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Acronyms

AC Alternating Current.

ARIMA Autoregressive Integrated Moving Average.

CCGT Combined Cycle Gas Turbine.

CE Contingent Event.

CFD Contract for Differences.

CR Contingency Reserves.

DisCo Distribution Company.

DOPF Dual Optimal Power Flow.

DR Demand Response.

DSP Demand Side Participation.

FIR Fast Instantaneous Reserve.

FK Frequency Keeping.

GenCo Generation Company.

HVDC High Voltage Direct Current.

IR Instantaneous Reserve.

kNN *k* Nearest Neighbours.

MCP Marginal Clearing Price.

ML Machine Learning.

MW Mega Watt.

MWh Mega Watt-hour.

NI North Island of New Zealand.

NZ New Zealand.

OCGT Open Cycle Gas Turbine.

OPF Optimal Power Flow.

PLSR Partially Loaded Spinning Reserve.

POPF Primal Optimal Power Flow.

SCED Security Constrained Economic Dispatch.

SI South Island of New Zealand.

SIR Sustained Instantaneous Reserve.

SOE State Owned Enterprise.

SVM Support Vector Machine.

TSO Transmission System Operator.

TWDSR Tail Water Depressed Spinning Reserve.

UFE Under Frequency Event.

UP Uniform Pricing.

vSPD Vectorised Scheduling, Pricing and Dispatch.

List of Terms

k Nearest Neighbours A mathematical technique which attempts to find similar points using a distance metric.

Ancillary Service A service required for the stable operation of the power system which is not concerned with the direct provision of energy. For example, Regulating, Contingency Reserves or Voltage Support.

Benmore A node in the South Island, typically taken to be the reference location. Is also the location of the southern entry point to the HVDC interconnection.

Concept Drift Large shifts in a market place over time which traditional modelling techniques are unable to account for, e.g. a major piece of infrastructure upgrade or a regulatory change.

Contingent Event An unexpected de-synchronisation of a generation unit resulting in a loss of generation supply to the market. This causes a power imbalance and a resulting decline in frequency. If severe enough, this leads to an Under Frequency Event requiring the dispatch of Contingency Reserves to arrest cascade failure.

Demand Response Consumers participating in the electricity market through price based signals, for example an information dashboard, submitting bids to the System Operator or otherwise.

Demand Side Participation A scheme through which consumers are encouraged to participate in the electricity market. For example, hot water ripple control.

Diagnonalisation A technical term where two competitors iterate towards equilibrium in a repeated game like fashion. Equilibrium is said to exist when no participants may unilaterally improve their outcomes by changing their offers. In this Thesis it is used in Chapter Three to achieve a numerical equilibrium.

Energy Used interchangeably with electricity throughout this thesis. For example the energy price is equivalent to the electricity spot price. Has been used to distinguish situations which have a reserve price.

Gentailer Gentailers are Generator Retailers or participants that are vertically integrated. They are very common in the NZEM and all major generation companies have substantial retail holdings.

Haywards A node in the lower North Island, northern end of the HVDC interconnection, and a reference price for the lower NI.

HVDC Refers to the High Voltage Direct Current line which connects the North and South Islands of New Zealand. The asset is risk constrained and a significant source of reserve requirements.

Marginal Clearing Price See Uniform Pricing. All participants are paid the clearing price for energy of the marginally dispatched unit.

N-1 A method of reserve procurement where the largest risk setting asset in an electricity grid is secured against. In this case the network is secure against the unexpected failure of one asset.

Nodal Price A pricing regime where each *Node* within the grid has a separate marginal price. This is often referred to as Locational Marginal Pricing (LMP).

Optimal Power Flow The mathematical model the SO solves in order to ensure a feasible and optimal grid dispatch is obtained, subject to constraints within the Primal OPF. Has a second Dual OPF which defines the shadow prices of the constraints.

Otahuhu A node in the upper North Island near Auckland, the reference price for the Auckland region. Is also the location of a 400MW CCGT unit.

Primary Contingency Reserve Fast acting reserve which must respond within a second in order to *arrest* a fall in frequency typically caused by the unexpected disconnection of a supply side unit, e.g. a large generator or transmission line. In New Zealand this is known as FIR.

Regulating Reserve Load following reserve which used to track the deviations between energy and reserve between dispatch time periods. It is used to maintain frequency within a 30 minute dispatch window for non-contingent reserve related demand fluctuations.

Risk Setter An asset in the New Zealand Electricity Market which must be secured using Instantaneous Reserve. The unexpected desynchronisation of these assets can lead to frequency collapse and cascade failure.

Scheduling Pricing and Dispatch Model A network linear flow model operated by Transpower. SPD is used to solve for the optimal grid dispatch given the market offers submitted and forecasted demand. The Electricity Authority has developed a replica called vSPD which can recreate the results of SPD on a desktop class computer *ex post*.

Secondary Contingency Reserve Reserve intended to restore the system to a stable frequency following a Contingent Event. Must typically come into operation before primary reserve is exhausted and must remain dispatched for a (market dependent) minimum specified time. In New Zealand this is known as SIR.

Security Constrained Economic Dispatch (SCED) A method of dispatching an electricity market subject to technical constraints to ensure reliability. These constraints typically include capacity constraints on generation and transmission, as well as operating reserve considerations.

Sequential Market A market design strategy where distinct market dispatch models are solved iteratively. The output from the preceding solve is used as constraints for the secondary dispatch. An example of this strategy is to solve the least cost energy dispatch first and then to solve a secondary ancillary service dispatch problem.

System Frequency The operating frequency which the transmission grid is operating at. Frequency must be carefully controlled within a tight range to ensure no damage occurs to generation units. Reserves are used to maintain the frequency within the allowable band in response to unexpected demand fluctuations or unit desynchronisation. The frequency is nominally set to 50 or 60 Hz in most countries.

Tertiary Contingency Reserve A final form of reserve which is intended to replace the *higher quality* Secondary Reserve in case another event were to occur. Tertiary Reserve typically has significantly slower ramp times.

Uniform Pricing A form of auction where all "winners", in this case dispatched generators, will be paid the marginal clearing price for the trading period, as opposed to their bid price. Is differentiated from Pay as Bid auctions and encourages generators to bid closer to marginal costs.

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Chapter Two was based upon a conference paper submitted to ISGT 2014 and held in Kuala Lumpur Malaysia titled Constrained in Co-Optimised Electricity Markets - Practical Effects on Large Scale Intergrated Consumers

Nature of contribution by PhD candidate	Inspiration, Modelling, Data Analysis, Writing
Extent of contribution by PhD candidate (%)	90

CO-AUTHORS

Name	Nature of Contribution
Brent R Young	Editing
Golbon Zakeri	Editing + modelling

Certification by Co-Authors

The undersigned hereby certify that:

- the above statement correctly reflects the nature and extent of the PhD candidate's contribution to this work, and the nature of the contribution of each of the co-authors; and
- in cases where the PhD candidate was the lead author of the work that the candidate wrote the text.

Name	Signature	Date
Brent Young	B. R. Young	17/3/15
Golbon Zakeri	G Zakeri	17/03/15
Nigel Cleland	[signature]	17/03/15

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Chapter Three was based upon a paper which is currently undergoing peer review at IEEE Transactions on Power Systems titled Supply Function Equilibria in Markets with Reserve Constrained Transmission Lines

Nature of contribution by PhD candidate	Modelling, Data Analysis, Intuition, Coding, Writing
Extent of contribution by PhD candidate (%)	90

CO-AUTHORS

Name	Nature of Contribution
Brent Young	Editing and Discussion
Golbon Zakeri	Editing and Discussion + modelling

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- in cases where the PhD candidate was the lead author of the work that the candidate wrote the text.

Name	Signature	Date
Brent Young		17/03/15
Golbon Zakeri		17/03/15
Nigel Cleland		17/03/15

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Chapter Four is based upon unpublished work which has not currently been submitted for peer review

Nature of contribution by PhD candidate	Intuition, Modeling, Data Analysis, Writing
Extent of contribution by PhD candidate (%)	95

CO-AUTHORS

Name	Nature of Contribution
Brent Young	Editing, Discussions, Intuition
Golbon Zakeri	Editing, Discussions, Intution

Certification by Co-Authors

The undersigned hereby certify that:

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- in cases where the PhD candidate was the lead author of the work that the candidate wrote the text.

Name	Signature	Date
Brent Young	B.R. Young	17/3/15
Golbon Zakeri	[signature]	17/03/15
Nigel Cleland	[signature]	17/05/15

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Please indicate the chapter/section/pages of this thesis that are extracted from a co-authored work and give the title and publication details or details of submission of the co-authored work. Chapter Five is based upon two papers, a conference paper submitted to CMS14, Lisbon Portugal, titled Integrating Consumption and Reserve Strategies for Large Consumers in Electricity Markets	
Nature of contribution by PhD candidate	60
Extent of contribution by PhD candidate (%)	Intuition, Analysis, Writing, Extensions

CO-AUTHORS

Name	Nature of Contribution
Golbon Zakeri	Modeling, Coding, Editing
Geoff Pritchard	Modeling, Coding
Brent Young	Editing

Certification by Co-Authors

The undersigned hereby certify that:

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- in cases where the PhD candidate was the lead author of the work that the candidate wrote the text.

Name	Signature	Date
Golbon Zakeri	[signature]	17/03/15
Geoff Pritchard	[signature]	17/3/15.
Brent Young	[signature]	17/3/15
Nigel Cleland	[signature]	17/3/15

Chapter 1

Introduction

This chapter contains an introduction to electricity markets, co-optimised reserve markets, and demand response as a form of reserves. Electricity markets are complex collections of humans and machinery, subject to numerous technical, economic, and political requirements. Beginning in the late 20th century the deregulated electricity market came into effect, both in New Zealand and around the world. For the first time, private companies were able to compete to own generation plants, operate distribution lines and serve retail customers. Electricity markets have iteratively improved since the earliest attempts at market design, standardising upon a number of features such as locational marginal pricing and competitive offers.

Ancillary services, such as instantaneous reserve, have not been immune to the introduction of competition. Secondary markets are now solved simultaneously with energy markets through co-optimisation. This can have noticeable effects upon prices within the markets. Yet, no standard implementation of co-optimised reserve markets has been converged upon. Within this Thesis a particular form of market design, based on the New Zealand Electricity Market (NZEM) will be discussed.

Many markets are opening up ancillary service provision to consumers through products such as Interruptible Load and Direct Load Control. These consumers are supporting the grid and providing much needed flexibility to System Operators and generation facilities. The inclusion of demand side offers can improve social welfare, but is not without inherent limitations.

1.1 Motivation, Hypothesis and Structure

A particular class of electricity markets is co-optimised with *Instantaneous Reserves* (IR) within a single market design. These co-optimised markets are theoretically more efficient than other designs, due to the explicit compromise encapsulated within the model, yet they also introduce additional vectors through which market power may be exerted. To date, detailed studies of the effects of co-optimised markets on both supply and demand side market participants are a clear gap in the literature. Whilst the theoretical literature itself is rich in many areas, practical applications are still to be developed in many cases.

