304497 (29667)	-27%
h	412347 (34602)	307920 (30989)	-25%
σ_γ	318688 (32988)	401580 (33188)	26%
ρ	373387 (33478)	346881 (33434)	-7%
σ_S	357420 (35081)	362848 (31831)	2%
p	361848 (37967)	358420 (28330)	-1%

Table 6.5: Mean profit outcomes for the main effects

trades will not necessarily reduce the bottom line profit (it may even result in a higher profit if some of the trades made losses). Reducing h could even have a desirable effect on profit if actual SMP's in the selected pumping hours are higher. The desirable effect would be a consequence of increasing the resultant cost to the Genco.

Demand threshold: d

Increasing d merely serves to exclude the Genco from potential trades, leading to reduced number of offers made and therefore lower overall profit. It was conjectured in the preliminary formulation of the model that an optimal d would be found such that under particular parameterisations, we could achieve a higher bottom line by offering in periods of higher demand when SMP's are correspondingly higher. The initial conjecture could not be vindicated by the model. A possible generalisation of the model which would lead to a non-monotonic dependency on d would be to reformulate it according to the following question: "If we are constrained to generate for a prespecified number of hours (e.g. one per day), what would be the appropriate demand level at which the trader ought to enter the market?" In this way the modeller could identify ways that the Genco could benefit from any inherent correlation structure between demand and price. Alternatively, as mentioned in Chapter 5, we could introduce a correlation structure between the stochastic errors (σ_γ's) for the Actuals (D_a and S_a) and determine whether the trader is then able to benefit by exploiting this correlation structure. In this model, however, the stochastic errors were independently sampled. In summary, increasing d reduces the number of offers made and thus the number of acceptances and profits achieved.

Price influence: β

In the context of this model, increasing the influence of the Genco brings the final SMP closer to the offer price, reducing the profitability of any accepted offers (since offer prices are always less than expected SMP, and therefore generally less than actual SMP), and thus reducing the final profit outcome. It will be seen in the next section that β has *no* effect on the number of acceptances under the existing parameterisation; the reduction in profits is purely attributable to the reduced final SMP's received in the market clearing mechanism. In a situation where MC's were higher than SMP's with the trader offering above MC, there may be scope for reduced acceptances. Generalisation of the model could again be achieved through a modified value for e (i.e. an alternative cost curve). Since the trader always offers between forecast MC and forecast SMP, the final SMP will be pushed lower when β is positive. Another interesting generalisation would be to permit the trader to offer above expected SMP (i.e. $p > 1$) and observe the differences attributed to β-values under this scenario. A simplification of the model to $\beta = 0$ would allow the focus of the strategic analysis to be on a price-taking Genco in a purely competitive market.

Pumping efficiency: e

The greater the efficiency, the lower the cost to the Genco of producing electricity and the greater their overall profits. This parameter is a key one in the model, as it says a great deal about the Genco's cost function. When their costs are lower, the trader will automatically submit offer prices that are lower (all things equal), being constrained to an interval of $[C_f, S_f]$ for the offer. Also, the lower the costs, the smaller the cost threshold will be and the more times the trader will choose to enter the market on the basis of cost. The inclusion of demand-side bidding would also alter the model formulation in such a way that the Genco's costs would depend on its success in bidding for pumping energy, and would result in a completely different cost function. The model could easily be adapted to such a scenario.

Cost threshold: f

Similarly to d above, increasing the value of the cost threshold also results in lower overall profits, once again suggesting that a Genco should always enter the market, regardless of how high their marginal cost is expected to be. The result may be a consequence of the costs for this unit (a pumped storage scheme) being quite low, and the potential for losses negligible under the current scenarios and formulation. We might generalise here by considering smaller values for e or even vary it in a non-linear manner (by way of a 3-level instead of 2-level design) and end up with profits that are non-monotone with respect to the cost threshold.

Parameter f is distinct from d in the sense that it constrains the unit's capacity in terms of costs, rather than its availability in hours as per system demand fluctuations. As we are representing a pumped storage scheme, costs will depend directly on the SMP's in the hours selected for pumping. It may be found that for another type of generating plant (with costs which depend on prices of primary fuels such as coal), the correlation with prices would be weaker, and we could achieve results that are non-monotone with respect to f. Having two levels for this factor is tantamount to a linear cost function (assuming the forecast of MC is constant). The discussion here leads us into the realm of generator cost functions which is not explored now, however the interaction with other cost parameters such as e will still be discussed. In this formulation, increasing f reduces the number of offers made and thus the number of acceptances and revenue received.

Demand precision: σ_D

In preliminary runs, this parameter was only significant for particular values of d and, as expected, there was a decrease in the profit margin for a reduction in precision. For a given value of d, a reduction in precision causes the Genco's strategy to be misguided as their expectations of the true values of demand are incorrect more of the time. They will consequently — in the case of lognormal variable values — be forced *not* to enter the market for a greater proportion of available trading hours, since more of their expected demand values will be greater than the threshold, d. Examining Table 6.2, one observes that the (implied) confidence interval is more asymmetrically skewed to the left (i.e. negatively skewed) for higher values of σ_D, so the tendency to overestimate the demand will be greater than the tendency to underestimate it. The effect of increasing σ_D has a similar effect to increasing d, therefore validating the model in the sense that a poorer information set (or a less proficient trader) will reduce the Genco's profitability.

Pumping/generating hours: h

For a change in level from 6 to 10 hours, a decrease in profit arose amounting to 7%. There are several plausible explanations for the decrease. At first glance, the outcome appears strange, because by granting the trader more hours to trade in, one would expect higher profits to accrue to the Genco. An explanation lies in two related arguments:

1. A value of 10 surpasses the optimum number of hours for achieving the maximum profit with respect to h; generating in too many hours results in greater overall costs (through higher SMP's in particular pumping hours).

2. The Genco has exceeded the scheme's limits with respect to efficiency, so an alternative (higher) pair of values for e in the formulation would have the opposite effect and result in increased profit.

Preliminary runs had in fact indicated that under the current formulation, there was an optimal level of h (a value between 6 and 12) that maximised the profits received. (A limit of 12 implies that the unit is required to pump for the equivalent number of hours for which it generates in any given day. The equivalence of pumping and generating hours allows the storage levels of the upper reservoir to be maintained, and obviously the unit cannot generate while pumping.)

An interesting area of exploration here would be to find how the optimal number of hours varies under alternative scenarios defined by particular configurations of the other parameters (for example e). A normative formulation could also be developed to determine exactly which hours of the day are the most profitable to generate (and pump) in.

The model has even further potential for generalisation with respect to h: it could be redefined as an independent variable with daily variations due to scheduled (or unscheduled) maintenance, or other similar production constraints imposed upon the trader. In a realistic application, such modifications would depend on the actual scenarios experienced by a trader, and on the aim of the model.

Actuals' stochasticity: σ_γ

An overall increase in profits of 26% is observed when increasing this factor from 0.12 to 0.29. Increasing the stochasticity of the underlying demand and SMP, essentially increases the 'optionality' that the Genco has with respect to strategy. Increased stochasticity (especially in the underlying SMP's) gives the trader the opportunity to benefit from a wider range of expected SMP's (especially on the upside due to the lognormal model, and increased negative skewness resulting from higher volatility). SMP's will also have a wider range in pumping hours where the Genco can benefit from the extended range of downside SMP values. Consequently the Genco enters the market more frequently as trades become more profitable, simultaneously benefiting from lower costs and higher prices. The effect is analogous to the effect of volatility on an option price in a derivatives market. When variability of the underlying variables is high, there is more opportunity for making money through exercising the 'option' to trade. A similar argument will apply to the effect of stochasticity on demand (more actual and forecasted demand values on the upside combined with a constant threshold, d). With this model it is not possible to identify to which of the stochasticities (demand or price) the improvement in profits should be attributed.

Actuals' smoothing parameter: ρ

Increasing the amount of exponential smoothing in the stochastic process for the Actuals has a moderately significant impact (slight reduction), however this factor is of little interest as none of its interactions with other factors were important other than moderately significant interaction with σ_γ (which is expected due to the construction of the AR(1) process [refer to p. 112]). When ρ is higher there is a greater level of correlation between errors, an overall reduction in 'randomness' and thus a reduction in the previously described 'optionality' in the generic market. The greater the randomness, the higher the profits achievable. Further experimentation here may not reveal much, unless the AR(1) process was extended to something more complex, though it would be prudent to test an alternative set of values for ρ to confirm this supposition.

SMP precision: σ_S

Little change is observed in the profit when reducing the price-forecasting accuracy. The small change is contrary to the modeller's conjectures, as one would expect a poorer information set and lower forecasting proficiency (higher σ_S) would decrease profits. In fact, a small (possibly spurious) increase of 2% is observed.

Increasing σ_S to 0.26 will on average result in an absolute over-estimation of SMP's (again owing to the lognormal model). Forecasts of costs and SMP's will be higher, shifting the interval $[C_f, S_f]$ to the right. The Genco will now only enter the market at higher cost thresholds and offer their energy at correspondingly higher prices. In any event, the actual costs and SMP's will be the same (besides a small increase due to price-influence) and thus lower than the estimates and the profitability will remain largely unchanged.

The initial conjecture was that having a greater forecasting precision for the SMP's allows the Genco to more accurately allocate hours to pumping in the most profitable manner. By increasing σ_S the cost forecast becomes less accurate so the Genco should choose to pump in hours when the SMP is higher than expected (effectively failing to choose the lowest price hours in which to pump and highest SMP hours in which to generate). Strangely, for this metasimulation, the factor was not significant, nor did it even produce the conjectured effect. As in the case of parameter p (described below), it is likely that more significant effects are at play which have smothered the primary effect of σ_S, and for more extreme values for the levels of this factor, it may have turned out to be statistically significant. On closer examination, and given the price-setting context of this model, the misallocation of both pumping and generating hours, is made up for by the higher prices offered, higher resultant actual SMP's, and the increased profit (and the fact that price-influence is not exerted on the SMP's in the pumping hours).

To summarise: overestimating the SMP's in generating hours simply inflates the market prices without resulting in a loss to the Genco.[1] This point prompts an investigation where SMP's are analysed as an explicit output. A trivial modification to the algorithm could output the resultant SMP's and would prove useful for cursory examination by a regulator or system operator who wished to measure the extent of market power impact on social welfare.

There are also interactions with this factor which are important. A plausible explanation is that parameter p is currently too close to the extremes of its values in this formulation, such that its effect smothers that of σ_S in conjunction with stochastic variation. A worthwhile check would be to re-run the experiment at values for p of say 0.3 and

[1] Recall from the simulation algorithm in Figure 5.1 that prices are 'influenced' as soon as an offer is *submitted* by the Genco.

0.7 to confirm the explanation, or under fixed values for σ_S and σ_γ. Alternatively we could examine higher order (3-way interactive) effects in a design of higher resolution. Another possibility would be to choose more extreme value for the levels of σ_S and note any changes in p-values.

Offer price parameter: p

The initial conjecture with respect to this parameter would be that by offering energy at prices closer to forecasted SMP's (i.e. when $p = 0.9$) would serve to increase our offer price and reduce the likelihood of the offer being accepted (as it will be pitched at a value nearer to the SMP). The Genco should be better off offering near their forecast MC (i.e. $p = 0.1$) especially if it is a price-taker.

In preliminary runs, p was not a significant parameter at lower values, only becoming important when offer prices were close to the realised SMP's. It is peculiar that this factor does not appear to be statistically significant — actually it is the least significant of all the factors. In preliminary runs there were circumstances when it was significant (and in fact monotone in a manner consistent with d and f), however the effect seems to be smothered by other factors. The fact that there are interactions with p that are important suggest that there may be some underlying third order effects. The results shown in the next section demonstrate that an increase in p clearly results in a reduced number of offers accepted. The reason for this anomaly lies in the interaction $\beta \times p$ described below. In summary, any change in offers accepted as a result of increasing the offer price, is counterbalanced by an opposing increase in profits. The counterbalancing is due to the SMP (received after a successful offer) being elevated since parameter β is greater than 0.

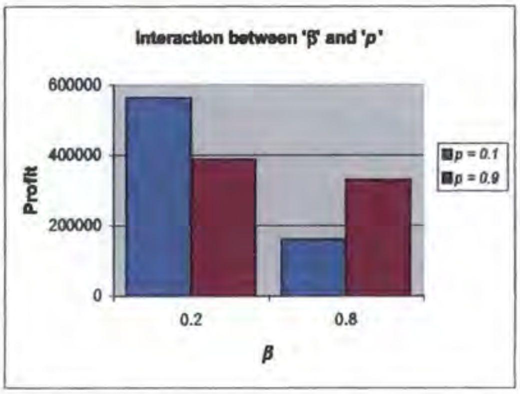
Since we are modelling in a price-setting realm, the resultant SMP's are weighted toward whatever offers prices this Genco makes, and — as for σ_S above — the supposition could be confirmed through a comparative analysis of SMP's under price-taking ($\beta = 0$) and price-setting ($\beta > 0$) scenarios.

6.2.2 Interactions

The eight most significant interactions will be discussed in the order of their significance. Of these interaction terms, the first of the two interacting effects is to be considered the primary effect, and the second the qualifying effect of interest. The x-axis in each graph therefore represents the differences due to primary effects and the shaded/coloured bars highlight the differences due to qualifying effect.

Qualifying effects were defined intuitively. Where possible, the primary effect is exogenous and the qualifying effect is strategic. In this fashion we can explain the results of the model in terms of how to construct a trading strategy under different scenarios. Where both factors are exogenous, the primary factor was chosen as the one least likely to be under the control of the Genco in reality. Clearly in many instances it would have been possible to reverse the order of the variables and interpret the results in an alternative manner, though this action would conflict with a favourable attribute of this model, namely its simplicity.

The $\beta \times p$ interaction



	β=0.2	β=0.8
p=0.1	563872	159824
(SE)	(54032)	(17500)
p=0.9	388683	328156
(SE)	(42027)	(37905)

Figure 6.1: Bar graph of mean profit: interaction between β and p

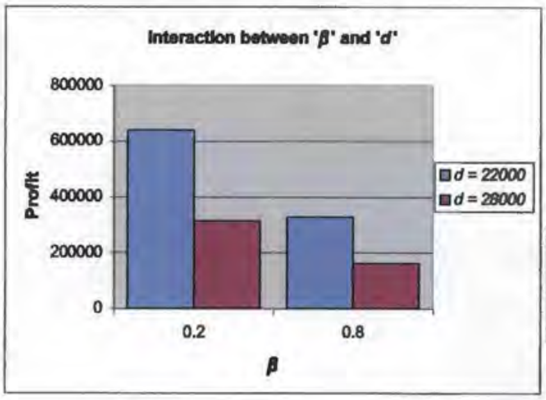
The $\beta \times p$ interaction was the most pronounced of the interactions in terms of significance, and is very important from the point of view of analysing competitive markets as it substantiates much of the research outlined in Section 3.2. One should note that the effect of offering closer to forecast SMP ($p = 0.9$) is to reduce profit when the Genco has less price influence, and to increase profit when price influence is greater. In other words, when the Genco exerts influence over the price ($\beta = 0.8$, offering closer to their expected SMP will in fact *increase* their profits. The increase happens due to their influence which inflates the actual market SMP which they then receive for energy generated. The result was confirmed in a preliminary run with values of (0.1, 0.5) and (0.3, 0.6) for β and p respectively.

The analogy confirmed here is that it pays to offer higher prices to the pool when endowed with greater control over the price.

The $\beta \times d$ interaction

When price influence is lower ($\beta = 0.2$), the resultant SMP's are also less controllable, so the absolute loss in profit when increasing d is greater than when influence is high. Factor d is more influential on profit when β is lower.