The working hypothesis for this piece of work was that the ancillary services markets could be used to influence outcomes in the primary energy market for different participants.

In following this hypothesis the four key contributions of this Thesis are:

1. The enumeration of the mechanisms through which reserve market co-optimisation can bind and influence the marginal energy price.

2. The development of a Supply Function Equilibria model which has been used to determine the incentives for market participants. These participants offer a combined energy and reserve product in a market with reserve constrained transmission lines.

3. The development of a k nearest neighbours model to *ex ante* assess the optimal price response for a large consumer of energy in a co-optimised market.

4. The development of an optimisation model under uncertainty to determine the optimal combined energy and Interruptible Load (IL) offer for a large consumer in a reserve co-optimised market.

This thesis is organised in two parts, a theoretical assessment is undertaken in Part I and a series of practical case studies in Part II. The case studies draw directly upon the context of the theoretical work through the consideration of industrial scale demand response within the New Zealand Electricity Market (NZEM). This chapter presents a generalised literature review of electricity markets in general with specific additions made in text in each chapter.

The two theoretical sections, Chapter 2 and Chapter 3, cover the effects of reserve constraints on electricity markets from an aggregate assessment, assessing the unit level constraints which may bind and influence price. This is extended to understand the incentives seen by combined generator-reserve providers in a co-optimised market in a transmission investment setting. In Chapter 2 the understanding of the effect on pricing is applied to a number of years in the NZEM to identify the trading periods with binding reserve constraints. Chapter 3 is more theoretical, focussing upon a case study of the upgraded HVDC interconnection in the NZEM, and illustrates that the benefit of the $700 million NZD upgrade was principally due to the reduced reserve required.

In Chapter 4 data mining techniques are used to understand the situations leading to reserve constraints ex ante. The techniques are presented in terms of a conditional decision model for an *Interruptible Load* (IL) consumer. In Part II two applied models are presented. Chapter 5 presents Boomer-Consumer, a stochastic optimisation model which a large consumer of energy (who also offers interruptible load) may utilise to determine their effect upon energy and reserve prices.

1.2 Electricity Markets

Access to low cost and reliable sources of energy have powered the advancement of human society. Energy is used in various shapes and forms to produce food, clean drinking water, heat our homes, as well as to produce the goods and services which raise our collective standard of living. Modern society as it exists today would not have occurred without a ready access to energy (Bartleet and Gounder, 2010), even as the trend between economic well being and energy consumption declines for advanced economies[1]. Historically, this energy has been irreversibly extracted from the earth, drawn up in the form of coal, oil, and natural gas. These fossil fuels are convenient due to their low cost and ease of transportation, but the world is awakening to the dangers of being reliant upon a single source of fuel with negative externalities.

With easily accessible conventional fossil fuel reserves declining and governments designing policies to mitigate climate effects, renewable energy sources are expected to provide a growing percentage of the world's energy supply. To replace the convenience of carbon-based forms of energy requires that renewable energy sources must be reliable and low cost. Renewable energy sources should also integrate with the existing infrastructure in place, such as the electrical grid and automotive technologies, for wide spread adoption. Currently, renewable sources predominately produce energy in the form of electricity including wind, solar, geothermal, tidal and hydro power.

The reliable provision of energy is a key concern for the integration of renewable energy as some forms are considered intermittent - their

[1] A possible symptom of the drive towards energy efficient systems and a serviced based economy as opposed to one based on raw primary material extractions which is still highly energy intensive.

output does not follow a neat production schedule. Electricity is not a economically storable form of energy currently[2]. The requirement for instantaneous balancing of supply and demand is a key constraint dictating the designs of electricity markets. Renewable generation is often located far from existing demand centres and networks of high voltage transmission lines are required to ensure continuous supply. These networks can span countries and continents with the balancing of energy injection and withdrawal, managed through electricity markets.

The fully renewable grid is still hypothetical at this stage and the world will continue to rely upon fossil fuels for the immediate future. The fossil fuel grid has traditionally been supply side oriented but increased demand side participation is necessary to facilitate higher penetration of renewable energy[3]. Demand side participation can improve economic efficiency by increasing the elasticity of demand (Kirschen, 2003) and enable renewable energy by partially smoothing the inherent volatility of intermittent generation sources (Pina et al., 2012). However,

[2]The author notes the recent strides made in battery technology but as of the writing of this Thesis (2015) no large scale solutions had been brought to market for the efficient integration of batteries into electricity markets at either the household or the grid level. Further challenges exist to integrate these technologies and is a frontier which will require great attention in the upcoming years. However, battery technologies have not followed Moore's Law with incremental improvements not revolutionary improvements being more likely as time goes on.

[3]Some countries have managed to include high penetration of renewable energy without high levels of demand side participation with the two obvious examples being Norway, New Zealand and Denmark. In Norway and New Zealand the natural geography is highly favourable to hydro generation technology, a flexible and dispatchable form of renewable energy. Current predictions estimate that the world will need high levels of non-dispatchable renewable energy from sources such as tidal generation, wind energy and solar power. Denmark as a country with a high level of wind power springs to mind, with wind offering powering substantial portions of the grid. However, Denmark has strong interconnectors to the wider European grid and benefits from the buffering effects this provides. Nether of these approaches are scalable as they rely upon the randomness of geography in the first two cases and access to a large, predominately thermal grid to smooth generation in the later scenario.

demand side management is still new and has its own challenges (Strbac, 2008) which are currently limiting adoption.

Electricity markets are partially shaped by the differing geographical and political environments in which they arise. In each case the objective is to increase both economic and energy efficiency, although at times these goals may be at odds with one another. Private allocation of capital is seen as more efficient than a central bureaucracy as competition minimises uneconomic investments and therefore improves social welfare. In many markets this allocative efficiency has been favoured at the potential expensive of energy efficiency (Gunn, 1997). In some markets this has favoured carbon-based forms of generation as no central body capable of internalising the externalities associated with renewable energy exists (Kelly, 2007).

Electricity markets have long, medium and short term objectives. The principal consideration in the long term is capital allocation. Markets must promote an optimal level of investment - not too much but nor too little. As investments must be commissioned well in advance (Cramton, 2003) there exists significant uncertainty regarding their future value. In improperly designed markets where signals are inappropriate, the risk of capacity shortages exists (Wen et al., 2004).

In the medium term, coal stockpiles, upstream natural gas contracts and hydro reservoir levels must be effectively managed to ensure the secure forward supply of energy. Reservoir hydro generators are particularly sensitive to market designs as the price must adequately represent the opportunity cost of releasing water today. Markets must send the right signals to managers over time to accomplish this objective. Tools such as stochastic dual dynamic programming (SDDP) (Halliburton, 2004) can be used to price the economic cost of water and help manage the medium term supply. Hydro dominated markets face the risk of energy shortages if sustained periods of reduced inflows occur (Goodwin, 2006).

The short term balancing and economic dispatch of electricity markets is the final consideration. In a given trading period the most efficient configuration of generation units to meet the expected supply should be dispatched. This dispatch must take into account intermittent renewable generation as well as unit commitment and ramp rate technical requirements, as such the ability to meet demand in any given period is partially given by the past and partly by expectations about future periods. At this level prices are produced which, in aggregate, form the basis of the medium and long term decisions made by market participants.

To ensure short term reliability, Ancillary Services (AS) are procured from market participants. These AS are used to manage not only the energy balancing market, through frequency regulation, but also contingency security, voltage and reactive power requirements, as well as black start services (Lobato Miguelez et al., 2008). In this Thesis the discussion is concentrated on issues relating to system frequency and in particular, contingency reserve (CR) which is procured to secure the grid against unexpected events. Such events include instantaneous *tripping* (desynchronisation) of large generation units or transmission lines that cause an imbalance between supply and demand. Contingency Reserve services are often dispatched through markets, whereas other AS such as black start services are not actively traded.

Basic Market Design

Electricity markets coordinate the physical and financial transactions between producers and consumers across a distributed network. As electricity is a special (economic) *"good"* which may not be stored, the real time supply must always meet the real time demand. The short term goal of an electricity market is to facilitate a least cost dispatch of generation units subject to technical constraints. One common configuration is the centralised pool in which an independent System Operator (SO) coordinates energy exchange (between buyers and sellers of energy) subject to transmission congestion and losses across the network in order to maximise social welfare. An example of this system is illustrated in Figure 1.1.

The transmission grid connects a large number of nodes via a series of branches. Nodes in the network are points of significance related to injections or withdrawals of energy or substations with voltage transitions. As losses occur when energy is transported between nodes the marginal cost of procuring energy at a specific location varies. Mathematically transmission networks may be represented as network flow models (Bazaraa et al., 2011).

Two primary approaches to pricing electricity exist. Locational Marginal Pricing (LMP) (Schweppe et al., 1988) and System Marginal Pricing (SMP). Under LMP the price of electricity at a specific node is the marginal cost of procuring energy at that node, obtained via the dual variable from the network flow linear program. In SMP the same network flow program may be used to determine the optimal market dispatch but prices are determined by averaging the nodal prices. LMP accurately values the cost of consuming or supplying energy at the specific location and theoretically improves investment decisions relating to the transmission grid. LMP can introduce locational price risk for vertically integrated utilities who sell energy at one node and consume at a second. Financial Transmission Rights (FTRs) (Hogan, 2002) have been designed to mitigate this financial risk in some markets. SMP is at the other extreme and

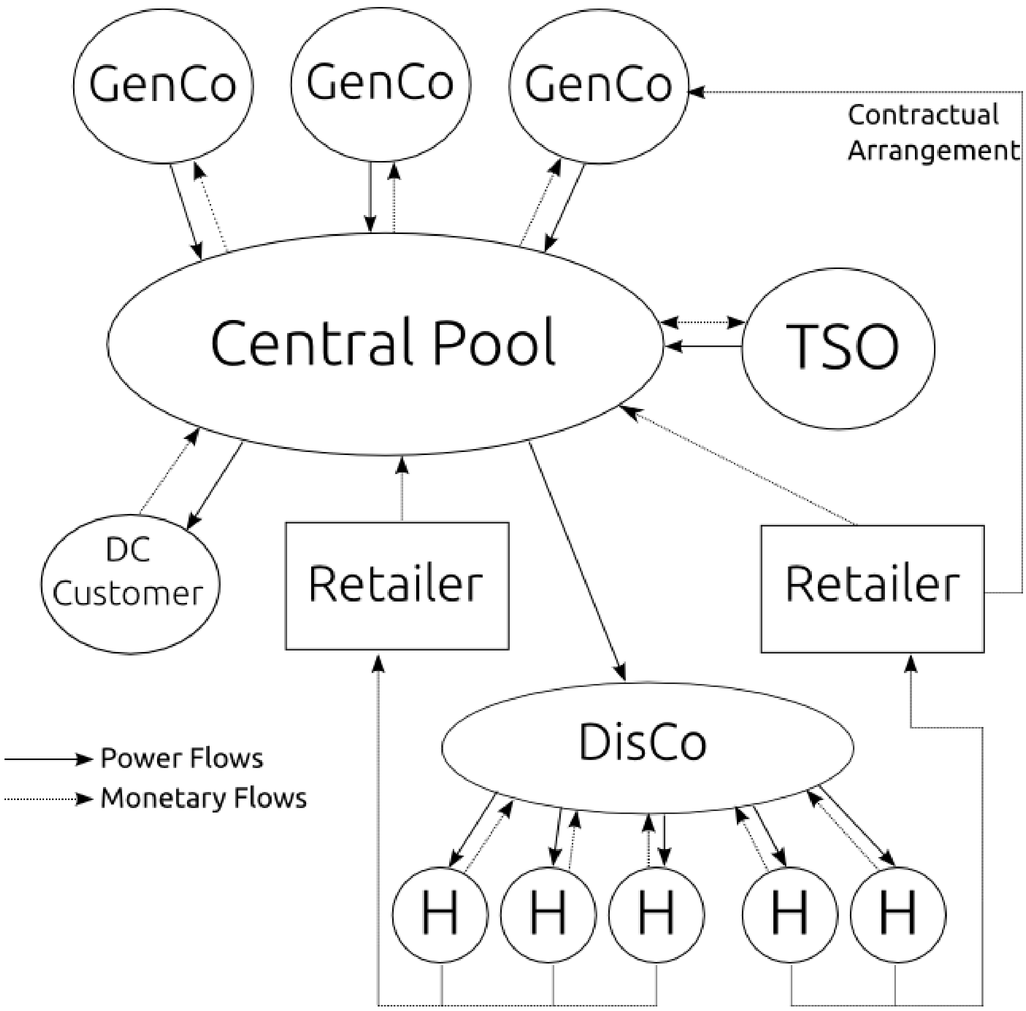

Figure 1.1: Overview of centralised pool markets in which a SO coordinates supply and demand through a centralised pool. Both energy and monetary flows are indicated; for example, a household receives their power from a (Distribution Company) DisCo but has a financial arrangement with a Retailer to pay a fixed price in this simplified example.

does not expose participants to geographical price risk[4]. This may lead to a simpler marketplace without complex financial contracts although locational signals to efficiently place generation plants may be lost. In this work we are primarily concerned with the LMP form of an energy market as locational based differences will form a large part.

In a centralised pool, market participants submit offers to an independent SO who uses these to construct the market dispatch. This dispatch is subject to constraints on transmission flows, voltage, ramping, and contingent event reserve requirements. The technical term for the collection of constraints and least cost objective is the Security Constrained Economic Dispatch (SCED) (Alvey et al., 1998). Participant submitted offers may be either simple (collection of price-quantity pairs) (Anderson and Philpott, 2002a) or complex (simple bids with additional specifications regarding must run status, minimum dispatch and ramping information).

The market clearing manager (who may also be the SO) is responsible for finalising payments to participants within the market[5]. Two payment mechanisms are common throughout the world, Pay as Bid (PAB) and Uniform Pricing (UP). Under PAB a participant will be paid their offer price for the given quantity dispatched. In the UP auction all participants will be paid the market clearing price (either LMP or SMP). Whilst theoretically lower cost, PAB auctions often devolve into "guess the final clearing price" games where participants are discouraged from bidding true marginal costs. In the UP auction few such incentive exists and eco-

[4]SMP can still expose markets to out of merit order dispatch due to transmission constraints. However, the final financial settlement process occurs outside of the market clearing process in this case. This is still a risk, albeit one which cannot be mitigated through financial transmission rights

[5]The settlements process is complex in its own right as retailers must be aware of what their portfolio position is subject to retail customer churn, changing contracts and actively traded forward markets

nomically efficient units traditionally bid at marginal prices, with mid range and peaking generation units competing to set the final clearing price. The remainder of this thesis will focus upon UP auctions as they are the most common form of payment system. We note the presence of PAB for completeness.

Requirement for Reserves and Ancillary Services

In a power system the supply of energy must be continuously kept in check with the corresponding demand for power. The measure of this balance is represented by the system frequency, typically specified at either 50 or 60 Hz and given by (1.1).

$$\Delta f = \frac{1}{2H}(\Delta P_m - \Delta P_L) \tag{1.1}$$

where Δf is the change in frequency, H is the inertia of the rotating masses which make up the system, ΔP_m is the change in mechanical power output from generation units providing control, and ΔP_L is the change in load power.

A system power balance is negative during a supply shortfall and positive when supply exceeds demand. A supply shortfall causes a decrease in the system frequency (if a large generation unit were to trip, instantaneously removing its output from the grid an Under Frequency Event (UFE) may occur). Positive power imbalances occur predominately due to unforeseen, downward, demand fluctuations or transmission outages. It is important that system frequency is tightly controlled in a safe operating range as generation units will desynchronise from the grid if frequency moves outside the safe band. In grids where individual generation or transmission assets are large relative to total demand, UFE's are of great cause for concern, requiring additional contingency reserves (CR). In large grids demand fluctuations may be significantly larger than generation unit capacity and thus regulating (balancing) reserves are of importance.

In order to limit potential damage to generation equipment, many units will desynchronise (disconnect) from the power system if the grid frequency deviates outside of the stable frequency band. As these units disconnect, the negative power balance will become exacerbated and frequency will continue to fall. This feedback cycle is known as cascade failure which eventuates into a system (or localised) black out. To prevent this, Instantaneous or Contingency Reserves (IR or CR) are procured from fast acting units. These units, either synchronised generation units or load curtailment from Interruptible Load (IL) consumers, quickly respond to any shortfall in supply in order to stabilise the system.

Electricity market dispatches can not feasibly provide real time balancing at the sub second level. Dispatches at this resolution are impractical and counter productive[6] and instead, markets are dispatched at greater time resolutions. To meet the continuously varying demand (within the dispatch window), a sub group of generation units is tasked with providing regulating reserve. These units continuously ramp their production level (both up and down) to meet demand (Ela et al., 2011).

The terminology used to describe the reserve in electricity markets throughout the world is often confusing. There exists no single set of common definitions and the terms themselves are often recycled between markets (Ellison et al., 2012). As each market procures Ancillary Services in a different fashion, we have provided a set of definitions which will be used in this thesis in the List of Terms. Additionally, we have illustrated the role of reserve products in Figure 1.2.

[6]This is an example of tight control in a system which would likely exacerbate any minor perturbation in frequency in the attempt to respond to it

In the first frame of Figure 1.2 regulating reserve is continuously adjusting output in order to match demand as indicated by the shaded area under the curve. At time t_{CE} a contingency event occurs resulting in a subsequent shortage in generation (outside the band of regulating reserve available). Frequency declines and primary contingency reserve is dispatched to arrest the fall in frequency. A persistent frequency deviation is in effect at the point and secondary contingency reserve is dispatched to alleviate it at time t_{SR}. After a significant period of time tertiary contingency reserve is brought on to release the secondary reserve at t_{TR}. Finally at time t_{Secure} all forms of contingency reserve have been released and the system is secure (and ready for another CE if needed).

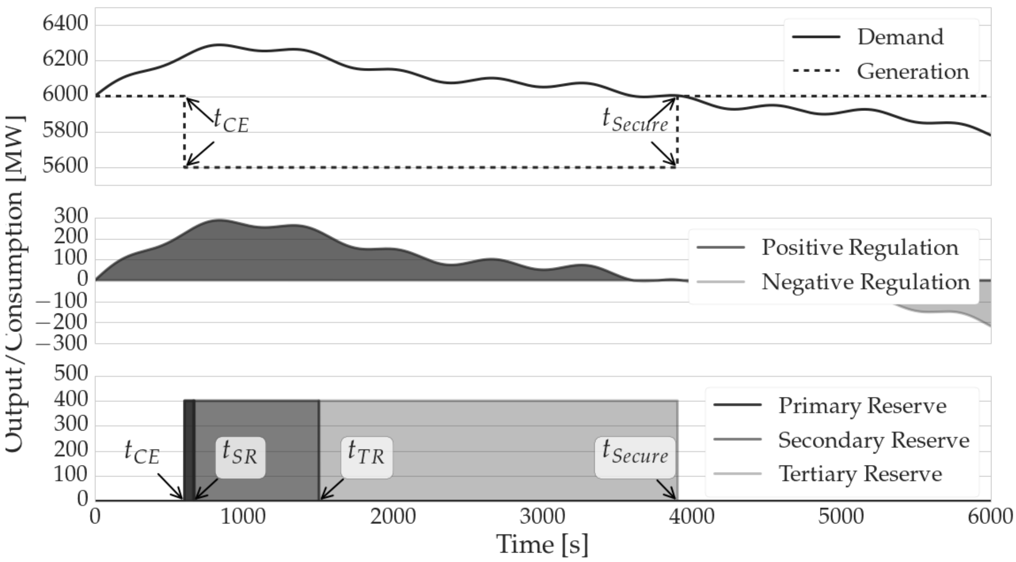

Figure 1.2: Visual Explanation of the differences between regulating and contingency reserves in an example power system. A contingent event occurs at t_{CE} requiring the dispatch of primary, secondary, and tertiary contingency reserve to maintain system security.

Figure 1.2 has been simplified considerably. In reality, due to governor response, the level of primary reserve required will not be equal to the full shortfall(Anderson, 2012). There also exist ramping requirements for different forms of reserve. The providers of primary reserve are often capable of providing secondary or even tertiary reserve (although the reverse is not necessarily true). Regulating reserve units can support the power system as needed with their automated ramping capacity. However, Figure 1.2 serves as a useful example model to understand reserve dispatch dynamics in a power system following a contingent event.

1.3 Co-Optimised Electricity Markets

Electricity markets are continuously in flux as situations arise requiring regulatory and design changes which can be contentious. Within the late 20th and early 21st centuries numerous restructuring efforts of failed market designs occurred around the world. The clearest example of electricity market failure were the catastrophic rolling blackouts in late 1990's California (Borenstein et al., 2002a). The England and Wales market has also been restructured multiple times (Bunn and Oliveira, 2001, 2003), ostensibly to mitigate market power and capacity adequacy concerns. Partially as a result of these failures, new designs intended to curtail the perceived shortfalls have been promoted. Some authors have identified the market design process itself as a problem, specifying that such should occur behind closed doors by a panel of experts away from industry lobby groups, governments and groups of consumers who have conflicting interests(Cramton, 2003).

Less standardisation has occurred in the design of ancillary service markets which supplement these energy markets. As such, there exists a great deal of variety. However, the worldwide trend has been towards a market based system (Gonzalez et al., 2014) as opposed to centrally mandated requirements. Market based systems are seen as more efficient (than centralised regimes), as the force of competition reduces dead weight losses. But a great deal of variability still exists, for example in Spain the provision of primary contingency reserve is a mandatory non remunerated requirement for generators (Lobato Miguelez et al., 2008). In New Zealand (NZ) this procurement occurs on a voluntary basis, via market remunerated reserve offers.