Constraining capacity with respect to demand reduces profit whether exerting little or large control over the price. When price outcome is further from the value offered, the Genco should be wary of withholding capacity because the reduction in profits will be substantial. In reality, the level of influence is very likely to be a function of the system demand for a pumped storage scheme (a natural price-setter in peak periods), and they

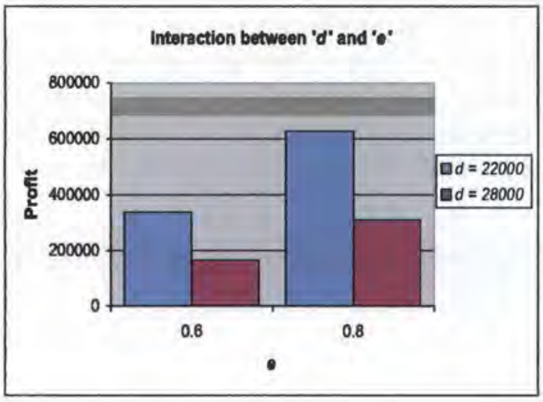


	β=0.2	β=0.8
d=22000	637837	327870
(SE)	(50746)	(36502)
d=28000	314718	160111
(SE)	(30359)	(20341)

Figure 6.2: Bar graph of mean profit: interaction between β and d

could exert a greater influence at high demand levels. In this case it would be beneficial for the Genco to constrain their capacity as they would then be able to achieve profits at whatever price they set: in effect they could exert their market power. This fact, however cannot be vindicated by the current model and certainly presents a possibility for further research.

The $d \times e$ interaction



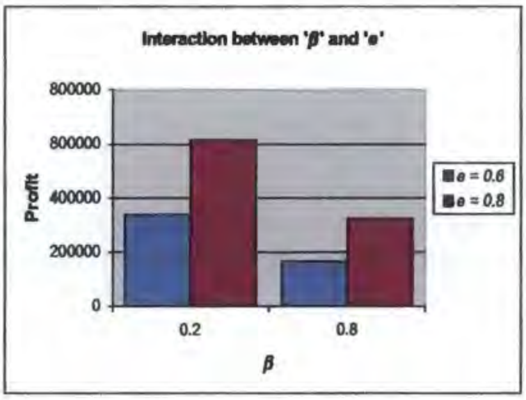
	d=22000	d=28000
e=0.6	338281	164361
(SE)	(37333)	(20807)
e=0.8	627426	310469
(SE)	(52106)	(30720)

Figure 6.3: Bar graph of mean profit: interaction between d and e

We observe a reduction in profits of around 174000 at high cost levels ($e = 0.6$) and around 317000 at low cost levels (e=0.8) when constraining with respect to d. The reduction is easily explained, because at lower cost levels, there is more profit at stake when reducing availability in terms of system demand. One would need to consider the three-way interactions between e, f and d in order to examine the overall effect of reduced capacity on the bottom line. A design of greater resolution would be necessary to confirm that, as interactions of third order would be confounded with other interactions at the current design resolution.

Increasing parameters d and f restricts available capacity. Decreasing e also restricts capacity (through higher costs), and both d and f are individually highly significant. In terms of model design, factor e's effects are more universal. To summarise this interaction: demand threshold has a higher impact at lower cost levels than at higher ones.

The $\beta \times e$ interaction



	β=0.2	β=0.8
e=0.6 (SE)	338459 (36206)	164182 (22668)
e=0.8 (SE)	614096 (51425)	323799 (35711)

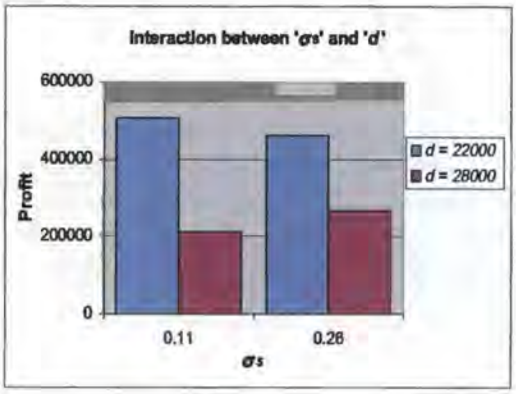
Figure 6.4: Bar graph of mean profit: interaction between β and e

This interaction between the contextual (β) and participant-specific (e) parameters is important. A reduction in costs (i.e. an increase in e) results in increased profit, however the increase is around 50% for both price-setting levels. So shifting the cost curve downwards (and thus widening the interval between expected SMP's and costs) enables the trader to submit offers *as* successfully whether the Genco can control prices or not. The reduction in cost is perhaps stronger than the difference as a consequence of price-control.

A reduction in costs ($e = 0.8$) leads to increased profits, though the increase is more profound when the Genco has less say in the final SMP. The profundity is a result of the lowering of offer price as explained in the subsection on e above, and the consequence that they will be lowering the SMP they receive for production. Obviously the reduction in profit is greater when a higher level of influence on price is commanded by the Genco. In summary, this interaction reveals that the cost curve of the Genco has more influence on the profit outcome when their price influence is lower than when it is higher.

The $\sigma_S \times d$ interaction

When the trader can more accurately forecast prices ($\sigma_S = 0.11$), the Genco suffers a greater absolute reduction in profits under constrained capacity when price forecasts are



	σ_S=0.11	σ_S=0.26
d=22000	505089	460617
(SE)	(54239)	(49834)
d=28000	209750	265079
(SE)	(25562)	(31909)

Figure 6.5: Bar graph of mean profit: interaction between σ_S and d

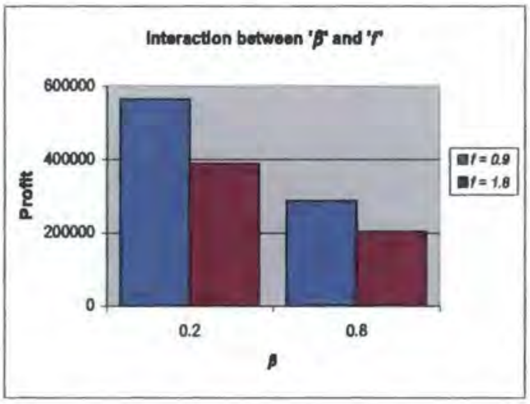
inaccurate. The large reduction is contrary to our expectations, as accurate price information should lead to a more informed decision on *when* to offer (since the highest and lowest price hours can be more accurately allocated to generating and pumping respectively). The results of the simulation indicate that the Genco suffers a larger reduction in profits withholding capacity (with respect to d) under good price information than withholding it under poor information. The results seem to indicate that they should in fact be cautious about entering the market when price conjectures are accurate, as they potentially stand to lose if they participate in the market.

An alternative view of this interaction is that by withholding capacity under good price conjectures, the Genco misses out on the trades which are more profitable (due to a better allocation of pumping and generating hours). It is interesting that the profit outcome under the 'poor-price-information/high-demand-threshold' scenario is in fact better than the 'good-price-information/high-demand-threshold' scenario. An explanation lies in the fact that there is an average increase in realised SMP values as explained in the subsection on σ_S above. To summarise — for the values of factors used in this experiment — price information is crucial when deciding which hours to withhold from the possibility of trading. Price information was only unimportant — for the particular parametric configuration of this experiment — when viewed as a main effect in isolation from other parameters.

A condensed explanation of this interaction is that demand threshold is more influential under good price information than under poor price information (i.e d has less of an effect on profit when the tendency to over-forecast prices is greater — in absolute terms — than the tendency to underestimate prices).

The $\beta \times f$ interaction

The effect of f is slightly more pronounced under low price influence than under high price influence.



	β=0.2	β=0.8
f=0.9	563655	285616
(SE)	(50273)	(36119)
f=1.8	388899	202365
(SE)	(46485)	(27995)

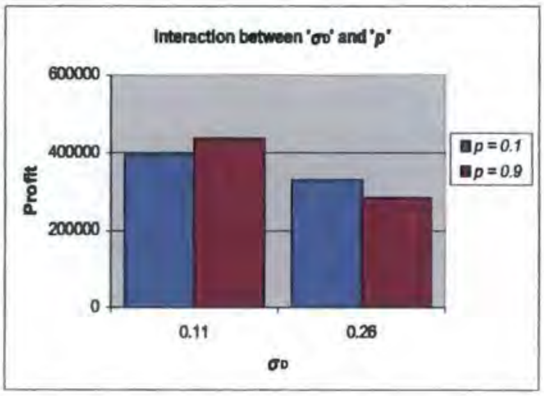
Figure 6.6: Bar graph of mean profit: interaction between β and f

Trading under constrained costs ($f = 1.8$) is more detrimental when price influence is lower as expected (given the monotonicity of profit with respect to f). When $\beta = 0.8$, the Genco can reap back some of the loss in trades by setting higher system prices.

The result here is a similar to the interaction between β and d, however capacity is now constrained by costs rather than by system demand levels. Increasing the cost threshold means that the trader should only submit an offer when the expected SMP's in potential generating hours are expected to be much higher than the cost estimates (assuming the level of h allows the trader this freedom). Thus, the final price received for accepted trades is higher.

In conjunction with the $\beta \times d$ interaction, this effect confirms that the effect of withholding capacity is greater when price influence is lower than when it is higher.

The $\sigma_D \times p$ interaction



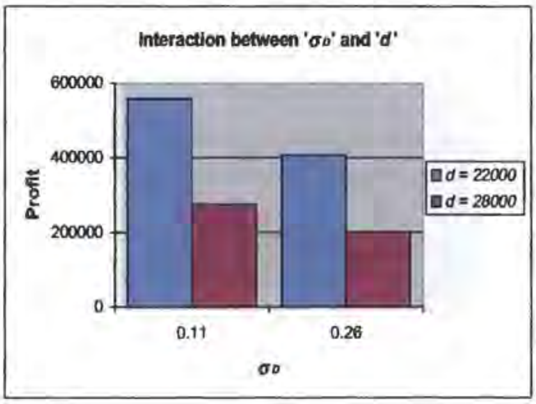
	σ_D=0.11	σ_D=0.26
p=0.1	395791	327906
(SE)	(55922)	(51548)
p=0.9	435750	281089
(SE)	(44627)	(29745)

Figure 6.7: Bar graph of mean profit: interaction between σ_D and p

Offering closer to the expected SMP results in larger profits when information on system demand is good, and smaller profits arise when offering close to expected SMP under poor information on system demand.

A trader who has more precise ideas about demand will be able to enhance the Genco's profits by offering production closer to the forecast of SMP, than a trader who is less able to accurately forecast demand (especially when the Genco's level of price influence is positive). At the outset, one would not have expected this interaction to have arisen at all, however when σ_D is large, demand forecast is less accurate, and the strategy in the market is less controlled (see main effect of σ_D). It is reassuring that such insights are vindicated by the model and may well be of use in reality for explaining the importance of applying a more controlled trading strategy.

The $\sigma_D \times d$ interaction



	σ_D=0.11	σ_D=0.26
d=22000	558390	407317
(SE)	(53559)	(47123)
d=28000	273151	201678
(SE)	(31046)	(25976)

Figure 6.8: Bar graph of mean profit: interaction between σ_D and d

In a more controlled situation with lower σ_D, the Genco stands to lose a great deal more by excluding their unit from the market with respect to the demand threshold. When greater information about the system variables is available, more offers should be encouraged as opposed to market abstinence. It is interesting to compare this result with that of σ_S and d where higher profits were achieved with constrained demand under poorer rather than better price information. An explanation lies in the inflationary effect of price-influence on the final price outcome.

Increasing the threshold has a slightly greater effect under good system demand information than under poor system demand information.

6.2.3 Interpretation

In the discussions of the previous section, we have described the observed effects of each of the parameters and significant interactions. Referring back to the classification of

Section 6.1, we have analysed the effects of the endogenous parameters, and the three groups of exogenous factors. The interpretation of these results will be further substantiated when the acceptances are analysed in the next section, however the following insights have already become apparent.

Endogenous parameters

The endogenous factors have told us about the trading strategy: circumstances have been suggested or outlined in each case under which an optimal trading strategy with respect to number of hours (h), demand threshold (d) and cost threshold (f) may be found. The initial analysis has *not* (as initially conjectured) divulged an approach for attaining the optimal offer price level (through p), because altering the offer price did not significantly impact on the Genco profits under the current parameterisation. It has, however been discovered that profits are highly dependent on the interaction of the offer price parameter with the ability of the Genco to set prices, and it has been confirmed that price-setters should offer closer to their price forecast, and price-takers closer to their estimated costs. The revelation here is encouraging, as the model has achieved this discovery with relative simplicity when compared to the price formation methods of Section 3.2.

Contextual parameters

Regarding contextual parameters it has been confirmed that extra stochasticity (higher σ_γ) improves the firm's profitability under the current formulation. Positive price influence ($\beta > 0$) reduces profits, because on average the trader will offer below the expected SMP, therefore reducing actual realised SMP values. It would be worth experimenting with levels of β closer to zero to reveal additional insights, as a value of 0.8 is probably unrealistically high. Improved efficiency results in larger overall profits, as expected, and has further implications owing to the interactions of e with d and e with β.

Areas of exploration can be identified for the model's general stochasticity, σ_γ. Such exploration is possible in four ways (refer to p. 121):

1. Utilising a model for stochastic errors *other* than a lognormal/multiplicative one, as the errors may tend to skew the variables toward the upside (to be confirmed with more in-depth analysis of empirical data of the variables).
2. Introducing two *distinct* price and demand stochasticities (or even adding a cost stochasticity).
3. Introducing a correlation structure between price and demand stochasticity.
4. Changing the AR(1) model to a more complex representation of stochastic volatility, and perhaps more in the vain of the stochastic volatility models of Chapter 2. (This last modification is more essential for the price stochasticity than for the stochasticity of demand.)

The model has therefore produced the desired consequences of, and therefore been validated by the higher optionality. However, the results have also identified the need for a more specialised formulation of stochasticity in order to gain further insights into the appropriateness and robustness of strategies.

Proficiency parameters

The results from reduced SMP precision (σ_S) did not produce the expected effect of correspondingly reduced profits. It is believed that its significance was smothered by other significant parameters under the current formulation and the effects of the lognormal assumptions counterbalanced to produce no apparent difference in profit. Reduced precision under a price-influence scenario tended to inflate SMP's such that greater revenues were achieved despite the losses arising from offers being pitched in the wrong hours.

Parameter σ_D produced the expected effect of reducing profits due to less informed withholding of capacity with respect to demand. Interestingly its interactions with two other strategy parameters (p and d) were also important and highlighted some interesting relationships between parameters, achieving one of the model's specified intentions.

The potential deficiency of the lognormal model for forecasting of prices and demand was also highlighted. The distribution of forecasts is asymmetrically skewed (to the left), especially when the σ-values are higher. The effect carries through to the interpretation of parameter σ_γ above. In summary there is a potential argument for the introduction of additive errors (for both forecasting and stochasticity) in (at least) parts of the model formulation.

The levels of ρ used did not reveal any startling results, however much of what has been said about the stochasticity applies to this parameter too, especially with regard to revision of the models for stochasticity. The analyses of forecasting biases (ξ_D and ξ_S) have been left for further study, however in the light of the revelations provided by other parameters, including them in the experiment is likely to produce some informative results, and may preclude the need for an alternative (non-lognormal) model for the forecasting accuracy. For example, introducing levels of negative bias could mitigate the effect of the tendency to forecast values for system and demand which are too high due to the lognormal effect. Such modifications could lead to the implementation of a prescriptive performance and assessment model for traders and/or information quality.

The results and insights of the analysis of the primary dependent variable will be qualified in the next section, which concentrates on the analysis of mean acceptances. This analysis of the secondary dependent variable will be conducted in the light of the insights revealed in the current section.

6.3 Analysis of Mean Acceptances

Before confirming the practical significance of the effects on mean profit, one needs to clarify whether variations in profit as a result of parameter changes are dependent on changes in the numbers of accepted offers, and to determine which (if any) of the factor changes induce changes in profits without corresponding changes in the number of acceptances. The results are also important as they reveal another important facet of the research in Chapter 3, namely the *probability of acceptance*.[1] For this section we shall now examine an analysis of results with 'mean acceptances' as the dependent variable.