As requirements for ancillary services differ throughout the world, market designers have developed numerous strategies for ensuring the stable operation of the power system. These strategies may solve the market dispatch problem via algorithms in a sequential design, or optimisation in a simultaneous market. At the unit level, turbines may provide both energy and reserve which must be recognised through constraints within the designs.

Electricity markets are, by nature, mathematical simplifications of the physical reality. The most common simplification used in many market approximations is the DC load flow model instead of full AC representation. Often, these simplifications have a cost, with one argument by Hogan (1996) that real electricity markets need both real and reactive power prices in order to efficiently price voltage magnitude constraints. Other simplifications may improve mathematical convenience at the cost of introducing administratively set variables which can have a major influence on competitive decision making. The Value of Lost Load (VoLL) is often subjectively priced which has a significant effect on the level of capacity investment induced.

AS may be procured through market mechanisms or mandatory participation requirements. In markets with mandatory participation, a legal obligation to support the grid exists, however generators can apply for special dispensation to avoid this (wind turbines or photovoltaic solar may not be able to offer support via governors). In market based systems, prices are used to encourage an efficient level of participation within the market, with scarcity situations encouraging market entry. The caveat of this approach, from a systemic point of view, is that scarcity pricing occurs as a result of a physical deficiency within the market which may increase the risk of service interruptions.

Throughout the literature sequential markets have been considered in; Soleymani et al. (2007), where a participant's ability to offer spinning reserve in a second market is constrained by the energy dispatch of the first market. In Wang et al. (2005), an algorithm for sequential dispatch with a flexible operating reserve capacity is optimised. In Luh et al. (2006), an algorithm to minimise payment costs, not offer costs, has been developed which leads to reduced market clearing prices within a hypothetical test grid. Finally, in Chitkara et al. (2009), competition in reactive power markets was modelled using constraints given by the clearing of an initial energy market. Gonzalez et al. (2014) provide a review paper and claim that sequential markets are most suited for a simple bidding process. Simple bids are those with price-quantity pairs but are less suitable for complex bidding (additional technical information is included with bids such as ramping, "must run" conditions and so forth). Fully co-optimised markets may be non convex and joint markets can be a simplified method of ensuring a unique solution.

Simultaneous, co-optimised, market designs are an attractive method of procuring AS. In the co-optimised market, the optimal prices and dispatch of multiple products (energy, regulating reserve, contingency reserve) can be produced by a single linear program. This has the advantage of producing a total least cost solution (optimal social welfare), subject to market offers and individual unit constraints. In sequential markets there exists a risk for gaming to occur as participants schedule their generation offers in order to constrain the secondary markets, which may be priced inefficiently. Co-optimised markets reduce the risk of this occurring as the trade off between energy and reserve is explicitly included in the design.

Both New Zealand (Alvey et al., 1998) and Singapore (Lu and Gan, 2005), small island based grids characterised by large units relative to total demand, have introduced co-optimised contingency reserves to protect against UFEs. These markets operate under *N-1* security considerations - the largest asset must be covered (with reserve) on a 1:1 basis. The *N-1* market design attempts to optimise the level of reserve procured in a deterministic fashion (no stochastic considerations of unit failure probabilities are included). *N-1* is not the only method of determining the reserve requirements. Two other methods may also be used, a manual reserve requirement and a procuring reserve as a percentage of demand. Methods of procuring reserve along with examples where this occur are enumerated in Table 1.1.

Stochastic models have not been covered in Table 1.1. As generators do not have a uniformly random failure rate, the potential to reduce the cost of reserve requirements without compromising security exists. By taking into account the likelihood of unit failure the level of excess reserve procured can be minimised. Not only does this reduce costs, but is also potentially safer as the risk of *over frequency* events following reserve dispatch is mitigated.

Intermittent generators, such as wind and solar, can exacerbate frequency related events[7]. As intermittent generation is less reliable than traditional thermal or hydro resources it may require additional oper-

[7]Whilst some run of the river hydro generators may be intermittent these units typically have greater inertia. Furthermore, at some level the output from these units can

ating reserves (Ela et al., 2011). Numerous attempts to determine the optimal level of spinning reserve in systems with a high renewable energy penetration have been made (Lee, 2007; Sorknaes et al., 2013; Soder, 1993; Doherty and O'Malley, 2005). Integrating intermittent generation into reserve requirements may be considered a subclass of stochastic optimisation of reserve requirements. The difference between deterministic and stochastic methods may be stated as:

Deterministic Optimisation: What level of reserve is required in the worst case scenario of a single asset failure (*N-1*)

Stochastic Optimisation: What level of reserve is required to secure the system under a probabilistic assessment of unit failure rates to ensure the loss of load probability (LoLP) does not exceed the technical limit.

Stochastic market designs introduce new terms such as past failure rates and loss of load probabilities. These terms indicate the addition of new information and the designation of a new security benchmark. Although a full overview of the stochastic reserve requirement is beyond the scope of this review, there is much further reading on the subject (Bouffard et al., 2005a,b; Bouffard and Galiana, 2004, 2008; Amjady et al., 2009; Aghaei et al., 2009; Gooi et al., 1999).

This section has illustrated the methods and difficulties of co-optimising energy and reserve offers in an electricity market. In Chapter 2 and Chapter 3 a discussion on particular forms of reserve and their influence upon both the price and competitive behaviour will be undertaken. The influences are unique to the specific formulation of energy and reserve

be controlled in a limited fashion. As such, we limit ourselves to those units who fall outside the market dispatch mechanism.

market, hence the focus upon the alternative forms of procurement in this section to provide a background to the wider problem space. All designs have advantages and disadvantages, and there exists no universally agreed upon solution, as a feedback loop between market design and market infrastructure exists. Markets with more intermittent and hydro generation will benefit from one design, a fully thermally dominated market from another. Small markets will have different requirements to large ones. Island markets differ from those with interconnections to other countries. As the market designs are inherently linked to geographical realities, such as resource availability, a comparison of the various models used throughout the world has been covered in Section 1.5.

Table 1.1: Examples of different reserve procurement strategies

Strategy	**Comments**	**Suitability**	**Countries**
N-1	The largest generation asset is secured on a 1:1 basis with reserve	Suitable for small markets where individual unit capacity is large relative to potential shifts in demand	New Zealand, Singapore
% Demand	A percentage of demand is chosen as the reserve requirement, separate reserve requirements for up regulating and down regulating reserve may also be required. This can also double as regulating reserve.	Suitable for large electricity markets where the size of an individual unit is small relative to peak demand	Spain
Fixed	An *exogenous* risk requirement is set. This can often be included with the N-1 and % demand cases to ensure that a minimum quantity of reserve is dispatched at all times.	General - is suitable in many situations but is also inherently conservative with the estimates	South Island, New Zealand

1.4 Integrating Demand Response

Increasing the participation of consumers in electricity markets is fundamental to realising future efficiency gains[8]. Two frameworks, Demand Response (DR) and Demand Side Participation (DSP), exist through which participation can occur. The strategies differ via their definitions; DR requires consumer action, whereas DSP may be controlled via a centralised control centre. The difference between responding to price signals at one end and automatic hot water ripple control (Gillingham, 2009) at the other are clear examples of the extremes. The two frameworks may be defined as:

Demand Response (DR): A scheme where a consumer takes action in response to a signal; which may be price or a System Operator request. Remuneration may occur through a market bidding scheme, or alternatively, through side payments. A DR scheme is as such linked to short term market activity such as spot prices.

Demand Side Participation (DSP): A scheme where a consumer does not actively take part. Examples include; hot water ripple control as a form of peak shaving, Direct Load Control (DLC) of air conditioning units, and IL as a form of spinning reserve for contingencies.

Electricity markets have (traditionally) been seen as short run inelastic, with demand treated as a fixed (exogenous) constant with no response built into the clearing model. Consumers as a whole may be represented by an aggregated demand curve. However, at the individual

[8] If electricity market liberalisation were to be considered in stages then the break up of the centralised monopolies and development of a competitive market place would be the first stage. The rise of distributed generation and two way communication between the grid and consumers through the *smart grid* may be considered as stage two.

level the decision for customers is often binary. The choice whether to curtail or consume represents a discontinuous action, with the consumer willingness to face disruption at the current compensation level varying with time[9]. Compensation may be direct in terms of a financial transfer or indirect, through a contractually lower hedge price, if the consumer exposes themselves to price risk. System Operators may be willing to pay consumers to curtail as an alternative to capital investment (Transpower, 2014a).

Ancillary service markets are already realising the benefits of consumer participation. In New Zealand for example large consumers support the grid during contingent under frequency events by curtailing load via the Interruptible Load scheme. For the potential (and inconvenience) of executing this curtailment consumers are remunerated through the markets proportional to the Instantaneous Reserve (IR) price for the trading period. Prices as such act as a signal to the relative scarcity of IR within the market. IL can be used to provide fast acting primary and secondary contingency reserve with response times ranging in the hundreds of milliseconds. Molina-Garcia et al. (2011) consider demand response as a source of frequency control whilst Huang and Huang (2004) propose a method of real time balancing using a combined IL and direct load control (DLC). For consumers the participation is a potential source of revenue, helping to offset high energy bills with minimum disruption. For generators and system operators the additional flexibility of demand

[9]Alternatively, a binding contract with the consumer to participate in demand curtailment schemes may be part of a retail agreement. Typically such schemes are thought to reduce tariffs as the retailer is able to shave peak loads, mitigating the requirement for expensive generation plants. These retail agreements are more common for vertically integrated utilities who must build generation plants to meet future demand. For a sole retailer the incentive is to *flatten* their load profile by minimising maximum demand (which must be hedged) as compared to average demand (or volume) through which cost is recovered.

side operating reserves alleviates the pressure on generation units, permitting higher capacity utilisation and more efficient dispatches. In this thesis, consumer participation in the context of reserve markets only has been assessed.

Demand in Reserve Markets

The ability of consumers to contribute to ancillary service markets is dependent upon both favourable market structures and technological enablers. Participation in reserve markets has an element of speed implicit in the requirements. Following a contingent event, supply and demand must be brought into balance as quickly as possible. Thus, automated action is a prerequisite of AS integration and may be implemented through either DLC or IL. Under DLC, consumers may choose to place non essential loads under the control of a centralised operator who may ramp consumption levels in response to changing market conditions. Whereas, in IL schemes loads are completely curtailed following an event without operator response.

To enable participation of loads as a source of contingency reserve they must be capable of; curtailing quickly, maintaining the curtailment for a minimum period of time, restoring the load on command. To accomplish these objectives loads should have some form of inherent process storage, be of sufficient size and preferably have automated curtailment processes (Kirby, 2003). Price responsive loads alone are insufficient. Instead, some form of DLC is required to meet the speed requirements of AS markets where events can occur in less than a second (Callaway and Hiskens, 2011).

DLC and IL are complimentary to one another with (appropriately applied) DLC leading to less disruption for consumers than the full curtailment of IL. As DLC and IL can reduce the requirements for generator based spinning reserve they may increase social welfare. To effectively integrate small loads into ancillary service markets requires a degree of aggregation. One proposed option, Virtual power plants, consisting of many aggregated units operating in sync, can be used to provide spinning reserve and consistent generation profiles from a disparate group of technologies. A virtual power plant consists of a group of technology types which coordinate internally to produce a single market outcome. Virtual power plants combine disparate technology sources ,such as air conditioning loads, electric vehicle charging, and intermittent renewable generation, to maintain a fixed (net) grid consumption level. Virtual power plants often require special dispensation from system operators as they are typically located across more than one node and thus disrupt LMP. But their inclusion has been shown to improve social welfare in some limited case studies (Wang et al., 2013; Ruiz et al., 2009).

Market dispatch models often need to be adapted in order to facilitate consumer participation. Loads cannot be reduced without consequence. Often there exists a period of *energy payback* following load curtailment (Strbac et al., 1996), this is often called a *rebound effect*. There are also temporal constraints to load curtailment. Over time the number of allowed curtailment periods may be limited by consumer willingness. It has been suggested that market models must account for the temporal flexibility of loads over time, which can have implications on the marginal value of reserve (Karangelos and Bouffard, 2012).

The integration of demand side resources is inherently non-linear. Wang et al. (2003) consider a model designed to integrate demand side offers for numerous products such as up-spinning reserve, down-spinning reserve, energy, and standby reserve. The approach is formulated as a mixed integer non-linear objective function which is solved through linearisation techniques. Probability based market clearing models have previously been proposed (Bai et al., 2006; Aminifar et al., 2009). These models seek to minimise generator production costs by using IL as a source of spinning reserve. Both models optimise the Expected Energy Not Served (EENS) metric and show that IL relaxes constraints and releases generation units back to the energy market.

The literature on the optimisation of large scale consumers, capable of price making within the AS markets, is limited. Partly this is due to non-scalability - the optimal solution for a single production site does not necessarily hold for other consumers. Large scale consumers represent a valuable resource as many are already exposed to time of use pricing (Barbose et al., 2004; Albadi and El-Saadany, 2007) as well as participating in AS markets. Furthermore they are of sufficient size to have a tangible effect upon market dispatches.

1.5 The New Zealand Electricity Market

The New Zealand Electricity Market (NZEM) has been used for the practical examples within this thesis due to the large number of natural experiments which have occurred in recent history[10]. New Zealand (NZ) is a small country of approximately four million people spread across two islands (named North and South). Initially a British colony located on the Ring of Fire in the South Pacific, New Zealand has a strong history of electrification and renewable energy, particularly reservoir hydro, wind and geothermal. As part of government efforts to curb greenhouse

[10] A natural experiment is one where an interesting result is observed as opposed to non status quo phenomena in the market. These can include adverse weather conditions, disruptions to demand and regulatory changes

gas emissions a goal of 90% renewable energy by 2025 was set and later scrapped through a change in government in 2008 (Krumdieck, 2009).

New Zealand, through a combination of abundant natural resources and low total demand, has achieved a high penetration of renewable energy assets. Hydro makes up the majority of the generation capacity, with the level of wind and geothermal capacity increasing in recent years due to a spate of investments. As such, the countries which draw the most immediate comparison are Norway and Chile who have large hydro reserves and a dependence upon extensive transmission networks. No solar subsidies exist in New Zealand and as such rooftop photovoltaic (PV) and concentrated solar power (CSP) systems are relatively uncommon (Kelly, 2007). Population is clustered in the temperate North Island yet historically generation has been built around the South Island hydro lakes. This has led to a long, skinny transmission grid designed to move energy great distances (Read, 1997).

Hydro reservoir management is of primary importance to the stable operation of the NZEM over the medium term. In "Dry Years", when inflows are low and reservoir levels reach historic lows, the price of energy on the wholesale spot market may trade at many multiples to the long run average for extended periods of time. Dry Years are somewhat random, with recent events in 2001, 2003, 2008 and 2012[11]. To assist in managing the release of water from these reservoirs, stochastic dual dynamic programming (SDDP) is used to determine the value of water. This value of water serves as the economic "fuel cost" of reservoir hydro units based upon the opportunity cost. Extensive literature exists regarding the use of water value models in the NZEM (Pereira and Pinto, 1991; Halliburton, 2004; Pritchard and Zakeri, 2003; Philpott et al., 2010).

[11] Ultimately this is linked to the accuracy of long range weather forecasts and La Nina and El Nino effects can be observed.

In the 80s and 90s, under the trend of liberalisation which was sweeping the world, the NZEM was deregulated. Key events in this process include the formation of the Electricity Corporation of New Zealand (ECNZ) in 1987 as an S.O.E which signalled the beginning of operation under market conditions. In 1994 Transpower, the grid owner operator, was separated from the ECNZ (Goodwin, 2006). The first privately owned electricity company (Contact Energy) was formed in 1996 from the partial sale of ECNZ assets. In 1999 the assets of the ECNZ were finally separated into four major companies (Mighty River Power, Meridian Energy, Genesis Energy and Trustpower). To date, these five companies still control more than 95% of generation capacity in the NZEM.

The market was initially designed with a "light touch" regulatory scheme based upon transparency and disclosure[12]. Under the initial formation of the market no independent regulator was created with regulation falling under the umbrella of the Commerce Commission. Following dry year events in 2001 and 2003 the Helen Clark Labour government of the time regulated the industry through the formation of the Electricity Commission. In 2010 a second overhaul under the John Key National government dissolved the Electricity Commission with the formation of the new Electricity Authority (Shen and Yang, 2012).

[12]The exact history of the formation of the NZEM is a fascinating area for study which appears to illustrate the potential for the best of intentions to lead to unintended outcomes. Namely, an alternative interpretation is that market participants could compete with one another in a constructive way which would lead to a stable power system. Failure of this to occur, as given by the high risk of shortages during *dry years* which could be stated was due to excessive operation of hydro units for short term gain partially led to the formation of an independent regulatory body.

Integration of Reserve in the Market Model

The NZEM is a co-optimised market for energy and instantaneous (contingency) reserve, but not for regulating reserves. Primary (Fast Instantaneous Reserve (FIR)) and secondary (Sustained Instantaneous Reserve (SIR)) reserve are integrated with the energy dispatch through three measures:

1. The optimised objective function explicitly includes reserve offers for which cost is minimised.
2. N-1 security: the demand for reserve is specified by the supply of energy and the grid configuration as the largest generation or transmission risk in each of the North and South Islands.
3. Unit level co-optimisation: a unit may be dispatched for both energy and reserve and has a series of technical constraints linking them.

The NZ market has an *N-1* security requirement which can be considered both endogenous and deterministic. There exists three large combined cycle gas turbines (CCGTs) located at Stratford, Otahuhu[13] and Huntly[14], which are all approximately 400 MW in size. Sufficient FIR and SIR is procured to clear the largest of these generators in the North Island only or northward HVDC transmission, whichever is largest. In the South Island, a single Manapouri unit of approximately 120 MW in size is considered the generation risk setter in the absence of southward HVDC transmission flow. Both primary (FIR) and secondary (SIR) reserve markets exist with separate prices for each island.

[13]Owned by Contact Energy,
[14]Owned by Genesis Energy

The NZ market has nodal energy prices (Schweppe et al., 1988), but island reserve dispatch and prices. Each of the two major islands has a separate AC grid with its own reserve requirement. These markets are connected via an HVDC connection which has recently been upgraded (Transpower, 2005). This connection is the single largest potential source of risk and thus, reserve transfers between islands have not been considered wise. A national reserve market has been proposed. This market would enable reserve in one island to secure a generation (but not transmission) risk in the other (Krichtal, 2006; Krichtal and Edwards, 2013) taking advantage of new features of the HVDC connection, in particular round power, which enables the utilisation of both poles at low (total) transfer levels (Krichtal and Edwards, 2012). Whilst promising, the proposal is still at the consultation stage and has not currently been implemented.

Eligible generators and IL providers are required by the SO to submit energy and reserve offers for each thirty minute trading period. The SO uses these offers to clear the market on a five minute basis, ensuring that sufficient supply is procured to meet demand at all nodes. Offers must be submitted to the SO at least two hours (four trading periods) in advance of a trading period (gate closure period).

Dispatch pricing provided by the SO is indicative only. Final prices are determined by the market clearing manager *ex post* and participants are paid relative to their final metered output and the final nodal energy and island reserve prices (Final prices may differ considerably from indicative dispatch prices). The uncertainty over final prices introduces a large degree of risk for consumers of energy who wish to respond in real time (EA, 2014).

There are approximately 5-10 Contingent Events (CE) requiring the dispatch of reserve per year. These events are randomly distributed and typically have no relationship to prices. A high reserve price is not indicative of an increased likelihood of an event occurring. Instead, it indicates the relative scarcity of reserves.

The HVDC cable is the single largest CE risk and is susceptible to both monopole and bipole outages. On the 12^{th} of November 2013 an error on the HVDC connection disrupted the transfer of 1000MW into the North Island. This event required the dispatch of the Automatic Under Frequency Load Shedding (AUFLS) scheme in NZ to prevent frequency collapse and cascade failure. Such large events are known as Extended Contingent Events (ECE), an *N-2* risk. Figure 1.3 illustrates the frequency response of the NZ grid with AUFLS dispatched at 47.8 Hz (Twigg, 2013).

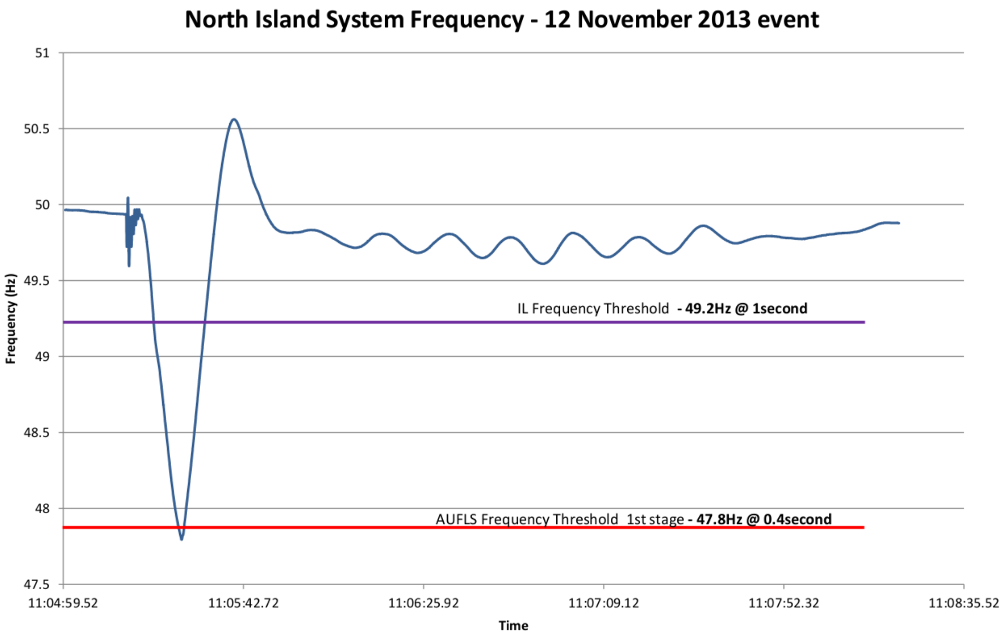

Figure 1.3: Under Frequency Event in the North Island of New Zealand caused by HVDC pole trips on the 12^{th} November 2013 (Twigg, 2013).