The ANOVA table for offers accepted is shown in Table 6.6. Degrees of freedom (DF) for all effects equal 1, so the Sum of Squares equal the MSE's and have been omitted from the table. It can be seen that factors σ_S, ρ and β have no significant impact at the 5% level on the numbers of offers accepted, at least for this particular configuration of factor levels. Parameter h was significant at the 5% level with the others all significant at the 1% level. Moreover, β has been replaced by p as one of the most significant effects when comparing profits to acceptances.

6.3.1 Main effects

Table 6.7 shows the means of the main effects for the factorial design. The low value and high value for each of the parameters in turn are shown (non-significant ones have been included for illustrative purposes). The figures in brackets show the standard errors (SE's) of the means.

The results of all of the main effects will now be discussed in order of significance.[2]

Cost threshold: f

The reduction in offers accepted is commensurate with the reduction in profits observed in Section 6.2. Increasing the cost threshold for entering the market, reduces the number of offers made by the trader and excludes the Genco from potential (profitable) trades. The situation would be different if the cost structure was such that trades would result in losses. There is scope here for testing alternative values of e in the model (or even having a cost structure independent from the SMP's) that could result in non-monotone effects with respect to f. The percentage reduction in acceptances (55%) is greater than that of profits (33%) suggesting that successful trades at the higher thresholds are more profitable than the ones at lower cost thresholds, and is what would be realistically expected. For future runs, a reduction in the differential between factor levels would be prudent for f, so as to eliminate some of the smothering of other effects.

[1] A complete analysis of probability of acceptance would require an associated analysis of the third dependent variable, offers made. The analysis of acceptance probability has already been identified for potential future studies.

[2] Note that the same comments regarding statistical significance that were discussed on p.138 apply here too.

Factor	Effect	MSE	F-value	p-value
f	-68.5	150253	453.1	0.000
p	-56.8	103068	310.8	0.000
d	-56.1	100633	303.4	0.000
e	31.3	31408	94.7	0.000
σ_γ	9.7	3014	9.1	0.004
σ_D	-7.9	2010	6.1	0.016
h	-6.7	1451	4.4	0.040
σ_S	5.4	938	2.8	0.097
ρ	-2.9	262	0.8	0.377
β	-0.4	6	0.0	0.896
$d \times p$	19.9	12615	38.0	0.000
$h \times f$	-19.5	12116	36.5	0.000
$d \times f$	15.4	7582	22.9	0.000
$f \times p$	15.0	7217	21.8	0.000
$\sigma_S \times d$	12.5	5004	15.1	0.000
$f \times e$	11.2	4002	12.1	0.001
$h \times d$	-11.1	3973	12.0	0.001
$\sigma_D \times p$	-10.2	3317	10.0	0.002
$d \times e$	-9.2	2702	8.1	0.006
$\sigma_\gamma \times d$	8.7	2406	7.3	0.009
$p \times e$	-7.9	2015	6.1	0.016
$\sigma_D \times f$	7.7	1896	5.7	0.019
$\beta \times \sigma_\gamma$	5.0	795	2.4	0.126
Error		331.6	*DF*:	72

Table 6.6: Abbreviated ANOVA table for analysis of Acceptances

Offer price parameter: p

The drastic reduction observed here is very important for the analysis, especially since this parameter was not statistically important for the profit. Pitching offers close to SMP will reduce the number of acceptances by almost half *without* the commensurate reduction in profit, suggesting that though the Genco has half of its offers accepted when $p = 0.9$, the ones that are accepted must be significantly more profitable to make up for the lost trades. A likely explanation for this apparent anomaly lies in the fact that price-influence, β, is positive and the actions of the Genco in the pool will sway the SMP's in the direction of the their (higher) offers. The explanation could be confirmed with a repeat of the metasimulation with $\beta = 0$. If confirmed, it would illustrate the importance of the Genco's ability to affect the price in the market under this model.

Demand threshold: d

A similar percentage reduction in profits to that of acceptances has resulted from the increased demand threshold (approximately 50%). By constraining capacity with respect to demand, the Genco is excluded from all trades, both profitable and unprofitable ones. The same argument as the one in Section 6.2 applies for an investigation into the optimality of d

Pumping efficiency: e

A significant increase in acceptances of 41% takes place when the cost function of the Genco is set at a lower level with $e = 0.8$. Percentage-wise, the increase in profits is more than double this value, confirming that any additional trades will also be more profitable ones when costs are lower. The importance of the cost variable in the model is therefore emphasised, even if merely suggests the need for a more accurate representation (which could be achieved with the collaboration of the Genco concerned). The differential between the experimental values of e could also be reduced in future experiments so as to avoid smothering of importance of the other parameters, since the absolute effects are

Factor	Mean Acceptances		
	Low Value (SE)	High Value (SE)	Change
f	125 (7.4)	56 (5.3)	-55%
p	119 (8.4)	62 (5.0)	-48%
d	119 (8.4)	62 (5.0)	-48%
e	75 (7.3)	106 (7.7)	41%
σ_γ	86 (8.1)	95 (7.3)	10%
σ_D	94 (7.9)	87 (7.6)	-7%
h	94 (6.5)	87 (8.8)	-7%
σ_S	88 (8.1)	93 (7.4)	6%
ρ	92 (7.6)	89 (7.9)	-3%
β	91 (7.9)	90 (7.6)	-1%

Table 6.7: Mean acceptances outcomes for the main effects

quite large.

Actuals' stochasticity: σ_γ

A 10% increase in acceptances arose when the stochasticity was greater, a direct result of the optionality described in the previous section. However it is more the profitability of the trades which increases (by 26%), than the number of successful offers (10% increase).

Demand precision: σ_D

The 7% reduction in acceptances is less consequential than the reduction in profits as a result of poorer demand forecasts, suggesting that the trades lost as a result of poorer demand may in fact be the more profitable ones. As a result of the lognormal model, the strategy will be one of *not* entering the market more often, when σ_D is higher, and may be confirmed with an analysis of offers made. The evidence here is the first result that the model has provided that indicates towards trades at higher demand thresholds being more profitable (and that there is a correlation between SMP and demand which may be stronger at higher levels of both, and may be confirmed by examining the correlation between SMP and demand outputs). The evidence is important as it gives insights into the development of a strategy for 'peaking-type' plants.

Pumping/generating hours: h

Similar magnitudes of reductions in profits and acceptances were observed for an increase in h as for the increase in σ_D. Accepted offers is subject to a reduction of 7%. Further interpretation is not really viable without investigating the non-monotonicity of this parameter in greater detail (as described in the previous section). A useful insight at first glance however, is that the trades in the extra hours lead to lower profitability overall, and the Genco is better off selecting from a smaller number of hours in the day (under the current cost and price-influence scenarios).

SMP precision: σ_S

Here a similar (seemingly spurious) increase in acceptances (as for profits arose) and any smothering effects mentioned apply to both acceptances and profits.

Actuals' smoothing parameter: ρ

The smoothing parameter was not statistically significant, though similar explanations for the effects of ρ on profits in Section 6.2 are likely to hold here too.

Price influence: β

Importantly, β is not nearly as relevant for this analysis, nor are its interactions with the other factors, greatly contrasting with the results of Section 6.2. The lack of importance tells us that for levels of price influence between 0 and 1, there is no effect on the probability of acceptance that can be attributed to the adjustment of the SMP (given the fact that trader has decided to enter the market). Any reduction in profit noted in the previous section can therefore be purely attributed to the lowering of the SMP's and resultant revenues due to price influence. The effect holds true since the SMP's are significantly higher than the costs for this unit (by virtue of efficiency and hourly SMP differentials) and the trader offers capacity below the expected SMP. So price influence appears to reduce the value of profit without affecting the probability of offers being accepted, demonstrating a desirable feature of the model that could be further exploited by varying the cost functions through altering e. The change in costs would have to be such that there is a potential for losses to be made, when offers are rejected due to the Genco's price influence (e.g. if costs were higher in relation to the SMP's, fewer offers would be accepted).

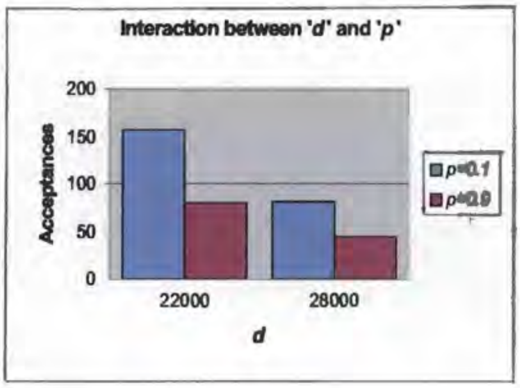
6.3.2 Interactions

Interactions between most of the endogenous strategy parameters were statistically significant in the analysis of acceptances, a result that is contrary to the analysis of mean profit where β was the dominant parameter among the interactive effects. Essentially we are now permitted to analyse the interactions of the remaining nine parameters without having to consider the effect of price-influence (under the assumption that there are no significant third or higher order effects with β that are significant). The six most significant interactions are now discussed in order of their statistical significance. A further four were also statistically significant at the 1% level, however the actual magnitudes of the interactions were marginal, and therefore not worthy of detailed discussion.

The $d \times p$ interaction

When capacity is constrained by imposing a high demand threshold, offering closer to the expected SMP will not lead to such a drastic a reduction in the number of accepted offers as when capacity is not constrained. A trader who has lower volume constraints with respect to offerable capacity should take care not to offer too close to the SMP so as to avoid reductions in the number of offers accepted. One who has greater volume constraints need not be too concerned about bidding closer to expected SMP, other things being equal.

The acceptances are more robust to changes in the offer price under constrained capacity than under unconstrained capacity.



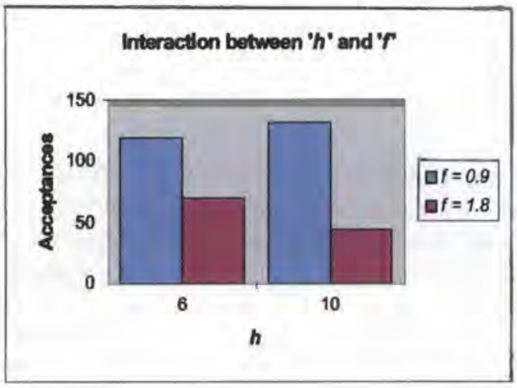
	d=22000	d=28000
p=0.1	157	81
(SE)	(11.6)	(7.5)
p=0.9	80	44
(SE)	(7.5)	(4.8)

Figure 6.9: Bar graph of mean acceptances: interaction between d and p

The $h \times f$ interaction

The reduction in the number of acceptances is greater in magnitude when increasing the cost threshold at $h = 10$ than when increasing it at $h = 6$. The greater reduction is likely to occur because a trader who has additional hours in which to trade, is probably faced with a greater number high cost trades, so imposing additional cost constraints reduces the number of offers made and hence the number of acceptances. The choice is easier when there are fewer hours (with lower costs for pumping and higher potential SMP's in generating hours). The fact could be confirmed through an analysis of the offers made.

Interestingly, increasing h from 6 to 10 also resulted in higher numbers accepted at lower levels of f even though as a main effect it resulted in an overall reduction. The higher numbers of acceptances did not carry through to the profit outcome possibly because there were other considerations (e.g. more profitable trades from fewer hours) that held more weight in that analysis. This type of result can offer valuable insights into

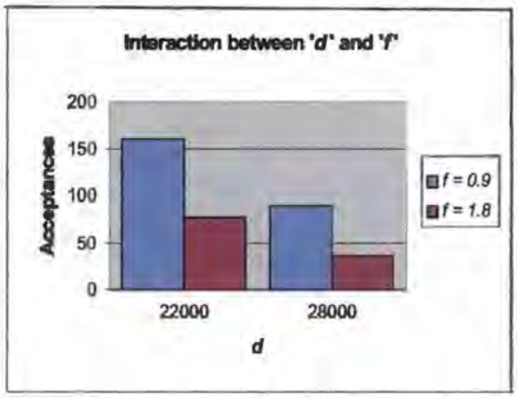


	h=6	h=10
f=0.9	118	131
(SE)	(8.1)	(12.4)
f=1.8	69	43
(SE)	(8.1)	(6.2)

Figure 6.10: Bar graph of mean acceptances: interaction between h and f

an analysis of the optimal offer strategy by indicating the optimal number of hours to enter the market under differing capacity scenarios. Even more profound is that making more hours available resulted in an overall reduction in accepted offers (consistently with profits as well), suggesting an optimum h at some value less than 10. An experiment with (up to 12) levels of h under stationary scenarios for other factors could be used in a search for an optimum number of hours.

The $d \times f$ interaction



	d=22000	d=28000
f=0.9	161	89
(SE)	(10.2)	(6.1)
f=1.8	77	36
(SE)	(8.3)	(4.4)

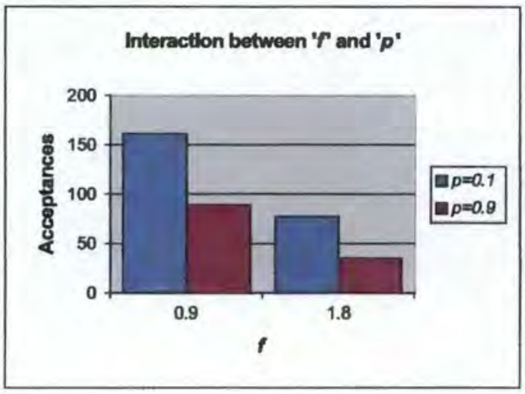
Figure 6.11: Bar graph of mean acceptances: interaction between d and f

Modifying the cost threshold is more influential at lower d than at higher d.

Although increases in both of these factors individually serve to constrain capacity, it is interesting to observe that increasing d leads to a much larger reduction in acceptances when f is low, though if d is low, at say 22000 MWh, then moving from $f = 0.9$ to $f = 1.8$ has an exacerbated effect. In a sense the withholding capacity with respect to demand and cost tends to result in a compounded effect. When one of the parameters is high — and the strategy is already constrained — then an increase in the other parameter will have a more pronounced reduction than it would have had the first one been low.

The $f \times p$ interaction

Offering at prices closer to the expected SMP seems to exacerbate the reduction in acceptances when f is higher, and is an expected result, since constraining capacity with respect to cost necessarily implies that more offers will be closer to the actual SMP's and consequently have a greater chance of being rejected. Further exploration would be required to determine if this decrease in probability of acceptance is justified by an increase in profits when both f and/or p are higher.



	f=0.9	f=1.8
p=0.1	161	77
(SE)	(10.2)	(8.1)
p=0.9	89	35
(SE)	(5.9)	(4.5)

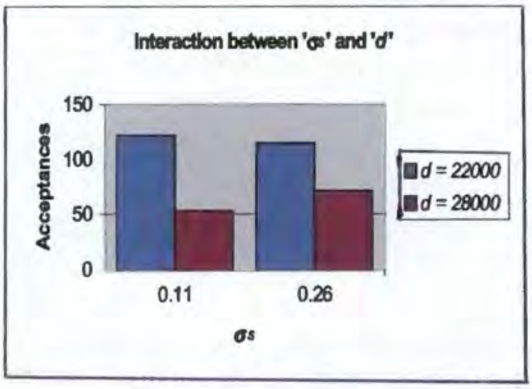
Figure 6.12: Bar graph of mean acceptances: interaction between f and p

The $\sigma_S \times d$ interaction

The effect is consistent with that of profits in Section 6.2 suggesting that this interaction reduces acceptances and hence profits in a corresponding manner. We find that a greater reduction in acceptances occurs when precision is greater and we increase the demand threshold (refer to the explanation in Section 6.2).