The costs for the Instantaneous Reserve market are separated into event related charges, which are allocated to a specific participant who causes a CE, and general costs which are allocated to all participants above a particular size, nominally 50 MW. The majority of the reserve costs fall on the owners of thermal generation plants as well as Transpower as the HVDC owner. Transpower passes these cost on to South Island generators (who are assumed to be the principal beneficiaries of the HVDC link) which has led to these participants attempting to avoid higher costs by delaying unit capacity upgrades (Barker, 2014).

Reserve may be procured from three separate sources; Interruptible Load (IL), Partially Loaded Spinning Reserve (PLSR) and Tail Water Depressed Spinning Reserve (TWDSR). IL is procured from consumers and is typically the fastest responding reserve. Large industrial consumers who directly consume from the high voltage grid are often connected via relays. These relays may be "tripped" reducing consumption instantaneously. Alternatively, smaller companies may participate under the umbrella of an aggregation company who mitigates the risk of individual non-compliance with dispatch instructions by utilising an aggregated portfolio based approach.

PLSR and TWDSR are procured from generators, specifically hydro units. Hydro units who offer PLSR may quickly ramp up their generation output following a UFE. Nominally the time period for this to occur is six seconds although this is largely arbitrary with four seconds being used in some markets[15]. Generation units dispatched as PLSR reserve must

[15] This six-second period was introduced due to the six-second resolution of the metering equipment used to determine compliance. As a result of this FIR is sometimes called six second reserve and SIR sixty-second reserve, referring to the time a unit has to reach the compliance level. In some other international markets the resolution is $4s$ and compliance may follow as a multiple of this period

retain sufficient spare capacity to meet their reserve obligations which introduces additional constraints to the market dispatch problem.

Contrary to PLSR, a TWDSR unit is not currently dispatched for energy in the electricity market. Thus, as the unit is not generating it is synchronised by using electricity to continuously rotate the turbine so that it may ramp quickly. TWDSR is the slowest, costliest form of reserve and is typically priced at a significant premium to other forms of reserve.

To optimise the operation of a hydro station consisting of a series of units, Drayton-Bright (1997) developed the approximate fan curve methodology. This methodology determines the optimal feasible region, as well as the economic opportunity costs of dispatching energy and reserve from a series of connected units. The fan curve method is utilised in the NZEM to approximate a mixed integer program and account for the combination of multiple hydro units within a single station.

New Zealand does not have fully co-optimised regulating reserve (known locally as Frequency Keeping). In New Zealand the regulating reserve requirements are 50 MW in the North Island and 25 MW in the South Island. Internationally, NERC (National Energy Reliability Council, a US institution) recommends that $1 - 2\%$ of peak demand is dispatched as regulating reserve (NERC, 2011). As peak NZ demand is currently less than 7.5GW, NZ currently exceeds the 1% minor threshold. This requirement is fixed and is not optimised in the market dispatch model. The procurement of regulating reserve may interact with the energy and reserve markets. Designated Frequency Keeping units must retain sufficient min-max operating bands to continue reserve provision subject, to minimum supply and rated capacity constraints.

Comparison to Markets Worldwide

Electricity markets throughout the world often agree on the major details but differ on the subtleties. In terms of electricity market design, there are a number of considerations to take into account. Each combination of options will introduce subtle differences in market design and subsequently, participant behaviour. With respect to New Zealand, the Singapore market is the best comparison not only in terms of market design but also the physical system (Small nation with large thermal units relative to total demand). In Singapore, reserve requirements can be significant and are co-optimised in a method equivalent to the NZEM (Wong et al., 2012; Chang, 2007; Lu and Gan, 2005).

As part of this thesis we compare the NZEM to a selection of other deregulated markets including Singapore, PJM (Pennsylvania Jersey Maryland interconnection) (PJM, 2014),and Alberta (Brausen, 2009; AESO, 2013). Singapore has been chosen as it is closely related to the NZEM, PJM as it is the largest deregulated market to undertake co-optimisation, and Alberta as an example of a smaller (interconnected) market implementing co-optimisation. European markets have not been considered due to the scope of the interconnected European grid: As frequency is balanced across the continent, the effect of unexpected disconnection is mitigated and the European market challenges are not as applicable to the market designs studied in this thesis. An overview and comparison of the different markets is shown in Table 1.2

Table 1.2: Comparison of New Zealand to other electricity markets throughout the world

	New Zealand	Alberta	PJM	Singapore
Energy Market	Yes	Yes	Yes	Yes
Nodal Prices	Yes	No	Yes	Yes
Payment Method	MCP	MCP	MCP	MCP
DA Market	No	Yes	Yes	Yes
Capacity Market	No	No	Yes	Yes
Reserve Types	Regulating Primary Secondary	Regulating Spinning Supplemental	Regulating Synchronised Non Synchronised	Regulating Primary Secondary Tertiary
Co-Optimised Regulating Reserve	Partial	Yes	Yes	Yes
Co-Optimised Contingency Reserve	Yes	Yes	Yes	Yes
Contingency Reserve Time Frame	6s/60s	-	10min	8s, 30s, 10min
Gate Closure	2 Hours	2 Hours	12 Hours (DA)	65 min
Trading Period	30 min	60 min	60 min	30 min
Intra Period Prices	5 min	10 min	5 min	Ex Ante
Interchanges	No	$\tilde{7}$00 MW	Yes	Yes
Price Cap	No	$1000	$2500	No
Installed Capacity	9.1GW	14.5GW	167 GW (2009)	10.8 GW (2012)
Peak Demand	6.5 GW	11.1 GW	126.8 GW (2009)	6.4 GW (2012)
Dominant Supply	Hydro	Gas	Coal	Gas

Part I

Theoretical Understanding of Reserve Constraints

Chapter 2

Reserve Constraints in Co-Optimised Markets

In this chapter, a co-optimised energy and reserve market which has simultaneous energy and reserve dispatch is considered. In the co-optimised market, contingency reserves are procured under N-1 conditions which introduces new pricing mechanisms where energy prices may exhibit non-intuitive outcomes. The chapter uses case studies based upon the New Zealand Electricity Market, which have been modelled using a simplified two node dispatch model with reserve constraints.

We present the specific mechanisms through which reserve offers may influence the dispatch of generation and transmission assets and therefore, the final energy price. These mechanisms have been formulated as empirical tests and applied to the NZEM where more than 10,000 trading periods were identified as having reserve constraints over a five year time horizon. In aggregate, no effect on the long run average energy price was observed, although reserve constraints were over represented in an assessment of highly priced trading periods and thus we conclude it can have an effect on the volatility of spot prices.

This work was first published in early 2014 at the IEEE Asia Innovative Smart Grid Technologies (ISGT) in Kuala Lumpur, Malaysia. Portions of the analytical work, as well as updates to the implications of the effects observed, have been presented in other pieces of work.

2.1 Introduction

Motivation and Hypothesis

In a deregulated electricity market the procurement of ancillary services (AS) is important for the stable provision of energy. AS, including voltage support, reactive power, regulating reserves, and contingency reserves, all serve a specific purpose in the grid stability lexicon. In this chapter, we will focus upon contingency reserves (CR) and illustrate how the co-optimisation of CR may influence the optimal energy dispatch, as well as final clearing prices. We note that where we use the phrase *reserve*, it is taken to mean CR. This differs from some international jurisdictions where reserve is used to refer to regulating reserve, which is called Frequency Keeping in New Zealand.

In a co-optimised reserve market the least *overall* cost of serving demand is found using a large network flow, linear program (Bazaraa et al., 2011). The co-optimised market design differs from energy only markets via the inclusion of offers to supply reserve within the objective function. Reserve may be offered via price-quantity bids and offers may include additional technical information, such as ramp rates and unit capacity. Co-optimised markets are theoretically more efficient since the trade off between energy and reserve, at both the unit and system levels, may be made on the basis of price or cost. As units may be dispatched for both energy and reserve, co-optimisation is an effective method of determining a feasible dispatch, subject to both systemic and unit level constraints (Alvey et al., 1998).

Co-optimised markets are a source of additional revenue for market participants, with generators paid to maintain spare capacity. Consumers may also participate through IL and DR provision which can increase competition in the AS markets, leading to a more efficient dispatch (Wang et al., 2003). DR inclusion is not without difficulties as consumer load can fluctuate throughout a trading period and thus compliance risk is an issue.

For the system the cost of the improved efficiency of co-optimised markets is the increased model complexity. Complex linear programmes (LPs) may issue, what at first glance seems to be, opaque dispatch instructions in order to ensure the least *total cost* solution. The substitution effects of energy and reserve are difficult to visualise unlike one dimensional energy offers. The development of analytical tools for traders is thus more complex. The least total cost solution can lead to isolated, out of merit, dispatch in a single market which may expose companies to increased risk as unexpected dispatch behaviour occurs.

The aim of this chapter is to enumerate the mechanisms through which reserve market co-optimisation can influence the final dispatch instructions for combined energy and reserve offers. An *N-1* reserve market, where the reserve requirement is set through the largest active risk, from a limited set of generation units and transmission lines, has been modelled. This model is used to assess the mechanisms at both the systemic level, through the total provision of reserve, as well as at the unit level. At the systemic level, the availability of reserve may limit the potential dispatch of risk setting assets within the market. For individual units technical constraints on the combined energy and reserve dispatch can have a large effect on prices.

Existing Literature

There have been three streams of research in the literature concerning the co-optimisation of energy and reserve:

1. The specification of the optimal requirement for reserve for system stability.

2. Design of co-optimisation markets including pricing mechanisms.

3. The competitive effects of joint electricity markets (discussed in greater depth in Chapter 3)

Throughout the literature there has been a dearth of focus upon the practical effects of different market designs. That is, those pieces of work which seek to apply the lessons gained from theoretical work to operating electricity markets. This chapter (and the accompanying paper) is novel in the enumeration of the mechanisms through which constraints bind, and identification of these scenarios in the NZEM.

CR is procured in electricity markets (particular smaller markets where unit size is large relative to peak demand) to prevent cascade failure. The methods for procuring this reserve may be *endogenous, exogenous, deterministic, or stochastic*. The choice of method can have a large influence on both the total system reliability (as measured in terms of disruption to stable operation) and economic cost (as measured in terms of dollars). For a given event, there is an optimal system response and deviation from this level implies either greater cost or reduced reliability.

The simplest method of procuring reserve is to set a constant (potentially trading period dependent), exogenous, requirement for reserve. This blanket approach is used in some systems where an individual unit within a station may be risk setting, such as the South Island of New Zealand. Alternatively, it can set a minimum requirement for reserve in combination with other strategies. Endogenous strategies may be deterministic, for example the *N-1* requirement (Alvey et al., 1998) linked to generation, or a percentage based approach related to demand (NERC, 2011). Deterministic approaches link the reserve requirement to the market dispatch and thus benefit from the co-optimisation of energy and reserve offers.

Probabilistic or stochastic methods set the reserve requirement through the loss of load probability and incorporate historical failure rates in order to optimise the level of reserve procured. (Bouffard and Galiana, 2004; Gooi et al., 1999). Probabilistic methods are well suited for day ahead markets, where forced generation outages may lead to an unacceptably high loss of load probability with a deterministic criteria. High penetration of intermittent renewable technologies is also spurring discussion on probabilistic setting of reserve requirements, including the development of new techniques (Ortega-Vazquez and Kirschen, 2009; Lee, 2007; Bouffard and Galiana, 2008). There exists a rich vein of literature discussing the design of stochastic reserve requirements (Amjady et al., 2009; Bouffard et al., 2005a,b; Aghaei et al., 2009; Wong and Fuller, 2007).

Summary discussions of the design of co-optimised markets and the compromises involved are covered in greater depth in Galiana et al. (2005). There still exists no standard pricing methodology for reserve throughout the world. Over time markets have begun to shift from sequential designs to simultaneous solutions which minimise the requirement for complex heuristics through the implementation of well formulated optimisation programs.

Some authors (Galiana et al., 2005; Arroyo and Galiana, 2005) have argued that a single nodal security price for all forms of reserve exist. This assertion is based upon the assumption that higher quality forms of reserve (for example primary) may also be used for lower quality requirements (secondary and tertiary). As IL consumers may not fit this pattern multiple price markets are still in operation throughout the world in markets such as New Zealand (Alvey et al., 1998) and Singapore (Lu and Gan, 2005; Chang, 2007).

The choice of market design has a large influence upon the mechanisms through which the reserve market can constrain the energy market. In this chapter, the focus is upon markets where an endogenous, deterministic *N-1* security requirement is present. Other market designs have not been considered as they each have their own complexities.

Background

The NZEM is a co-optimised electricity market with *deterministic* security requirements. The largest active (on a MW basis) generation asset in each of the islands must be secured with CR to dispatched output level. Thus, individual unit configuration is important. From a risk perspective it is better to offer two units at 350 MW compared to one at 400 MW and the second at 300 MW. NZ is also rare within the world as the two islands (each containing their own AC network with an individual system frequency) are connected via a risk setting HVDC interconnection. This interconnection transports energy between the two islands and serves as a risk setter for the island receiving energy comparable to a large generation unit. Transfers may reach as high as 30% of total load in a receiving island and in many trading periods it is thus the largest risk.

Generation companies in the NZEM have strong geographical and technological links. For example, SI hydro is predominately owned by Meridian Energy and Contact Energy whereas NI hydro is owned by Mighty River Power and Genesis Energy[1]. These companies are vertically integrated and each has a share of the retail market. As prices are nodal (Schweppe et al., 1988), any divergence between these due to trans-

[1] A fifth company, Trustpower, owns a number of small hydro units

mission constraints, or reserve constraints upon transmission, increases the financial risk borne by these companies.

Chapter Structure

It is important to have both a theoretical understanding of how reserve constraints bind and a practical method of assessing this in a real world electricity market. In Section 2.2, a market dispatch LP is formulated with a simplified transmission network and *N-1* security requirements. This market dispatch is co-optimised at both the systemic and unit level with a full set of security constraints. The vectors through which constraints may bind are illustrated in Section 2.3, through the use of numerous case studies, which examine pricing behaviour under different conditions.

A practical method of identifying reserve constraints is proposed and implemented in Section 2.4. The mechanisms identified in Section 2.3 are reformulated as testable hypothesis of relationships between energy and reserve prices and applied to the NZEM for the years 2008 to mid 2014. In Section 2.5, the implications of the existence and magnitude of these constraints have been discussed, specifically in the context of the NZEM.

Specific Chapter Nomenclature

Parameters

p_g Vector of energy prices with associated quantities

p_r Vector of reserve prices with associated quantities

ρ Vector of proportionality values linking reserve and energy offers

R Maximal quantity value for each reserve offer

G Maximal quantity value for each energy offers

D Vector of nodal demand

F Maximum transmission capacity

Variables

g Vector of generation dispatch

r Vector of reserve dispatch

f Transmission flow

Mapping Matrices

M Mapping of generation or reserve units to nodes

E Mapping of reserve units to each generation unit for security purposes

A The Arc Node incidence Matrix

B Mapping of transmission flows to nodes

L Loop flow matrix

Dual Values

λ Nodal Energy Price

μ^1 Nodal Reserve Price (Generation Risk Setter)

μ^2 Nodal Reserve Price (Transmission Risk Setter)

ω Shadow Value upon maximal Reserve offer constraint

ϵ Shadow Value upon maximum unit capacity constraint

κ Shadow value upon proportionality constraint

$\tau^{\pm}$ Shadow value of transmission capacity constraint

α Shadow value of loop flow constraint

2.2 Formulation

The integration of CR into an electricity market requires that economic efficiency be optimised subject to technical feasibility. Each unit (as well as the system as a whole) should be dispatched optimally, subject to their own specific technical limitations. In this section a simplified co-optimised electricity market based upon the work of Alvey et al. (1998) and Lu and Gan (2005) as well as the current formulation of SPD (Transpower, 2008) is presented. The model has a simplified dispatch mechanism without losses, although loop flows have been included. The model is not intended for use in a full power system.

The model has been implemented with the following key features:

1. Co-optimised reserves in the objective function and constraints
2. Nodal Pricing (LMP) (Schweppe et al., 1988)
3. Deterministic (*N-1*) risk requirements for generation
4. Nodal reserve market and reserve requirements for transmission
5. Unit level ("inverse bathtub") constraints upon reserve and energy dispatch

In the market dispatch model the objective function contains the combined least cost dispatch of energy and reserve. This dispatch meets the power system demand and reserve requirements through a series of linear constraints. A single reserve product is used and we do not assess any relationships between multiple reserve products. Reserve formulations vary between markets with some authors claiming that only a single nodal security price for the combined products can exist (Galiana et al., 2005).

The objective function is simple least cost dispatch:

$$\min p_g^T g + p_r^T r \tag{2.1}$$

Losses are ignored and under Kirchoff's laws supply and demand must be satisfied at each node. For completeness we include loop flow and transmission capacity constraints. The associated shadow (dual) variables associated with each constraint are included in square brackets:

$$Mg + Af = d \qquad [\lambda] \tag{2.2}$$

$$Lf = 0 \qquad [\alpha] \tag{2.3}$$

$$|f| \leq F \qquad [\tau^{\pm}] \tag{2.4}$$

Security requirements are deterministically set as the single period output of either the largest generation unit or transmission entering a node. Hence, reserves are procured nodally as transmission is a form of risk. We "map" reserve units to potential risk setters. This mapping ensures that only certain reserve units may secure a given risk. This can be implemented either directly or indirectly by a *Risk* variable. A *Risk* variable leads to a single reserve price for multiple risk sources, however the direct approach has greater clarity in the associated dual formulation. As such we have formulated the dynamic reserve requirement through two constraints as:

$$Er - g \geq 0 \qquad [\mu^1] \tag{2.5}$$

$$Mr - Bf \geq 0 \qquad [\mu^2] \tag{2.6}$$

This leads to a situation where the actual reserve price is the maximum of the two nodal reserve prices. In practice, we can modify the linear programs to assess individual cases through the removal of one risk setter.

$$\mu = \max\{\mu^1, \mu^2\} \tag{2.7}$$

The constraints which limit the dispatch of reserve from individual units, not just the total requirement for reserve, must be considered. Reserve may be procured from either interruptible load (IL) or spinning reserve (SR) units. SR units are bound by a series of constraints limiting the dispatch of energy and reserve known, colloquially as the "*inverse bathtub constraints*" (Chakrabarti, 2007).

The three constraints are a linear representation of the limits upon the operation of multiple units within a generation station, which is particularly relevant to hydro stations. The inverse bathtub consists of three separate constraints and is visually represented in Figure 2.1. The first (proportionality) constraint is a substitute for an integer representation of the multiple unit level of a station. Hydro stations have different allowable operating states and hence reserve configurations. These configurations may be modelled using the approximate fan curve methodology (Drayton-Bright, 1997).

The first constraint (proportionality) limits the total amount of reserve provisioned as a fixed ratio of the generation dispatched:

$$r \leq \rho g \quad [\kappa] \tag{2.8}$$

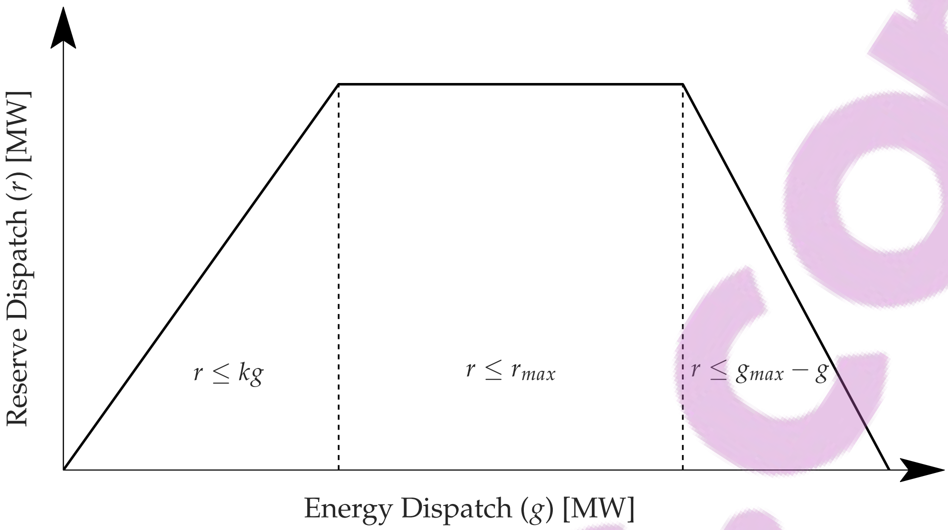

Figure 2.1: The inverse bathtub, a visual explanation showing the three separate feasible regions governed by separate linear constraints upon the dispatch of an individual generation facility.