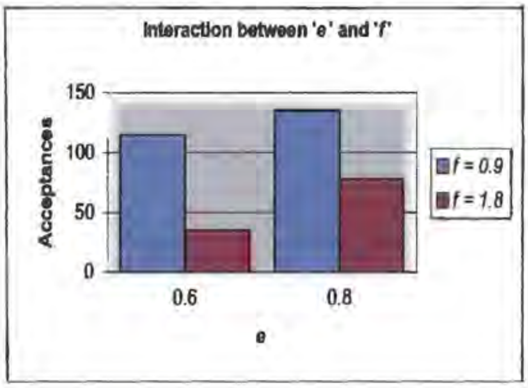
The $e \times f$ interaction

At lower levels of e (higher cost function), an increase in f resulted in a more drastic reduction in the numbers of offers accepted than at higher levels of e (lower cost function), and is an effect which was not picked up in the analysis of profit, probably owing to the smothering effect of price influence. Given higher costs we would submit fewer offers and



	σ_S=0.11	σ_S=0.26
d=22000	122	115
(SE)	(12.2)	(11.6)
d=28000	54	71
(SE)	(6.1)	(7.7)

Figure 6.13: Bar graph of mean acceptances: interaction between σ_S and d



	f=0.9	f=1.8
e=0.6	115	35
(SE)	(9.5)	(4.7)
e=0.8	135	78
(SE)	(11.2)	(8.0)

Figure 6.14: Bar graph of mean acceptances: interaction between e and f

therefore have fewer acceptances. Once again, this latter hypothesis could potentially be confirmed by means of an analysis where offers made is the dependent variable.

6.3.3 Interpretation

Profit dependency

The existence of five scenarios has been revealed by virtue of the analyses of this section, where results of Table 6.5 have to a large degree been qualified by those of Table 6.7:

1. There are circumstances under which the changes in observed profit are in fact due to a *commensurate* change in the number of offers accepted (e.g. with parameters d, σ_S and ρ).
2. Situations also exist where the change in acceptances is *compounded* by a corresponding change in profitability (e, σ_γ, h, σ_D) and;
3. The (hard-to-identify) situations where a change in observed acceptances is associated with an *opposite* change in profitability (f).
4. Scenarios where changes in profits are *independent* from any changes in acceptances (p, β).
5. Although they are not manifested in the main effects in the present parameterisation, there are likely to be instances when changes in profits are a consequence of a change in profitability of trades *rather* than a change in the number of accepted offers. There are particular interactions which allude to such an effect and could be confirmed by experimenting with alternative configurations of the parameters.

In summary, the mean profit can be explained by variations in the number of acceptances, and the imposed scenarios will determine the nature of the dependency. The most important qualifying effect, regarding the swapping of p for β as the important parameter in the analyses of the two dependent variables, has already been discussed in the analysis of profits in Section 6.2.

Non-qualifying effects

The analysis of acceptances as a dependent variable in its own right provides model validation, and highlights some of the interactions between the parameters.

Examining the parameters individually:

- Parameter p has the most significant impact on the number of acceptances, so offering closer to expected SMP will reduce the chance of the offer being accepted (as conjectured).
- Results for e are also intuitive: lower cost levels will allow the Genco to pitch offers which have a greater probability of being accepted.
- Increased stochasticity (σ_γ) enhances optionality resulting in a larger number of successful offers.
- Parameters ρ and σ_S have no significant effect on acceptances for their current levels (as for profit).
- Increases in h and σ_D both serve to reduce the number of acceptances (for reasons identified in the analysis of profits).
- Price influence (β) has no impact on the number of successful offers, and provides a favourable model feature in the sense that it can mimic a Genco which is able to control price without adversely affecting the likelihood that their offers are successful (and without necessarily implying that the accepted offers are more profitable).

Most of the strategy parameter interactions were significant, revealing some otherwise unknown relationships between them. For example:

- the effects of same-sign changes in d and f tend to exacerbate each other (as is the case with f and p).
- increasing the cost threshold, f has a more drastic effect when more hours are made available for pumping and generation (i.e $h = 10$) than with fewer hours; also, more acceptances are achieved at this level of h under a low cost threshold, and fewer under a higher cost threshold.
- The interaction between parameters d and σ_S is consistent with that in the analysis of profits.

Analysing the acceptances has certainly revealed a great deal more about the relative importance of the parameters. Many of the insights from the analysis of profits carries through to the acceptances and additional relationships between the strategy parameters have been identified in the individual descriptions. An obvious follow-up to this section would be to analyse the offers made. The analysis would enable a quantification of the probability of acceptance by giving a sample space from which the number of successful offers is observed under various proficiency, context, and strategy scenarios. Such an analysis is again outlined as an option for further research.

6.4 Conclusions

This final section details the success (or otherwise) of the model as a tool for thinking in the strategic decision support of a Genco.

A valuable tool for thinking

The model has proved useful in providing a medium for confirming, and/or disputing, intuitive beliefs about the behaviour of the system, and assessing its response and robustness in the wake of changing scenarios. It is also a useful platform for progressive development of an actual strategic decision support model, having a fundamentally simple yet versatile formulation (especially when compared to the high level stochastic simulation models of Chapters 2 and 3). Moreover the initial formulation has already been of use in identifying its own potential flaws and enabled suggestions of how to overcome these flaws.

Having decided on a parameterisation, the relative importance of the parameters can be examined through repeated outcomes under various strategic scenarios. Also, the inter-dependencies between these parameters can be examined through the analysis of the experimental design, and more of the subtle and unexpected effects can be identified. The initial conjecture when developing the model was that the parameters themselves would be of the most interest. The success of the modelling process in fact lies more in the interaction terms, and in the comparison between the effects on the two different benefit measures (for example the insights relating to price influence and offer prices). No doubt, further insights could be gained from a more formal examination of the relationships between the dependent variables themselves.

The results are presented in simple tables and graphs that are open to easy interpretation by both the modeller and the client Genco. Importantly, we have succeeded in mimicking the actions of a trader in a daily auction in a pool-type market for electricity.

The model has also been implemented with little data, and relatively little assistance from the client. The limited assistance favoured objectivity and encouraged a versatile, adaptable formulation, although a greater level of client cooperation would be required for the model to be implementable in reality.

A view to implementation

The 2-level design itself has obviously not been able to suggest optimality for the strategy parameters, but is a worthwhile experiment for providing an initial understanding of the relationships between parameters, and interpreting the model's functionality and attributes. The modelling approach is logical because optimisation can proceed now that the model has been understood and validated by its outputs.

The foundation has now been laid for further experimentation by way of:

- additional 2-level runs with additional parameters and/or alternative parameter values.
- 3-level factorial designs.
- designs of higher resolution.
- optimality runs for the strategy parameters.
- development of alternative models for stochasticity and/or forecasting precision.
- output of additional dependent and exogenous variables, and their subsequent analysis.
- combinations of one or more of the above.

The choice of which of the above point to implement will depend on the level of co-operation with a real Genco, and their strategic support requirements or modelling aims. The modifications will also depend on the quantity and quality of the available data. Having fulfilled the data criteria, the model may then be enhanced and refined with a view toward realistic implementation.

Chapter 7

Conclusions and Recommendations

This final chapter of the dissertation draws together the two main streams of this project, namely the concepts presented in the literature, and the development of a model under local conditions. It also summarises the ideas of this dissertation with a concluding account of the discoveries gleaned from Chapters 2 to 6. With these summaries, an integrated view of the subject will have then been achieved. Mathematical modelling in electricity markets is motivated in the light of the literature survey, the local conditions, and by the analyses of the outputs, as well as by the attributes of the unique simulation model which was developed for this thesis.

The outline of this chapter is as follows:

Section 7.1 summarises the literature surveyed in Chapters 2 and 3, describing the fundamental motivation for research into electricity markets. Within the summary we highlight some of the modelling approaches and their uses.

In Section 7.2. the local context is summarised and the model formulation is given a brief overview. The relevance of the literature survey to the local context will also be quantified.

An overview of the analyses and findings of the simulation model follows, with a view to motivating the approach within a greater mathematical modelling context. The relative advantages and disadvantages of the model as a decision support tool will also be given. The overview and discussions of the model are the focus of Section 7.3.

The final section concludes with some recommendations for future descriptive and normative studies using the model with appropriate adaptations. Potential modifications to the adopted approach are described, and we conclude with some final remarks on the thesis.

7.1 Literature Survey

7.1.1 Modelling activities in electricity markets

Some of the general challenges arising from deregulation were revealed in the literature survey of Chapter 2. It is clear from this survey that electricity companies, regulators and decision support scientists have been shaken by the unprecedented wave of deregulation that has taken place in the power industry.

Companies, in particular Genco's, have been faced with solving their generation-dispatch and unit commitment problems in conjunction with the influences of market forces. In the words of Baillo et al. [4], Genco's are now "forced to prepare and submit daily offers to an electricity market...". Performance success and business viability now depend on the bottom-line profits the companies are able to achieve. One of the primary consequences of the introduction of competition into the production and sale of electricity, has been the development of risk management tools in response to the increased uncertainties which now plague participants. Ironically, ownership of portfolios of these tools has itself led to an additional need for strategic decision support. Such support is required for the day-to-day operations in the spot and forward markets (including reserves and ancillary markets), as well as for intermediate to long term strategic support for trading and production activities, financial contracting, and managing portfolios of contracts and instruments.

Regulators and system operators are also faced with increased challenges. The latter have to ensure the safe and reliable dispatch of generation plant in conjunction with the daily auction, and the former are faced with the challenge of ensuring that the transition to competition proceeds fairly, and that the market is suitably structured so that participants are not able to exert untoward levels of market power. The ultimate responsibility of the regulators is to ensure that the intended social welfare criteria of deregulation are achieved, as measured by the quality of supply received, and prices paid, by the end-user consumers.

Researchers are endowed with the task of assisting both companies and regulators in achieving their goals through strategic decision support. Types of assistance range from normative or descriptive models and/or normative or descriptive analyses. The combination of model and analysis ultimately leads to the prescriptive analyses presented to the client. Researchers' challenges also include the selection of appropriate modelling and analytical tools from a wealth of those developed by power systems engineers, operations researchers, and specialists in financial engineering. The difficulty of model selection is played out in a situation where individual national markets have very unique structures, varying levels of deregulation, different sources and degrees of uncertainty, and a wide range of principal needs that must be addressed by various players in the industry. Simulation — in various forms and levels of complexity — seems to be the fundamental method of enquiry, particularly with regard to the descriptive modelling approaches adopted by researchers.

7.1.2 Electricity Markets

Chapter 2 demonstrated the existence of a variety of modelling activities, all of which arise from the recent liberalisation of traditional monopoly markets; particularly those for electrical power. The study of electricity economics has developed into a subject in its own right. The reasons for the separate development are the nature of the commodity, the modern world's insatiable thirst for electrical energy, and a substantial dependence on its uninterrupted supply.

Some of the common terminology that one would expect to find in a textbook on the subject of electricity markets was introduced in Chapter 2. Electricity pools and auctions were defined, explaining their attributes and giving examples of variations in structure between and within markets.

Simulation techniques in the form of scenario analysis, system dynamics, and commercially implemented integrative modelling software are the main tools that have been identified for the strategic decision support of market players.

The topic of risk management in power markets was addressed somewhat generally with a few detailed examples included for illustrating concepts. However, it was apparent that risk management is also a very large subject on its own. An awareness of the types of risks as well as their assessment, quantification and management, are all crucial to the development of any model of electricity trade, especially for the market participants, and the researchers who support them. Models, particularly those for individual participants, should be developed with a view to ultimately devising a decision support structure for tackling risk management issues. Such developments are in addition to the (currently) more pressing need for decision support in daily trading activities, which is characterised by the search for optimal trading and production scheduling strategies.

The electricity spot price has proven to be a difficult variable to model accurately. It has been found by many researchers, and across various markets, to exhibit some interesting characteristics. The special mathematical features of the spot price variable, such as mean reversion. seasonality (stochastic volatility) and jumps make it difficult to handle in a modelling context. It is a key input or output variable in nearly all of the models of the literature [see subsection 7.1.3 on electricity prices below], including the price model of this thesis. The importance of the spot price lies in assessing levels of competition, in making the best strategy choices in the short, intermediate and long term, and in pricing derivatives and managing risks.

The special features of the electricity commodity, such as its non-storability and knife-edge balance of supply and demand, have led to tertiary markets which are unique in comparison to those of equities, interest rates and other commodities. In particular, derivatives are generally more complex in design, liquidity is limited, and risk management and instrument valuation present an even greater challenge. Some advanced analytical techniques have been developed by experts in derivative pricing and risk management, and futures-based pricing has become standard. Most of the methods for electricity derivative pricing and risk management tend toward simulation and numerical methods so that the inherent complexities may be effectively captured. It seems that the study and development of tertiary electricity markets has almost superseded the commoditisation process itself – probably as a result of the sudden unprecedented levels of uncertainty that have arisen, and the need to manage this uncertainty.

7.1.3 Generator Trading Strategies

Chapter 3 motivated the need for modelling and analysis of generator trading strategies. Within the discipline of trading strategies, there are three main concerns that much of the research tends to address. The concerns addressed are – with a variety of motives for both modelling and analysis – the notions of price formation, supply functions, and optimal offer strategies, all of which may be used in some way to capture the strategic behaviour of market participants.

Electricity Prices

Electricity prices are the key variable in any strategic decision support undertaken in electricity markets, and the unique characteristics of the variable emphasise the importance of choosing the appropriate modelling technique. Generally, prices (usually the SMP's of LMP's) are modelled as either endogenous or exogenous variables.

The exogenous approach tends to focus on developing a parameterised mathematical model of the price in order to forecast future values for short to long term valuation of generation assets, and as an input into derivative contract pricing and risk management tools. The approach is of more immediate relevance for price-taking Genco's, who wish to capture the uncertainty with respect to rival behaviour through the electricity price, and who use the SMP forecast as a key determinant of their hourly, optimal-profit, trading strategy.

The endogenous approach treats the electricity price as a key output in a system-wide model of a pool-type market. Broadly the approaches used are either equilibrium-based or non-equilibrium based. The actions of various market players, mainly generators – and to a certain degree in some research, the large consumers – which are in competition for high profit trades, are captured via various modelling approaches. The intersection of the aggregate supply function with the aggregate demand forecast gives the resultant price. Such models are useful for regulatory and system-design support, for deciding on an appropriate market structure and identifying instances of unwanted market power and concentration. The models are also used by price-setting Genco's to analyse their strategic behaviour while capturing the behaviour of other market participants. Endogenous price formation is often characterised by simulation and game-theoretic modelling approaches.

The approach adopted in the model of this dissertation was largely endogenous, however the fixed effects model employed here was then modified to capture and investigate the effect a price-setting Genco has on the ultimate price outcome, and on their own profits and probabilities of acceptance.

Supply functions

The key method of modelling the individual actions of Genco's – and in some of the literature, consumers' actions – in the daily power auctions is through supply functions. Supply functions represent Gencos' offering strategies and may have a number of mathematical constructs, though essentially they contain the information about the quantities of electricity offered to the pool and the associated prices for these quantities. The function is therefore determined with reference to underlying cost functions of suppliers, as well as expected prices, demands and system constraints. The simplest type is a single price for a fixed quantity of electricity, and is the type used in the model of this dissertation.

Other research has described and developed continuous functions, piece-wise linear functions, and the step/tranche functions which are most indicative of reality but are mathematically intractable.

The 'steps' in the step function are a natural way of representing the various units owned by a Genco, and the cumulative prices for offering these units into the power pool. Other types of supply functions are defined according to the specifics of market rules, or in accordance with modifications imposed by a modeller, or both. In models describing the impact of market design, supply functions are one of the key ways in which the factor governing this design may be controlled within the exploratory analyses.

Demand functions which represent the behaviour of consumers in the electricity market (where demand-side bidding has been introduced) can be designed in an analogous manner to that of supply functions.

Optimal Offering Strategies

Closely related to the issue of supply functions, representations of the optimal strategies for participants are also important for describing their behaviour, and indeed for determining the actual supply functions submitted by Genco's. Optimal strategies can be applied in a normative context for individual Gencos, or in a more descriptive manner when analysing the behaviour of other participants — either from the point of view of one competitor or from that of the system operator or regulator.

Many strategies have been proposed with some often complex optimisation routines employed to solve for the optimal supply function. The procedure varies greatly with regard to the degree of complexity and the number of factors taken into account. Some of the variables are system demand, SMP, marginal cost, competitor behaviour, previous periods' strategies, derivative positions, and technical or system constraints, among others.

Strategies also vary depending on whether markets are perfectly competitive or oligopoly in nature, whether an individual participant is a price-taker or price-setter, and whether the strategy horizon is short, intermediate or long term.

The approach in the model of this dissertation has been to use an exploratory model where the Genco offers a fixed capacity at a price which is some level in the interval between the MC and SMP forecasts. The model is devised with the ultimate intention of finding the optimal offer price level. A *fundamental difference* that exists in the description of offer strategy in Chapter 5's model, is the development of a parameterised decision process, which examines the expectations of the key variables, and where decisions are invoked on various threshold values of the forecasted variables.

7.1.4 Research — fundamental needs and unsolved problems

The fundamental needs for decision support tools by market participants can be classified according to the types of models that can be found in the literature.

Normative models have been developed for finding the optimal offer strategy, production schedules or the optimal risk-aware portfolio of power contracts and derivatives.

Descriptive models are more common and can be either system-wide or Genco-specific. They are used for examining the effects of strategies, market design, information, uncertainty, type of supply functions and type of cost functions on particular dependent outcomes. The outcomes may include price-formation, offer strategy, competitor behaviour, and social welfare. Less subtly, there are models that price derivatives and measure various risk exposures.

One of the apparent difficulties encountered is the lack of consensus among researchers as to exactly which type of approach is the most appropriate for treating uncertainties, e.g. those relating to prices. Indeed, the model of this dissertation is also unique. A major challenge relates to the design of a sufficiently competitive market, amid historical and proposed reforms, and taking an active role in suggesting alternatives.

Pricing of the complex derivative instruments traded in advanced electricity markets has come along way, drawing on the most complex of the methods developed by researchers in other tertiary markets. Without a substantive reliance on an underlying forward market, many of the suggested pricing techniques are of little use for instruments which are based on the electricity spot price. Risk management has generally lagged in development, and techniques are slow in being adapted; possibly due to the ongoing development and adjustment to the market structures, and the general lack of liquidity for risk management tools.

7.2 Local Context and Model Formulation

7.2.1 The Notional Client

Chapter 4 described the local context under which the issues arising from the literature survey were examined. The Eskom Peaking Cluster of the EPP was an obvious choice as a notional client for the development of the simulation model. The South African market had not fully deregulated at the time of writing owing to various political obstacles, although unbundling had already taken place and the generation sector had been divided into notional clusters in preparation for full-scale competition. The sector was not yet fully competitive as sales through the pool at the spot price were still being hedged through forward contracts with the holding company. The hedging was not taken into account in the model, as it was construed as being a temporary feature, and the model's aim was to focus on a fully competitive situation, from the perspective of a single Genco/cluster, with the possibility of including it at a later stage.

Different types of generating plant will have correspondingly different strategies, and the pumped storage unit was the obvious choice given the data which was made available. Additionally, there are important social implications for understanding the behaviour of peaking units The status of the pumped storage scheme as a marginal unit in peak periods also made it an interesting candidate for the exploratory modelling. It was also of interest from a theoretical point of view, as its cost structure is unique, relying on the SMP's in the pumping hours, and lending itself to the development of demand-side bidding models in the future (albeit from the perspective of a 'producer-buyer' of electricity). The notion of demand-side bidding is a useful concept paving the way for future inclusion of consumer participation in the market once it has advanced to that stage, and when the demand curve becomes non-vertical. Thus the use of a pumped storage unit as an illustrative client was motivated.

In summary, the South African market (currently dominated by Eskom) — and the EPP itself — can be defined as a uniform-price, day-ahead market with no demand-side bidding (at the time of consultation), and a limited market for a few OTC derivative contracts traded between participants. The grid is an independent entity overseen by the NER. Genco's/Clusters may offer a step-like supply function (one for each hour of the following day) to the EPP. Each function consists of tranches reflecting the number of units owned by the cluster, with cumulative volumes of power that depend on the potential capacities of the individual units. Assuming that a cluster wishes to make one or more of their units available, they must submit prices for the various blocks of capacity, to the EPP. Successful offers earn the SMP per unit of capacity contracted in the relevant hour, after the real-time production has been recorded and finalised.

It should be noted that although the EPP represents a uniform price market, which tends to encourage generators to offer close to their MC, particular marginal/peaking-type units will often tend to offer closer to their expectation of SMP. The tendency was examined in the analyses of Chapter 6.

7.2.2 Relevance of Literature

The literature surveyed in this dissertation was a small sample of a huge body of work on the subject, much of which is very recent and ongoing in nature. The important aspects gleaned highlight the types of problems encountered in power markets, but also indicate a level of diversity and disparity between the adopted approaches in tackling the challenges of strategic decision-making. The techniques have little in common with each other, or even with those used in the industry applications. It seems therefore, that there is a distinct lack of cohesion in the approaches, which can be explained by one or both of the following:

- Individual markets exhibit unique characteristics with regard to design, level of deregulation, presence of derivative markets, and type of primary fuels or generating plants used. Consequently, decision support will be motivated by differing needs.
- The subject is perhaps too broad (and the sample of literature too small) to reveal any commonalities or consensus in approach. The model of this dissertation is no exception!

One of the key insights arising from this study is the emphasis on model *simplicity*, and the wealth of detail and potential for experimentation that can be achieved using a model with only a few parameters. The approach is also logical as it is ground-up, building-block in nature. The simple approach is one embraced by the model of Chapter 5, and herein lies a the major inconsistency with regard to simplicity. Of the models discussed in Chapters 2 and 3, the simple stylised simulations models are of greater appeal than those which are over-parameterised, and which attempt to capture every intricacy of the electric power system, together with the specifics of the new market conditions.

Much of the literature was therefore more of a peripheral interest to the study in the local context, however it proved useful in enlightening potential modifications to the model and areas for further exploration.

7.2.3 The Model

The aims of the model were outlined in detail in the introductory chapter [Section 1.3]. The model, in its ultimate form, has achieved the nine express intentions outlined therein. The specifics of the model were discussed in detail in Chapter 5 and some of the fundamental features are now revised in this subsection.

Although the model is not a complete description of reality, it has a simple structure with only three key variables: demand, cost and price. Its structure is one which can be easily modified to focus on specific areas of exploratory analysis, for example, the effect on the Genco's profits when it is able affect the price outcome through its own actions in the market. It also has a relatively small number of parameters which have a meaningful interpretation and fall naturally into homogenous groups pertaining to trading strategy, and endogenous or exogenous influences.

Through repeated simulations of a trader's actions in the daily auction, the effects and interactions of the selected parameters can be measured by carefully selecting levels for the parameters, and by using statistical techniques for designing and analysing the experimental outcomes. Several simplifications of a complex reality were made when designing the model, for example with regard to the supply function. Such simplifications were necessary, for both enabling preliminary formulation, and stressing the importance of ignoring unwanted complexities, which were thought to be non-relevant for the chosen study.

Firstly, the state variables for a generic generation market were defined, and the set was refined and given specific parametric and functional definitions. One of the key advantages of the simulation model was that there was a distinction between the (unknown) *actual* values which had deterministic and stochastic components, and the Genco/trader's view of reality, used in their daily trading strategy (which itself was governed by a set of endogenous parameters). An analyst using this model is able to control various key features in the experimentation:

- A deterministic model of the underlying variables, which may be based on historical data or some other model or source of information. The implementation of a fixed effects model using some data was given in Section 5.2 for illustrating such an adaptation.
- Uncertainties occurring in reality; represented by the stochastic simulation errors of the actuals.
- Proficiency of the client Genco in 'guessing' this reality before its realistic manifestation.
- A particular trading strategy governed by parameter values, and an associated decision rule captured in the construction of the algorithm.

The stochastic errors and forecasting ability can be sampled from prespecified parametric distributions. Parameter values for the other features can be chosen through preliminary 'trial-and-error' simulation runs or by using fixed values that are representative of reality.

The form of the final model is versatile, and open to adaptation with respect to both inputs and outputs, investigation horizon, trading rules, and parameter choices. Various possibilities were outlined in Chapters 5 and 6 and suggestions made where appropriate.

7.3 Analyses and Findings

7.3.1 Simulation Results

The experimental design and runs were explained in the first section of Chapter 6. The analysis was first conducted using mean profit as the dependent variable, and then using the mean acceptances. The latter served to qualify the results of the former, and further analysis could have been conducted on the remaining dependent variable, the mean offers, however the idea was left for future work. In both cases the main effects of the 2-level design, describing the effect of each of the parameters were discussed in detail. A selection of the most significant interactions were described and interpreted in each case.

The meaning of the parameters was validated in most cases for the chosen levels, and explanations given where results were not as expected. The interactions were also of interest in explaining the relationships between the parameters. The main and interactive effects were of interest, however the emergence of other items of interest in the modelling process were also of great value. A prime example of the emergence of new items of interest was the ability to qualify profit with offers accepted, and isolate the corresponding differences in the effects of parameters between the two responses.

The immediate plausible options for future exploration under the *present formulation* range from using a different set of parameter values, to implementing 3-level designs (or designs of higher resolution to explore at least quadratic effects), to inclusion of other parameters not yet experimented with (such as the forecasting biases). Many other minor model modifications were also suggested and could be easily implemented.

No difference in the analyses were observed between the one month and twelve month runs suggesting there is some unnecessary modelling of the deterministic functions, and/or that there is something lacking with regard to the variable correlation structure. A further difficulty with the model was identifying an appropriate parameter set for the experiments, especially given the relatively long running time for the simulations. The processing time could be mitigated through more efficient programming (and a faster computer!) and with greater assistance from the client in interpreting parameter values (including data provision).

7.4 Recommendations for Further Study

7.4.1 Capturing historical evolution

One of the simplifications made in the original model formulation was that daily trading decisions were conducted independently of one another. Hence the model is in fact one of daily strategy, notwithstanding the fact that a 31 day horizon was used.

An obvious refinement which would complicate the model to some degree — but would be necessary to extend the length of the strategy horizon — would be to conjecture a strategy dependent on the historical outcomes of previous trading actions. For example, in the terminology of Section 5.2, we could offer a price y_t for a block of energy in hour t such that

$$y_t = f(y_{t-24}, y_{t-48}, \ldots, y_{t-24j}, P_{t-24}, P_{t-48}, \ldots, P_{t-24k})$$

Here we have a more general case where the strategy in the model would depend on a history of offers up to j days before, and profits in the hours up to k days prior to the current trading hour; the offer price for hour t would depend on the history in some way as governed by the function $f(\cdot)$.

The above modification is a very simple example. Of course one would also wish to allow for the estimates $D_f(t), C_f(t)$ and $S_f(t)$ in such a representation of trading strategy, however the example does serve as an initial illustration of the type of modifications that could be considered if the client Genco were able to motivate the need for such detail. Moreover, it is only the offer price that has been considered as a potential regressor. The 'when' part of the strategy could also be analogously reformulated.

7.4.2 Forward contracting and derivatives

A possible realistic refinement of existing model representation would be the inclusion of forward contracts. The profit variable in the model could be adjusted to include a term for the income/loss arising from any forward agreement/CFD positions in the daily trading model. A simple addition of the terms defined on page 50 (Chapter 2) would suffice as an initial modification to the output, although there are many possible variations on this theme.

Should the South African market become completely liberalised (and a more liquid market for contracts and derivatives becomes a reality), the techniques covered in Section 2.5 would prove useful for designing appropriate financial instruments, and for valuing them and managing their associated risks. There are a range of options, swaps and risk management techniques that were explained in that section.

7.4.3 Risk management

Chapter 2 gave some vital indications as to the ultimate use for many models of electricity markets. Herein lie many obvious adaptations to the model of this dissertation.

One possibility is to examine the distribution of profit outcomes of the simulation experiments. In Chapter 6 only the mean profits and mean acceptances were treated as the response of interest. From the distributions one could devise various metrics for risk such as VaR which could be used to measure profit variability and/or robustness to various parameterisations. Measurement of variability and robustness to parameterisations constitute what we understand by *sensitivity analysis* and can be applied to profit distributions or even to distributions of acceptance probabilities. Analyses of this sort could be achieved through simple modification of the way in which the outputs of the experiments are handled in the both the output module of the algorithm, and in the post-run analysis.

7.4.4 Analysis of input variables

Section 2.4 also provided a selection of models for spot prices. The models may be tested and/or validated on the historical data provided by Peaking, and a suitable model for prices in the South African market could be developed. The testing and validation of data would constitute a quantitative analysis of the SMP's and could be used to investigate whether the SMP's in the EPP exhibit the mean reversion, stochastic volatility and jumps which characterise the prices in other markets.

Similar investigations could also be conducted on the other input variables such as demand and marginal cost (especially for thermal generators in the latter).

Correlation structures between system variables could also be investigated through statistical analysis of historical data, and then be included in the model where appropriate.

7.4.5 Other possibilities

There are many other potential modifications which could be enacted. Such modifications have been summarised above and some specifics were also mentioned in Chapters 5 and 6. A selection of the modifications that were mentioned were:

- Formulation of a generic representation of *other types* of generating units.
- Including *more detail* with regard to system and technical constraints such as outages.
- Introduction of *demand-side bidding* for the pumping costs (discussed in Chapter 5).

More generally, there is scope for more advanced research in the way of:

- Normative modelling under a parameterised version of the model. Examples — for a single generating unit — include finding the optimal offering strategy (under various scenarios or parameterisations), and introducing multiple criteria for determining the optimal strategies. The modelling could also be done with respect to a Genco by amalgamating generating units (i.e. increasing the complexity of the supply function).
- System-wide descriptive models: by adding replicates of the single Genco into the system model (with some distinguishing modifications), a model could be devised of two or more Genco's that could even be extended to include large consumers. Such models could be used for supply function and price-formation analyses.

7.4.6 Final comment

The theoretical nature of the study and academic interpretation should not belie the ability of this model to be used in a realistic implementation. The client of the analysis, supplied useful generic information on the importance of particular variables in the trading process, namely the SMP, MC, system demand and competitor behaviour. The system variables have all been suitably represented in the formulation and subsequent analysis. The one important aspect that has not been captured, but which offers a natural avenue for further research, is the success of historical offers and profit takings. The appropriate modifications for incorporating offer and profit history were explained earlier in this section.

A critical examination of the suitability of the model in providing a robust method of strategic analysis has been made, and the approach exhibits versatility, simplicity, and ease of implementation. The model has much of the appeal in the manner of Bower and Bunn [8], who favour "stylised models, ignoring much of the complexity of market" while allowing isolation of design aspects (e.g. uniform price versus pay-as-bid or daily versus hourly trading), encouraging learning through simulation, and measuring the effects of information availability. Such models can succeed with a few exogenous variables for the various uncertainties, and aim to capture the main ideals with regard to strategic decision-making.

The study of this dissertation has motivated the use of simple simulation-based modelling for understanding systems which are inherently as complex and dynamic as markets for electrical energy. The challenges arising from the two merging streams of production optimisation and market participation, can thus be explored, understood, and ultimately resolved.

Appendix A

Appendix

A.1 Ito's Lemma and Option Valuation Formulae

Ito's Lemma The lemma is a specific treatment of a stochastic variable and uses the assumption of being able to continuously hedge the value of another stochastic variable which is in the defining equation for the first variable. If x is the first variable and follows an Ito process:

$$dx = a(x,t)dt + b(x,t)dz$$

where dz is a Wiener process and a and b are functions of x and t. The variable has drift of a and variance b^2. Ito's lemma shows that a function G, of x and t follows the process then

$$dG = \left(\frac{\partial G}{\partial x}a + \frac{\partial G}{\partial t} + \frac{\partial^2 G}{\partial x^2}b^2\right) + \left(\frac{\partial G}{\partial x}b\right) dz$$

Thus G also follows an Ito process with drift equal to the term in the first bracket and variance rate equal to the square of the term in the second bracket.

Black-Scholes formula for the price of a simple call option:

1. Price of a call option on the spot asset

$$C(t) = S\Phi(d) - Ke^{-r(T-t)}\Phi(d - \sigma\sqrt{T-t})$$

where

$$d = \frac{\ln(S/K) + (r + \frac{1}{2}\sigma^2)(T-t)}{\sigma\sqrt{T-t}}$$

and

$C(t)$	is the value at time t of a European call option with strike price K and maturity date T
$\Phi(\cdot)$	is the cumulative distribution function of a $N(0,1)$ random variable
r	is the risk free rate of return
σ	is the standard deviation of spot price returns

2. Formula for an option on a futures agreement

$$C(t,s) = P(t,T)[F(t,s)\Phi(h) - K\Phi(h - \sigma\sqrt{T-t})]$$

where

$$h = \frac{\ln[F(t,s)/K] + \frac{1}{2}\sigma^2(T-t)}{\sigma\sqrt{T-t}}$$

and

$C(t,s)$	is the value at time t of a European call option on a futures contract maturing at s and with strike price K and option maturity date T
$P(t,T)$	is the value of a T-maturity pure discount bond

Put-Call Parity

$$C(t) + Ke^{-r(T-t)} = P(t) + S$$

Here $P(t)$ is the corresponding European put price. The put-call parity formula often used for calculating the value of a corresponding put option once we know the price of the call.

American option – A general analytical formula for valuing an option with early exercise possibilities is:

$$C(t) = \max_{\theta \in \Psi[t,T]} E_t \left[exp\left(-\int_t^\theta r(u)du \right) C^*(\theta) \right]$$

where

$C^*(\theta)$	is the payoff when exercised at time θ
$\Psi[t,T]$	is the class of all early exercise strategies implicitly determined from the spot price tree

A.2 Experimental Design

The three generators of the fraction alias arrangements that were chosen to avoid confounding of main and second order effects (with each other and with higher order effects) were:

p with $\beta \times \sigma_\gamma \times h \times f$

e with $\sigma_\gamma \times h \times \sigma_D \times \sigma_S$

ρ with $\beta \times h \times \sigma_D \times d$

Table A.1: Design matrix for the $2^{(10-3)}$ fractional factorial design

Run	β	σ_γ	h	σ_D	σ_S	d	f	p	e	ρ
1	0.2	0.12	6	0.11	0.11	22000	0.9	0.9	0.8	0.3
2	0.8	0.12	6	0.11	0.11	22000	0.9	0.1	0.8	0.1
3	0.2	0.29	6	0.11	0.11	22000	0.9	0.1	0.6	0.3
4	0.8	0.29	6	0.11	0.11	22000	0.9	0.9	0.6	0.1
5	0.2	0.12	10	0.11	0.11	22000	0.9	0.1	0.6	0.1
6	0.8	0.12	10	0.11	0.11	22000	0.9	0.9	0.6	0.3
7	0.2	0.29	10	0.11	0.11	22000	0.9	0.9	0.8	0.1
8	0.8	0.29	10	0.11	0.11	22000	0.9	0.1	0.8	0.3
9	0.2	0.12	6	0.26	0.11	22000	0.9	0.9	0.6	0.1
10	0.8	0.12	6	0.26	0.11	22000	0.9	0.1	0.6	0.3
11	0.2	0.29	6	0.26	0.11	22000	0.9	0.1	0.8	0.1
12	0.8	0.29	6	0.26	0.11	22000	0.9	0.9	0.8	0.3
13	0.2	0.12	10	0.26	0.11	22000	0.9	0.1	0.8	0.3
14	0.8	0.12	10	0.26	0.11	22000	0.9	0.9	0.8	0.1
15	0.2	0.29	10	0.26	0.11	22000	0.9	0.9	0.6	0.3
16	0.8	0.29	10	0.26	0.11	22000	0.9	0.1	0.6	0.1
17	0.2	0.12	6	0.11	0.26	22000	0.9	0.9	0.6	0.3
18	0.8	0.12	6	0.11	0.26	22000	0.9	0.1	0.6	0.1
19	0.2	0.29	6	0.11	0.26	22000	0.9	0.1	0.8	0.3
20	0.8	0.29	6	0.11	0.26	22000	0.9	0.9	0.8	0.1
21	0.2	0.12	10	0.11	0.26	22000	0.9	0.1	0.8	0.1
22	0.8	0.12	10	0.11	0.26	22000	0.9	0.9	0.8	0.3
23	0.2	0.29	10	0.11	0.26	22000	0.9	0.9	0.6	0.1
24	0.8	0.29	10	0.11	0.26	22000	0.9	0.1	0.6	0.3
25	0.2	0.12	6	0.26	0.26	22000	0.9	0.9	0.8	0.1
26	0.8	0.12	6	0.26	0.26	22000	0.9	0.1	0.8	0.3
27	0.2	0.29	6	0.26	0.26	22000	0.9	0.1	0.6	0.1
28	0.8	0.29	6	0.26	0.26	22000	0.9	0.9	0.6	0.3
29	0.2	0.12	10	0.26	0.26	22000	0.9	0.1	0.6	0.3

Table A.1: (continued)

Run	β	σ_γ	h	σ_D	σ_S	d	f	p	e	ρ
30	0.8	0.12	10	0.26	0.26	22000	0.9	0.9	0.6	0.1
31	0.2	0.29	10	0.26	0.26	22000	0.9	0.9	0.8	0.3
32	0.8	0.29	10	0.26	0.26	22000	0.9	0.1	0.8	0.1
33	0.2	0.12	6	0.11	0.11	28000	0.9	0.9	0.8	0.1
34	0.8	0.12	6	0.11	0.11	28000	0.9	0.1	0.8	0.3
35	0.2	0.29	6	0.11	0.11	28000	0.9	0.1	0.6	0.1
36	0.8	0.29	6	0.11	0.11	28000	0.9	0.9	0.6	0.3
37	0.2	0.12	10	0.11	0.11	28000	0.9	0.1	0.6	0.3
38	0.8	0.12	10	0.11	0.11	28000	0.9	0.9	0.6	0.1
39	0.2	0.29	10	0.11	0.11	28000	0.9	0.9	0.8	0.3
40	0.8	0.29	10	0.11	0.11	28000	0.9	0.1	0.8	0.1
41	0.2	0.12	6	0.26	0.11	28000	0.9	0.9	0.6	0.3
42	0.8	0.12	6	0.26	0.11	28000	0.9	0.1	0.6	0.1
43	0.2	0.29	6	0.26	0.11	28000	0.9	0.1	0.8	0.3
44	0.8	0.29	6	0.26	0.11	28000	0.9	0.9	0.8	0.1
45	0.2	0.12	10	0.26	0.11	28000	0.9	0.1	0.8	0.1
46	0.8	0.12	10	0.26	0.11	28000	0.9	0.9	0.8	0.3
47	0.2	0.29	10	0.26	0.11	28000	0.9	0.9	0.6	0.1
48	0.8	0.29	10	0.26	0.11	28000	0.9	0.1	0.6	0.3
49	0.2	0.12	6	0.11	0.26	28000	0.9	0.9	0.6	0.1
50	0.8	0.12	6	0.11	0.26	28000	0.9	0.1	0.6	0.3
51	0.2	0.29	6	0.11	0.26	28000	0.9	0.1	0.8	0.1
52	0.8	0.29	6	0.11	0.26	28000	0.9	0.9	0.8	0.3
53	0.2	0.12	10	0.11	0.26	28000	0.9	0.1	0.8	0.3
54	0.8	0.12	10	0.11	0.26	28000	0.9	0.9	0.8	0.1
55	0.2	0.29	10	0.11	0.26	28000	0.9	0.9	0.6	0.3
56	0.8	0.29	10	0.11	0.26	28000	0.9	0.1	0.6	0.1
57	0.2	0.12	6	0.26	0.26	28000	0.9	0.9	0.8	0.3
58	0.8	0.12	6	0.26	0.26	28000	0.9	0.1	0.8	0.1
59	0.2	0.29	6	0.26	0.26	28000	0.9	0.1	0.6	0.3
60	0.8	0.29	6	0.26	0.26	28000	0.9	0.9	0.6	0.1
61	0.2	0.12	10	0.26	0.26	28000	0.9	0.1	0.6	0.1
62	0.8	0.12	10	0.26	0.26	28000	0.9	0.9	0.6	0.3
63	0.2	0.29	10	0.26	0.26	28000	0.9	0.9	0.8	0.1
64	0.8	0.29	10	0.26	0.26	28000	0.9	0.1	0.8	0.3
65	0.2	0.12	6	0.11	0.11	22000	1.8	0.1	0.8	0.3
66	0.8	0.12	6	0.11	0.11	22000	1.8	0.9	0.8	0.1
67	0.2	0.29	6	0.11	0.11	22000	1.8	0.9	0.6	0.3
68	0.8	0.29	6	0.11	0.11	22000	1.8	0.1	0.6	0.1
69	0.2	0.12	10	0.11	0.11	22000	1.8	0.9	0.6	0.1
70	0.8	0.12	10	0.11	0.11	22000	1.8	0.1	0.6	0.3
71	0.2	0.29	10	0.11	0.11	22000	1.8	0.1	0.8	0.1

Table A.1: (continued)

Run	β	σ_γ	h	σ_D	σ_S	d	f	p	e	ρ
72	0.8	0.29	10	0.11	0.11	22000	1.8	0.9	0.8	0.3
73	0.2	0.12	6	0.26	0.11	22000	1.8	0.1	0.6	0.1
74	0.8	0.12	6	0.26	0.11	22000	1.8	0.9	0.6	0.3
75	0.2	0.29	6	0.26	0.11	22000	1.8	0.9	0.8	0.1
76	0.8	0.29	6	0.26	0.11	22000	1.8	0.1	0.8	0.3
77	0.2	0.12	10	0.26	0.11	22000	1.8	0.9	0.8	0.3
78	0.8	0.12	10	0.26	0.11	22000	1.8	0.1	0.8	0.1
79	0.2	0.29	10	0.26	0.11	22000	1.8	0.1	0.6	0.3
80	0.8	0.29	10	0.26	0.11	22000	1.8	0.9	0.6	0.1
81	0.2	0.12	6	0.11	0.26	22000	1.8	0.1	0.6	0.3
82	0.8	0.12	6	0.11	0.26	22000	1.8	0.9	0.6	0.1
83	0.2	0.29	6	0.11	0.26	22000	1.8	0.9	0.8	0.3
84	0.8	0.29	6	0.11	0.26	22000	1.8	0.1	0.8	0.1
85	0.2	0.12	10	0.11	0.26	22000	1.8	0.9	0.8	0.1
86	0.8	0.12	10	0.11	0.26	22000	1.8	0.1	0.8	0.3
87	0.2	0.29	10	0.11	0.26	22000	1.8	0.1	0.6	0.1
88	0.8	0.29	10	0.11	0.26	22000	1.8	0.9	0.6	0.3
89	0.2	0.12	6	0.26	0.26	22000	1.8	0.1	0.8	0.1
90	0.8	0.12	6	0.26	0.26	22000	1.8	0.9	0.8	0.3
91	0.2	0.29	6	0.26	0.26	22000	1.8	0.9	0.6	0.1
92	0.8	0.29	6	0.26	0.26	22000	1.8	0.1	0.6	0.3
93	0.2	0.12	10	0.26	0.26	22000	1.8	0.9	0.6	0.3
94	0.8	0.12	10	0.26	0.26	22000	1.8	0.1	0.6	0.1
95	0.2	0.29	10	0.26	0.26	22000	1.8	0.1	0.8	0.3
96	0.8	0.29	10	0.26	0.26	22000	1.8	0.9	0.8	0.1
97	0.2	0.12	6	0.11	0.11	28000	1.8	0.1	0.8	0.1
98	0.8	0.12	6	0.11	0.11	28000	1.8	0.9	0.8	0.3
99	0.2	0.29	6	0.11	0.11	28000	1.8	0.9	0.6	0.1
100	0.8	0.29	6	0.11	0.11	28000	1.8	0.1	0.6	0.3
101	0.2	0.12	10	0.11	0.11	28000	1.8	0.9	0.6	0.3
102	0.8	0.12	10	0.11	0.11	28000	1.8	0.1	0.6	0.1
103	0.2	0.29	10	0.11	0.11	28000	1.8	0.1	0.8	0.3
104	0.8	0.29	10	0.11	0.11	28000	1.8	0.9	0.8	0.1
105	0.2	0.12	6	0.26	0.11	28000	1.8	0.1	0.6	0.3
106	0.8	0.12	6	0.26	0.11	28000	1.8	0.9	0.6	0.1
107	0.2	0.29	6	0.26	0.11	28000	1.8	0.9	0.8	0.3
108	0.8	0.29	6	0.26	0.11	28000	1.8	0.1	0.8	0.1
109	0.2	0.12	10	0.26	0.11	28000	1.8	0.9	0.8	0.1
110	0.8	0.12	10	0.26	0.11	28000	1.8	0.1	0.8	0.3
111	0.2	0.29	10	0.26	0.11	28000	1.8	0.1	0.6	0.1
112	0.8	0.29	10	0.26	0.11	28000	1.8	0.9	0.6	0.3
113	0.2	0.12	6	0.11	0.26	28000	1.8	0.1	0.6	0.1

Table A.1: (continued)

Run	β	σ_γ	h	σ_D	σ_S	d	f	p	ϵ	ρ
114	0.8	0.12	6	0.11	0.26	28000	1.8	0.9	0.6	0.3
115	0.2	0.29	6	0.11	0.26	28000	1.8	0.9	0.8	0.1
116	0.8	0.29	6	0.11	0.26	28000	1.8	0.1	0.8	0.3
117	0.2	0.12	10	0.11	0.26	28000	1.8	0.9	0.8	0.3
118	0.8	0.12	10	0.11	0.26	28000	1.8	0.1	0.8	0.1
119	0.2	0.29	10	0.11	0.26	28000	1.8	0.1	0.6	0.3
120	0.8	0.29	10	0.11	0.26	28000	1.8	0.9	0.6	0.1
121	0.2	0.12	6	0.26	0.26	28000	1.8	0.1	0.8	0.3
122	0.8	0.12	6	0.26	0.26	28000	1.8	0.9	0.8	0.1
123	0.2	0.29	6	0.26	0.26	28000	1.8	0.9	0.6	0.3
124	0.8	0.29	6	0.26	0.26	28000	1.8	0.1	0.6	0.1
125	0.2	0.12	10	0.26	0.26	28000	1.8	0.9	0.6	0.1
126	0.8	0.12	10	0.26	0.26	28000	1.8	0.1	0.6	0.3
127	0.2	0.29	10	0.26	0.26	28000	1.8	0.1	0.8	0.1
128	0.8	0.29	10	0.26	0.26	28000	1.8	0.9	0.8	0.3

A.3 Simulation Results

Table A.2: Results for the $2^{(10-3)}$ fractional factorial design

Run	Mean Profit	Mean Acceptances	Mean Offers
1	902502	118	185
2	379372	185	185
3	869421	182	185
4	651059	108	185
5	668507	230	273
6	398696	137	276
7	969996	160	262
8	373778	266	269
9	386549	69	185
10	134099	178	185
11	1093194	184	185
12	515773	81	185
13	1024575	277	285
14	493733	133	283
15	383415	106	249
16	107272	201	244
17	582020	107	185
18	251723	183	185
19	1115600	185	185
20	885156	120	185
21	1035930	263	265
22	697626	159	266
23	563638	124	232
24	200880	203	238
25	545421	79	185
26	235621	185	185
27	763023	176	185
28	326973	76	184
29	438613	192	244
30	175943	98	243
31	623018	118	252
32	253783	237	249
33	359944	61	92
34	127375	81	82
35	522913	126	137
36	302628	72	124
37	176579	56	66
38	119910	38	73
39	412996	71	117

Table A.2: (continued)

Run	Mean Profit	Mean Acceptances	Mean Offers
40	197821	128	130
41	139573	37	75
42	32980	77	83
43	581553	130	134
44	355372	77	148
45	297897	74	75
46	132494	34	68
47	216796	52	118
48	39660	89	109
49	333540	80	139
50	135335	129	139
51	812849	160	163
52	549951	103	159
53	508039	128	129
54	352724	78	130
55	276868	67	129
56	131967	117	134
57	383333	77	146
58	129056	143	148
59	423337	131	146
60	237767	71	152
61	230895	96	119
62	86758	48	117
63	394425	68	144
64	126412	133	139
65	1089720	170	170
66	771593	104	168
67	434977	47	83
68	225197	92	92
69	158811	17	34
70	78419	34	34
71	872332	120	120
72	552136	69	116
73	501468	105	106
74	198571	30	107
75	637721	71	165
76	270225	163	163
77	343159	43	136
78	189220	135	135
79	327040	61	61
80	160307	19	66

Table A.2: (continued)

Run	Mean Profit	Mean Acceptances	Mean Offers
81	424027	65	65
82	271390	34	66
83	833577	97	152
84	370634	157	157
85	477194	57	101
86	203527	98	98
87	377995	47	47
88	181023	19	39
89	861395	162	162
90	391928	61	161
91	337431	37	105
92	120228	98	99
93	70161	8	47
94	56097	48	49
95	698334	123	124
96	369831	48	129
97	342473	52	52
98	225507	30	47
99	262893	27	46
100	87449	37	37
101	46367	5	9
102	25341	10	10
103	361963	51	51
104	299382	35	59
105	137475	27	27
106	60702	8	29
107	281528	34	81
108	154412	92	92
109	103107	12	38
110	50743	34	34
111	198852	32	32
112	57310	7	27
113	220829	32	32
114	132726	16	32
115	567845	64	99
116	202590	92	92
117	219404	26	48
118	107660	50	50
119	167046	21	21
120	149912	15	28
121	444296	86	86

Table A.2: (continued)

Run	Mean Profit	Mean Acceptances	Mean Offers
122	227300	36	88
123	148074	17	55
124	88993	62	62
125	41548	4	24
126	26495	23	24
127	455720	73	73
128	168805	23	68

A.4 VBA Code

```
Option Explicit

'SIMULATION PARAMETERS:

'Iterations and time horizon
Public N As Integer, T As Integer

'Offer price factor
Public bidprop As Double

'Strategy parameters
Public min_D As Double, bidfac As Double

'Bias parameters
Public xi_D As Double, xi_S As Double

'Precision parameters
Public sigma_D As Double, sigma_S As Double

'Noise in actuals
Public rho As Double, sigma_gamma As Double

'Efficiency parameter for pumped storage scheme
Public eff As Double

'Influence parameter for a price-setter
Public beta As Double

'Hours of pumping/trading
Public hrs As Double
'assigning dimensions and types to variables
```

```
'Unit fixed capacity per hour
Dim g As Double

'variables for actuals' stochasticity
Dim gammaD(0 To 8760) As Double, gammaS(0 To 8760) As Double

'Actual demands and SMP's
Dim D_a(1 To 8760) As Double, S_a(1 To 8760) As Double

'Forecast demands and SMP's
Dim D_f(1 To 8760) As Double, S_f(1 To 8760) As Double

'Daily, yearly and final profits
Dim Sum_profit(0 To 24) As Double, yearly_profit() As Double, _
yvalues() As Double

'Daily, yearly and final numbers of offers accepted
Dim Sum_accept(0 To 24) As Integer, yearly_accept() As Integer, _
total_accept() As Integer

'Daily, yearly and final numbers of offers made
Dim Sum_offer As Integer, yearly_offer() As Integer, _
total_offer() As Integer

'Day and iteration indexes
Dim day As Integer, Iter As Integer

'row offset for outputs

Dim row_offset As Integer

'metasimulation variable
Public v As Integer
Dim vmax As Integer


Sub Metasimulation()

Application.ScreenUpdating = False

'Clear output area
Worksheets("Results").Range("a:z").Clearcontents

vmax = Application.WorksheetFunction.CountA(Worksheets("Inputs"). _
Range("a50", "a30000"))
```

```
Call Actual
Call Set_parameters

For v = 1 To vmax
    beta = Worksheets("Inputs").Range("a50").Offset(v - 1, 1).Value
    sigma_gamma = Worksheets("Inputs").Range("a50").Offset(v - 1, 2)_
.Value
    hrs = Worksheets("Inputs").Range("a50").Offset(v - 1, 3).Value
    sigma_S = Worksheets("Inputs").Range("a50").Offset(v - 1, 4).Value
    sigma_D = Worksheets("Inputs").Range("a50").Offset(v - 1, 5).Value
    min_D = Worksheets("Inputs").Range("a50").Offset(v - 1, 6).Value
    bidfac = Worksheets("Inputs").Range("a50").Offset(v - 1, 7).Value
    bidprop = Worksheets("Inputs").Range("a50").Offset(v - 1, 8).Value
    eff = Worksheets("Inputs").Range("a50").Offset(v - 1, 9).Value

    row_offset = (N + 7) * (v - 1)

    Randomize
    Call Simulate

    Call Output

    'save workbook after each simulation
    ActiveWorkbook.Save

Next v

End Sub
Sub Set_parameters()

'time horizon
T = Worksheets("Inputs").Range("c10").Value
'simulation iterations
N = Worksheets("Inputs").Range("c11").Value

'Capacity
g = Worksheets("Inputs").Range("e31").Value

'SMP influence
'beta = Worksheets("Inputs").Range("e35").Value

'Pumped Storage efficiency
'eff = Worksheets("Inputs").Range("f11").Value

'Trading/Pumping hours
```

```
'hrs = Worksheets("Inputs").Range("e39").Value

'Actuals' stochasticity
rho = Worksheets("Inputs").Range("c20").Value
'sigma_gamma = Worksheets("Inputs").Range("c21").Value

'Trader's conjecture biases and precisions (forecasts)
xi_D = Worksheets("Inputs").Range("c15").Value
xi_S = Worksheets("Inputs").Range("c16").Value

'Forecast precisions
'sigma_D = Worksheets("Inputs").Range("f15").Value
'sigma_S = Worksheets("Inputs").Range("f16").Value

'Offer price proportion
'bidprop = Worksheets("Inputs").Range("c25").Value

'Demand Threshold (when to bid)
'min_D = Worksheets("Inputs").Range("e21").Value

'Strategy factor (when to bid)
'bidfac = Worksheets("Inputs").Range("e25").Value

End Sub


Sub Actual()

'Worksheets("test").Range("b1:d8761").Clearcontents
    Call Demand
    Call SMP

End Sub
Sub Demand()

Dim i As Integer, j As Integer, k As Integer, l As Integer

Dim mu_D As Double

'Hourly, daily and monthly effects
Dim h(1 To 24) As Double, d(1 To 7) As Double, m(1 To 12) As Double

'variable for actuals
Dim Days(1 To 31) As Integer
Dim Sumdays(0 To 365) As Integer
```

```
'mean demand
mu_D = Worksheets("Demand").Range("c3").Value

'hourly factors
For k = 1 To 24
    h(k) = Worksheets("Demand").Range("b6").Offset(k - 1, 0).Value
Next k

'daily factors
For k = 1 To 7
    d(k) = Worksheets("Demand").Range("e6").Offset(k - 1, 0).Value
Next k

'monthly factors
For k = 1 To 12
    m(k) = Worksheets("Demand").Range("h6").Offset(k - 1, 0).Value
Next k

'algorithm for producing hourly log demand values
Sumdays(0) = 0
Worksheets("test").Range("b1").Value = "Demand"

For l = 1 To 12
Days(l) = Worksheets("demand").Range("i6").Offset(l - 1, 0).Value
Sumdays(l) = Sumdays(l - 1) + Days(l)
    For i = (24 * Sumdays(l - 1) + 1) To (Sumdays(l - 1) + Days(l)) * 24

        'Day of the week effects
        If (Int((i - 1) / 24) + 1) Mod 7 > 0 Then
            j = (Int((i - 1) / 24) + 1) Mod 7
            Else: j = 7
        End If

        'Hourly effects
        If i Mod 24 > 0 Then
                k = i Mod 24
                Else: k = 24
        End If

        'Total deterministic effect
        D_a(i) = mu_D + d(j) + h(k) + m(l)

        'Output demand to test
        'Worksheets("test").Range("b1").Offset(i, 0) = Exp(D_a(i))

    Next i
```

```
Next l

End Sub


Sub SMP()

Dim i As Integer, j As Integer, k As Integer, l As Integer

Dim mu_S As Double

'Hourly, daily and monthly effects
Dim h(1 To 24) As Double, d(1 To 7) As Double, m(1 To 12) As Double

'variable for actuals
Dim Days(1 To 31) As Integer
Dim Sumdays(0 To 365) As Integer

'mean demand
mu_S = Worksheets("SMP").Range("c3").Value

'hourly factors
For k = 1 To 24
    h(k) = Worksheets("SMP").Range("b6").Offset(k - 1, 0).Value
Next k

'daily factors
For k = 1 To 7
    d(k) = Worksheets("SMP").Range("e6").Offset(k - 1, 0).Value
Next k

'monthly factors
For k = 1 To 12
    m(k) = Worksheets("SMP").Range("h6").Offset(k - 1, 0).Value
Next k

'algorithm for producing hourly log SMP values
Sumdays(0) = 0
Worksheets("test").Range("c1").Value = "SMP"

For l = 1 To 12
Days(l) = Worksheets("SMP").Range("i6").Offset(l - 1, 0).Value
Sumdays(l) = Sumdays(l - 1) + Days(l)
    For i = (24 * Sumdays(l - 1) + 1) To (Sumdays(l - 1) + Days(l)) * 24

        'Day of the week effects
```

```
        If (Int((i - 1) / 24) + 1) Mod 7 > 0 Then
            j = (Int((i - 1) / 24) + 1) Mod 7
            Else: j = 7
        End If

        'Hourly effects
        If i Mod 24 > 0 Then
                k = i Mod 24
                Else: k = 24
        End If

        'Total deterministic effect
        S_a(i) = mu_S + d(j) + h(k) + m(l)

        'Output SMP's to test
        'Worksheets("test").Range("c1").Offset(i, 0) = Exp(S_a(i))

    Next i
Next l

End Sub


Sub Dailytrade()

'daily variables ordered as per forecast SMP's
Dim OS_f(1 To 24) As Double, OS_a(1 To 24) As Double
Dim OSinf_a(1 To 24) As Double
Dim OD_f(1 To 24) As Double, OD_a(1 To 24) As Double
Dim SumOS_f(0 To 24) As Double, SumOS_a(0 To 24)

'Actual and forecast marginal costs
Dim MC_a As Double, MC_f As Double

'Offer price
Dim y(1 To 24) As Double

'Potential offers
Dim offer(1 To 24) As Integer, countoffer(0 To 25) As Integer

'Hourly profits
Dim prof(1 To 24) As Double

'Accepted offers
Dim accept(1 To 24) As Integer
```

```
'Miscellaneous integers
Dim hr As Integer, k As Integer, l As Integer, m As Integer, _
r As Integer, s As Integer

For hr = 1 To 24
    Randomize

    'Generate actuals' noise
    gammaD(hr + 24 * (day - 1)) = rho * gammaD(hr - 1 + 24 * (day - 1))_
 +(1 - rho) * Application.WorksheetFunction.NormInv(0.001 + 0.998 *_
Rnd(), 0, sigma_gamma)
    gammaS(hr + 24 * (day - 1)) = rho * gammaS(hr - 1 + 24 * (day - 1))_
 +(1 - rho) * Application.WorksheetFunction.NormInv(0.001 + 0.998 * _
Rnd(), 0, sigma_gamma)

    'Forecast, demands and spot prices
    D_f(hr + 24 * (day - 1)) = D_a(hr + 24 * (day - 1)) + _
        gammaD(hr + 24 * (day - 1)) + Application.WorksheetFunction._
NormInv (0.001 + 0.998 * Rnd(), xi_D, sigma_D)
    S_f(hr + 24 * (day - 1)) = S_a(hr + 24 * (day - 1)) + _
        gammaS(hr + 24 * (day - 1)) + Application.WorksheetFunction._
NormInv (0.001 + 0.998 * Rnd(), xi_S, sigma_S)

    'Output demands and SMP's
    Worksheets("Calc").Range("b1").Offset(hr, 0) = Exp(D_f(hr + 24 *_
(day - 1)))
    Worksheets("Calc").Range("c1").Offset(hr, 0) = Exp(S_f(hr + 24 *_
(day - 1)))
    Worksheets("Calc").Range("d1").Offset(hr, 0) = Exp(D_a(hr + 24 *_
(day - 1)) + gammaD(hr + 24 * (day - 1)))
    Worksheets("Calc").Range("e1").Offset(hr, 0) = Exp(S_a(hr + 24 *_
(day - 1)) + gammaS(hr + 24 * (day - 1)))

Next hr

'Sort all by forecast SMP's
Call Sort

'Read in ordered variables
For k = 1 To 24
    OD_f(k) = Worksheets("Calc").Range("b1").Offset(k, 0)
    OS_f(k) = Worksheets("Calc").Range("c1").Offset(k, 0)
    OD_a(k) = Worksheets("Calc").Range("d1").Offset(k, 0)
    OS_a(k) = Worksheets("Calc").Range("e1").Offset(k, 0)
Next k
```

```
SumOS_f(0) = 0
SumOS_a(0) = 0

'Calculate average MC's: forecast and actual
For l = 1 To hrs
    SumOS_f(l) = SumOS_f(l - 1) + OS_f(l)
    SumOS_a(l) = SumOS_a(l - 1) + OS_a(l)
Next l

MC_f = (SumOS_f(hrs) / eff) / hrs
MC_a = (SumOS_a(hrs) / eff) / hrs

'Worksheets("Calc").Range("g1").Value = MC_f
'Worksheets("Calc").Range("h1").Value = MC_a

'Count total potential offers for the day
countoffer(hrs) = 0
For m = hrs + 1 To 24
    If OD_f(m) > min_D And OS_f(m) > bidfac * MC_f Then
        offer(m) = 1
        Else: offer(m) = 0
    End If
    'Worksheets("Calc").Range("h2").Offset(m - 1, 0) = offer(m)
    countoffer(m) = countoffer(m - 1) + offer(m)
Next m

'Limit number of actual offers to number of pumping hours and_
calculate offer prices
countoffer(0) = 0
For r = 1 To 24 - hrs
    If offer(24 - r + 1) = 1 Then
            'Check offer greater than MC_f else bid at MC
            If OS_f(24 - r + 1) > MC_f Then
                y(24 - r + 1) = MC_f + bidprop * (OS_f(24 - r + 1)_
- MC_f)
                'y(24 - r + 1) = MC_f * (1 + bidprop)
                'Worksheets("Calc").Range("g2").Offset(24 - r).Value = _
y(24 - r + 1)
            Else: y(24 - r + 1) = MC_f
            End If
        'effect on price through submission of offer (i.e exerting an _
influence on the price)
        OSinf_a(24 - r + 1) = (1 - beta) * OS_a(24 - r + 1) + beta *_
 y(24 - r + 1)
        'Worksheets("Calc").Range("f2").Offset(24 - r).Value = _
OSinf_a(24 - r + 1)
```

```
        Else: y(24 - r + 1) = 0
    End If
    countoffer(r) = countoffer(r - 1) + offer(24 - r + 1)
    If countoffer(r) = hrs Then
        Exit For
    End If
Next r

'Market clearing process: determining which of the offers are accepted
Sum_accept(hrs) = 0
Sum_profit(hrs) = 0

For s = hrs + 1 To 24
    If y(s) > 0 And y(s) <= OSinf_a(s) Then
        accept(s) = 1
        prof(s) = (OSinf_a(s) - MC_a) * g
    Else
        accept(s) = 0
        prof(s) = 0
    End If
    Sum_accept(s) = Sum_accept(s - 1) + accept(s)
    Sum_profit(s) = Sum_profit(s - 1) + prof(s)
Next s

Sum_offer = Application.WorksheetFunction.Min(countoffer(24), hrs)

'Worksheets("Calc").Range("k1").Value = Application.WorksheetFunction._
'Min(countoffer(24), hrs)
'Worksheets("Calc").Range("i1").Value = Sum_accept(24)
'Worksheets("Calc").Range("j1").Value = Sum_P(24)

End Sub


Sub Sort()

' Sorts a day's demands and prices by the forecast price value from _
smallest to largest
    Worksheets("Calc").Range("B2:E25").Select
    Selection.Sort Key1:=Range("C2"), Order1:=xlAscending, Header:=_
xlGuess, _
        OrderCustom:=1, MatchCase:=False, Orientation:=xlTopToBottom

End Sub

Sub Simulate()
```

```
ReDim yvalues(1 To N), total_accept(1 To N), total_offer(1 To N)

For Iter = 1 To N
    gammaD(0) = 0
    gammaS(0) = 0

    ReDim yearly_profit(0 To T)
    ReDim yearly_accept(0 To T)
    ReDim yearly_offer(0 To T)

    yearly_profit(0) = 0
    yearly_accept(0) = 0
    yearly_offer(0) = 0

    Worksheets("Calc").Select

    'yearly trade
    For day = 1 To T

        Worksheets("Calc").Range("b2:i25").Clearcontents

        Call Dailytrade

        yearly_offer(day) = yearly_offer(day - 1) + Sum_offer
        yearly_accept(day) = yearly_accept(day - 1) + Sum_accept(24)
        yearly_profit(day) = yearly_profit(day - 1) + Sum_profit(24)

    Next day

    yvalues(Iter) = yearly_profit(T)
    total_accept(Iter) = yearly_accept(T)
    total_offer(Iter) = yearly_offer(T)

    'Worksheets("Results").Range("b1").Offset(Iter, 0).Value = _
'yvalues(Iter)
    'Worksheets("Results").Range("c1").Offset(Iter, 0).Value = _
'total_accept(Iter)
    'Worksheets("Results").Range("d1").Offset(Iter, 0).Value = _
total_offer(Iter)

Next Iter

End Sub

Sub Output()
```

```
'Summary Statistics for profits and acceptances
Dim Max_prof As Double, Min_prof As Double, Av_prof As Double,_
 SD_prof As Double, _
Max_acc As Double, Min_acc As Double, Av_acc As Double, SD_acc_
 As Double, _
Max_off As Double, Min_off As Double, Av_off As Double, SD_off_
 As Double

Worksheets("Results").Select

'Column of iteration numbers
For Iter = 1 To N
    Worksheets("Results").Range("a1").Offset(Iter + row_offset, 0)_
.Value = Iter
Next Iter

'Headings for summary statistics rows
Worksheets("Results").Range("a1").Offset(row_offset + N + 2, 0).Value_
 = "Mean " & v
Worksheets("Results").Range("a1").Offset(row_offset + N + 3, 0).Value_
 = "Stddev " & v
Worksheets("Results").Range("a1").Offset(row_offset + N + 4, 0).Value_
 = "Min " & v
Worksheets("Results").Range("a1").Offset(row_offset + N + 5, 0).Value_
 = "Max " & v

'headings for columns in "Results"
Range("a1").Offset(row_offset, 0).Value = "RUN " & v
Range("b1").Offset(row_offset, 0) = beta
Range("c1").Offset(row_offset, 0) = sigma_gamma
Range("d1").Offset(row_offset, 0) = hrs
Range("e1").Offset(row_offset, 0) = sigma_S
Range("f1").Offset(row_offset, 0) = sigma_D
Range("g1").Offset(row_offset, 0) = min_D
Range("h1").Offset(row_offset, 0) = bidfac
Range("i1").Offset(row_offset, 0) = bidprop
Range("j1").Offset(row_offset, 0) = eff

    'Printing out results
    For Iter = 1 To N
        Range("b1").Offset(Iter + row_offset, 0).Value =_
 yvalues(Iter)
        Range("c1").Offset(Iter + row_offset, 0).Value =_
 total_accept(Iter)
        Range("d1").Offset(Iter + row_offset, 0).Value =_
 total_offer(Iter)
```

```
    Next Iter

    Range("b1").Offset(row_offset + 1, 0).Select
    Range(ActiveCell, ActiveCell.End(xlDown)).Name = "Profits"
    Range("c1").Offset(row_offset + 1, 0).Select
    Range(ActiveCell, ActiveCell.End(xlDown)).Name = "Acceptances"
    Range("d1").Offset(row_offset + 1, 0).Select
    Range(ActiveCell, ActiveCell.End(xlDown)).Name = "Offers"

    'Calculate summary statistics
Max_prof = Application.WorksheetFunction.Max(Range("Profits"))
Min_prof = Application.WorksheetFunction.Min(Range("Profits"))
Av_prof = Application.WorksheetFunction.Average(Range("Profits"))
SD_prof = Application.WorksheetFunction.StDev(Range("Profits"))

Max_acc = Application.WorksheetFunction.Max(Range("Acceptances"))
Min_acc = Application.WorksheetFunction.Min(Range("Acceptances"))
Av_acc = Application.WorksheetFunction.Average(Range("Acceptances"))
SD_acc = Application.WorksheetFunction.StDev(Range("Acceptances"))

Max_off = Application.WorksheetFunction.Max(Range("Offers"))
Min_off = Application.WorksheetFunction.Min(Range("Offers"))
Av_off = Application.WorksheetFunction.Average(Range("Offers"))
SD_off = Application.WorksheetFunction.StDev(Range("Offers"))

'Printing out summary statistics
Range("b1").Offset(row_offset + N + 5, 0).Value = Max_prof
Range("b1").Offset(row_offset + N + 4, 0).Value = Min_prof
Range("b1").Offset(row_offset + N + 2, 0).Value = Av_prof
Range("b1").Offset(row_offset + N + 3, 0).Value = SD_prof

Range("c1").Offset(row_offset + N + 5, 0).Value = Max_acc
Range("c1").Offset(row_offset + N + 4, 0).Value = Min_acc
Range("c1").Offset(row_offset + N + 2, 0).Value = Av_acc
Range("c1").Offset(row_offset + N + 3, 0).Value = SD_acc

Range("d1").Offset(row_offset + N + 5, 0).Value = Max_off
Range("d1").Offset(row_offset + N + 4, 0).Value = Min_off
Range("d1").Offset(row_offset + N + 2, 0).Value = Av_off
Range("d1").Offset(row_offset + N + 3, 0).Value = SD_off

End Sub
```

Bibliography

[1] Albuyeh, F. and Kumar, J. (2003). Decision support tools for market participants. *IEEE Transactions on Power Systems*, 18:512–516.

[2] Alvarado, F. (1999). The stability of electric energy markets. *Decision Support Systems*, 24:233–241.

[3] Anderson, E. and Philpott, A. (2002). Using supply functions for offering generation into an electricity market. *Operations Research*, 50:477–489.

[4] Baillo, A., Ventosa, M., Rivier, M., and Ramos, A. (2004). Optimal offering strategies for generation companies operating in electricity spot markets. *IEEE Transactions on Power Systems*, 19:745–753.

[5] Batlle, C. and Barquín, J. (2004). Fuel prices scenario generation based on a multivariate GARCH model for risk analysis in a wholesale electricity market. *Electrical Power and Energy Systems*, 26:273–280.

[6] Bertsimas, D., Kogan, L., and Lo, A. (2001). Hedging derivative securities and incomplete markets: An ε-arbitrage approach. *Operations Research*, 49:372–397.

[7] Bjorgan, R., Liu, C.-C., and Lawarrée (1999). Financial risk management in a competitive electricity market. *IEEE Transactions on Power Systems*, 14:1285–1291.

[8] Bower, J. and Bunn, D. (2000). A model-based comparison of pool and bilateral market mechanisms for electricity trading. *The Energy Journal*, 21:1–29.

[9] Bunn, D. and Day, C. (2002). Computational modelling of price-formation in the electricity pool of England and Wales. http://www.london.edu/.

[10] Clewlow, L. and Strickland, C. (2000). *Energy Derivatives: Pricing and Risk Management*. Lacima Publications, London.

[11] Conejo, A., Nogales, F., and Arroyo, J. (2002). Price-taker bidding strategy under price uncertainty. *IEEE Transactions on Power Systems*, 17:1081–1088.

[12] Conteh, M. (2003). Privatisation and liberalisation of the South African electricity industry. *Journal of Energy in Southern Africa*, 14:8–13.

[13] Day, C. and Bunn, D. (1999). Generation asset divestment in the England and Wales electricity market: A computational approach to analysing market power. Technical report, London Business School: Decision Technology Centre.

[14] Deng, S.-J., Johnson, B., and Sogomonian, A. (2001). Exotic electricity options and the valuation of electricity generation and transmission assets. *Decision Support Systems*, 30:383–392.

[15] Denton, M., Palmer, A., Masiello, R., and Skantze, P. (2003). Managing market risk in energy. *IEEE Transactions on Power Systems*, 18:494–502.

[16] Dhalgren, R., C-C, L., and Lawarrée, J. (2003). Risk assessment in energy trading. *IEEE Transactions on Power Systems*, 18:503–511.

[17] Ferrero, R. and Shahidehpour, S. (1997). Optimality conditions in power transactions in deregulated power pools. *Electric Power Systems Research*, 42:209–214.

[18] French, S. (1995). Uncertainty and imprecision: Modelling and analysis. *Journal of the Operational Research Society*, 46:70–79.

[19] Gary, S. and Larsen, E. (2000). Improving firm performance in out-of-equilibrium, deregulated markets using feedback simulation models. *Energy Policy*, 28:845–855.

[20] Ghosh, K. and Ramesh, V. (1997). An options model for electric power markets. *Electrical power and energy systems*, 19:75–85.

[21] Gountis, V. and Bakirtzis, A. (2004). Bidding strategies for electricity producers in a competitive electricity marketplace. *IEEE Transactions on Power Systems*, 19:356–365.

[22] Grant, D., Vora, G., and Weeks, D. (1997). Path-dependent options: Extending the monte carlo simulation approach. *Management Science*, 43:1589–1602.

[23] Hao, S. (2000). A study of basic bidding strategy in clearing price auctions. *IEEE Transactions on Power Systems*, 15:975–979.

[24] He, Y. and Song, Y. (2002). Integrated bidding strategies by optimal response to probabilistic locational marginal prices. *IEE Proceedings on Generation, Transmission and Distribution*, 149:633–639.

[25] He, Y., Song, Y., and Wang, X. (2002). Bidding strategies based on bid sensitivities in generation auction markets. *IEE Proceedings on Generation, Transmission and Distribution*, 149:21–26.

[26] Hesmondhalgh, S. (2003). Is NETA the blueprint for wholesale electricity trading arrangements of the future? *IEEE Transactions on Power Systems*, 18:548–554.

[27] Hobbs, B. (1995). Optimization methods for electric utility resource planning. *European Journal of Operational Research*, 83:1–20.

[28] Hull, J. C. (1997). *Options, Futures and Other Derivatives*. Prentice Hall International, Inc, New Jersey.

[29] Kahn, E. (1995). Regulation by simulation: The role of production cost models in electricity planning and pricing. *Operations Research*, 43:388–398.

[30] Kaleta, M., Ogryczak, W., Toczylowski, E., and Zóltowska, I. (2003). On multiple criteria decision support for suppliers on the competitive electric power market. *Annals of Operations Research*, 121:79–104.

[31] Keppo, J. (2002). Optimality with hydropower systems. *IEEE Transactions on Power Systems*, 17:583–589.

[32] Kleindorfer, P., Wu, D., and Fernando, C. (2001). Theory and methodology: Strategic gaming in electric power markets. *European Journal of Operational Research*, 130:156–168.

[33] Lan Zhang, P., Luh, X., and Merchel, G. (1994). Optimization-based inter-utility power purchases. *IEEE Transactions on Power Systems*, 9:891–897.

[34] Larsen, E. and Bunn, D. (1999). Deregulation in electricity: understanding strategic and regulatory risk. *Journal of the Operational Research Society*, 50:337–344.

[35] Makkonen, S. and Lahdelma, R. (1997). Stochastic simulation in risk analysis of energy trade. Conference Proceedings. 13th International Conference on Multiple Criteria Decision Making.

[36] Makkonen, S. and Lahdelma, R. (2001). Analysis of power pools in the deregulated energy market through simulation. *Decision Support Systems*, 30:289–301.

[37] Neame, P., Philpott, A., and Pritchard, G. (1999). Offer stack optimisation for price takers in electricity markets. Proceedings of Operational Research Society of New Zealand:
http://www.esc.auckland.ac.nz/Organisations/ORSNZ/conf34/Abstracts.html.

[38] Oren, S. (2001). Integrating real and financial options in demand-side electricity contracts. *Decision Support Systems*, 30:279–288.

[39] Otero-Novas, I., Meseguer, C., Batlle, C., and Alba, J. (2000). A simulation model for a competitive generation market. *IEEE Transactions on Power Systems*, 15:250–256.

[40] Philpott, A., Anderson, E., and Kaye, R. (1998). Optimal participant behaviour in electricity markets. Proceedings of Operational Research Society of New Zealand: http://www.esc.auckland.ac.nz/Organisations/ORSNZ/conf33/abstracts.html#80.

[41] Pilipović, D. (1998). *Energy Risk: Valuing and Managing Energy Derivatives*. McGraw-Hill, New York.

[42] Rajaraman, R. and Alvarado, F. (2003). Optimal bidding strategy in electricity markets under uncertain energy and reserve prices. Technical report, Power systems engineering research center. http://www.pserc.wisc.edu.

[43] Ray, D. and Cashman, E. (1999). Operational risks, bidding strategies and information policies in restructured power markets. *Decision Support Systems*, 24:175–182.

[44] Robson, I., Whittington, H., and Connelly, J. (1996). Decision support for energy trading between power generators. *Electrical power and energy systems*, 18:359–369.

[45] Ruusunen, J. (1994). Barter contracts in intertemporal energy exchange. *European Journal of Operational Research*, 75:589–599.

[46] Sioshansi, F. (2002). The emergence of trading and risk management in liberalized electricity markets. *Energy Policy*, 30:449–459.

[47] Taylor, J. and Majithia, S. (2000). Using combined forecasts with changing weights for electricity demand profiling. *Journal of the Operational Research Society*, 51:72–82.

[48] Tigler, J. and Butte, T. (2001). Weather derivatives: A quantitative analysis. Darmstadt University of Technology, Germany. Research Thesis.

[49] Vehviläinen, I. and Keppo, J. (2003). Managing electricity market price risk. *European Journal of Operational Research*, 145:136–147.

[50] Vlahos, K., Ninios, P., and Bunn, D. (1998). An integrative modelling approach for understanding competitive electricity markets. *Journal of the Operational Research Society*, 49:187–199.

[51] Wallace, S. and Fleten, S. (2003). *Handbooks in OR and MS*, volume 10, chapter 10 Stochastic Programming Models in Energy. Elsevier science B.V.

[52] Wen, F. and David, A. (2001a). Optimal bidding strategies and modeling of imperfect information among competitive generators. *IEEE Transactions on Power Systems*, 16:15–21.

[53] Wen, F. and David, A. (2001b). Optimal bidding strategies for competitive generators and large consumers. *Electrical power and energy systems*, 23:37–43.

[54] Wen, F. and David, A. (2001c). Strategic bidding for electricity supply in a day-ahead energy market. *Electric Power Systems Research*, 59:197–206.

[55] Weron, R. (2000). Energy price risk management. *Physica A*, 285:127–134.