The second constraint (maximum output) binds upon all reserve providers and specifies a limit on the quantity of reserve which may be dispatched in a single tranche:

$$r \leq R \quad [\omega] \tag{2.9}$$

The third constraint (combined output) is specific to generation units. The total quantity of energy and reserve dispatched must be less than the rated capacity of the station.

$$r + g \leq G \quad [\epsilon] \tag{2.10}$$

For each individual case study we will use a subset of the linear program. A subset permits us to isolate each of the effects which are occurring and . This linear program is set into two parts, a primal formulation along with the associated dual formulation. The full, general, linear program is as follows:

Primal Form

$$
\begin{aligned}
\min \quad & p_g^T g + p_r^T r & & \\
\text{subject to} \quad & Mg + Af = d & & [\lambda] \\
& r \le R & & [\omega] \\
& r + g \le G & & [\epsilon] \\
& f \le F & & [\tau^+] \\
& -f \le F & & [\tau^-] \\
& r - Kg \le 0 & & [\kappa] \\
& g - Er \le 0 & & [\mu^1] \\
& Bf - Mr \le 0 & & [\mu^2] \\
& g, r \ge 0 & & \\
& f \quad \text{free} & &
\end{aligned}
\tag{2.11}
$$

Dual Form

$$
\begin{aligned}
\max \quad & d^T\lambda + R^T\omega + G^T\epsilon + F^T(\tau^+ + \tau^-) & & \\
\text{subject to} \quad & M^T\lambda + \epsilon - K\kappa + \mu^1 \le P & & [g] \\
& \omega + \epsilon + \kappa + E\mu^1 \le P^r & & [r] \\
& A^T\lambda + \tau^+ - \tau^- - B^T\mu^2 = 0 & & [f] \\
& \omega, \epsilon, \tau^+, \tau^-, \kappa \le 0 & & \\
& \lambda \quad \text{free} & &
\end{aligned}
\tag{2.12}
$$

2.3 Case Studies

In this section we explore the effect of reserve constraints in different situations, through careful selection of parameters, for subsets of the full formulation covered in Section 2.2. Small models are useful due to their analytical tractability.As such, we work through each mechanism analytically, as well as through an empirically based case study.

Three simplified networks are used to understand reserve constraints as illustrated in Figure 2.2. Model 1 consists of a single node model with two generation providers and one reserve provider. It is used to explore the effects of reserve provision on risk setting generation units. Models 2 and 3 are two node networks where reserve is procured nodally with LMP for both energy and reserve. Model 3 differs from model 2 through inclusion of the set of "inverse bathtub" constraints. In this model reserve is procured from units who must also provide energy.

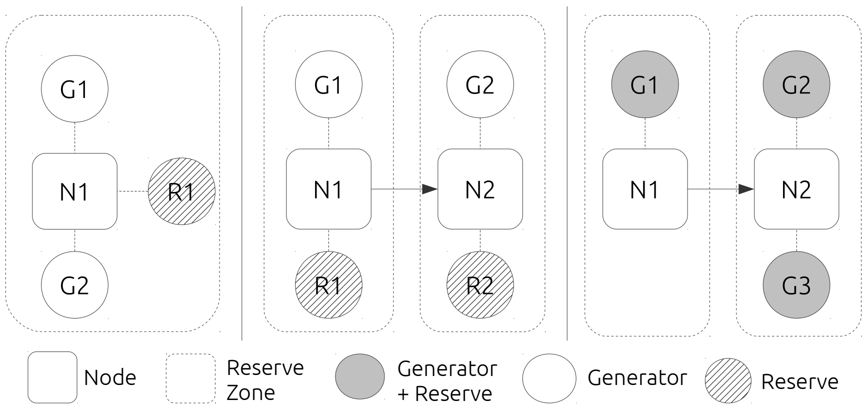

Figure 2.2: Illustration of the simple two node models used to examine the occurrence of reserve constraints in a practical setting, namely (a) a one node model used to assess the impact of reserve on generation dispatch, (b) a two node model with reserve constraints binding upon transmission lines and (c) where (b) is modified to introduced the set of inverse bathtub constraints.

Reserve Constrained Generation

Large generation units may, without warning, desynchronise from the grid leading to a rapid fall in system frequency. We consider a case where the level of generation dispatched from a unit must be cleared via *N-1* contingency reserves, which is procured from Interruptible Load participants only. No unit level effects between joint provision of energy and reserve from the same unit are considered.

Of interest is the case with no limits upon the dispatch of energy and reserve. In this situation, excluding the satisfaction of demand, the only constraint which may bind is the reserve constraint on generation units. Thus, the primal formulation simplifies to:

$$\begin{aligned} \min \quad & p_g^T g + p_r^T r & & \\ \text{s/t} \quad & Mg = d & & [\lambda] \\ & Er - g \geq 0 & & [\mu] \\ & g, r \geq 0 & & \end{aligned} \tag{2.13}$$

Consider an empirical example where g_1 is a low cost base load generator, g_2 an expensive peaking plant, and r_1 is an interruptible load provider. Both generators g_1 and g_2 are reserve constrained and therefore the dispatch of r_1 must be greater than the larger of the two. We consider two cases, the first where the reserve provider is priced in between the two generators and the second where it is more expensive than both generators. Empirically the initial system and final results are presented in Table 2.1.

Two possible outcomes exist. In the first case the low cost generator monopolises the full dispatch, $g_1 = r_1 = d$. For this to occur the final energy price is a combination of the marginal energy offer prices for p_{g_1}

Table 2.1: Reserve constrained generation indicating two modes of behaviour at different reserve price points. Prices are denoted in $/MWh and quantities in MWh.

	Low Priced Reserve	High Priced Reserve
d	300	300
p_{g_1}	20	20
p_{g_2}	60	60
p_{r_1}	**20***	**120***
g_1	300	150
g_2	0	150
r_1	300	150
λ	40	100
μ	20	120

and the marginal reserve price μ.

$$\lambda = p_{g_1} + \mu \tag{2.14}$$

The second situation is more complex. In this case the cost of provisioning reserve is steep, $120/MWh as compared to $20/MWh. Thus, it is cheaper to dispatch both generation units at reduced outputs to satisfy demand whilst minimising the reserve dispatch. When this occurs the marginal energy price, λ is given by (2.15):

$$\lambda = \frac{p_{g_1} + p_{g_2} + \mu}{2} \tag{2.15}$$

This creates two pricing situations, dependent upon the relative prices of both energy and reserve, as in (2.16). In each situation the marginal reserve price is set by the sole reserve unit $\mu = p_{r_1}$.

$$\lambda = \begin{cases} p_{g_1} + \mu & \text{if } p_{r_1} \leq p_{g_2} - p_{g_1} \\ \dfrac{p_{g_1} + p_{g_2} + \mu}{2} & \text{otherwise} \end{cases} \tag{2.16}$$

Reserve Constrained Transmission

In co-optimised markets, reserve constraints on generation units are typically the greatest cause for concern. Reserve constrained transmission is a relatively rare feature. It is usually only present in markets where two markets are connected via a (relatively) large transmission line which can serve as a point of failure. In these grids the failure of the transmission line would require corrective action in order to maintain system frequency in each of the two grids as they become "islanded". In mesh grids the failure of transmission lines, whilst concerning, may not need corrective action as sufficient spare capacity exists elsewhere in the network to maintain supply.

On occasion one market may be transporting a significant quantity of energy to the second market. If the transmission link between these markets were to fail this capacity must be replaced by reserve procured from within the geographical area. In these markets reserve has a spatial requirement and separate locational prices can exist. For example, in the NZEM there are distinct reserve prices for the North Island and South Island which reflect this phenomenon.

The security requirement of these interconnections are not fixed with actual flows dictated by the relative costs of generation in either island. These flows are security constrained and in a market system participants must be aware of the reserve requirements before submitting their offers.

We consider a special case of the primal problem outlined in 2.2 which includes only reserve constraints upon transmission. In this case:

$$\begin{aligned} \min \quad & p_g^T g + p_r^T r & & \\ \text{s/t} \quad & Mg + Af = d & & [\lambda] \\ & Mr - Bf \geq 0 & & [\mu] \\ & g, r \geq 0 & & \\ & f \quad \text{free} & & \end{aligned} \tag{2.17}$$

We consider an example equivalent to that in Table 2.1 except that there is now a nodal component to the generation units. Once again we consider two situations as outlined in Table 2.2.

Table 2.2: A reserve constrained transmission line creates a nodal price separation if reserve prices are low enough to enable transmission. In the high priced situation, transmission flow between the nodes is uneconomic due to the cost of securing the transmission. Prices are denoted in \$/MWh and quantities in MWh.

	Low Priced Reserve	High Priced Reserve
d_1	50	50
d_2	250	250
p_{g_1}	20	20
p_{g_2}	60	60
p_{r_1}	1	1
p_{r_2}	**20***	**100***
g_1	300	50
g_2	0	250
r_1	0	0
r_2	250	0
f_{1-2}	250	0
λ_1	20	20
λ_2	40	60
μ_1	1	1
μ_2	20	100

The key difference to the generator constrained case is that there is a locational component to the provision of reserve. g_1 is able to serve an additional unit of demand at n_1 unconstrained. However, if the demand is increased at n_2, the reserve dispatch must be increased accordingly to enable greater transmission flow, f. This leads to two pricing situations which are illustrated via the separation in nodal prices in (2.18)-(2.20).

$$\lambda_1 = p_{g_1} \tag{2.18}$$

$$\mu_2 = p_{r_2} \tag{2.19}$$

$$\lambda_2 = \begin{cases} \lambda_1 + \mu_2 & \text{if } p_{r_2} \leq p_{g_2} - p_{g_1} \\ p_{g_2} & \text{otherwise} \end{cases} \tag{2.20}$$

Combined Generation and Transmission Risk

It should also be considered what pricing mechanisms are in place when *both* generation and transmission between nodes are constrained via nodally procured reserve. In this situation, transmission between nodes must be secured by reserve secured from that node and therefore any generation at that node can also make use of this same reserve procurement. This situation is considered in Table 2.3, for both low and high reserve prices.

Once again two modes of behaviour occur as illustrated in (2.21)-(2.24). This behaviour is an aggregation of the single generator and single transmission case as outlined in Table 2.1 and Table 2.2.

Table 2.3: Reserve constrained generators and transmission lines exhibit more complex behaviours than either case alone. High priced reserve leads to low cost generation units being unable to fully compete. However, g_2 is also limited due to the reserve constraint and therefore full "blocking" of transmission does not occur.

	Low Priced Reserve	High Priced Reserve
d_1	50	50
d_2	250	250
p_{g_1}	20	20
p_{g_2}	60	60
p_{r_1}	10	10
p_{r_2}	**20***	**100***
g_1	300	175
g_2	0	125
r_1	300	175
r_2	250	125
f_{1-2}	250	125
λ_1	30	30
λ_2	50	95
μ_1	10	10
μ_2	20	100

$$\lambda_1 = p_{g_1} + \mu_1 \tag{2.21}$$

$$\mu_1 = p_{r_1} \tag{2.22}$$

$$\mu_2 = p_{r_2} \tag{2.23}$$

$$\lambda_2 = \begin{cases} \lambda_1 + \mu_2 & \text{if } p_{r_2} \leq p_{g_2} - \lambda_1 \\ \dfrac{\lambda_1 + p_{g_2} + \mu_2}{2} & \text{otherwise} \end{cases} \tag{2.24}$$

Constraints on Reserve Provision

In a co-optimised market there are linear constraints on how units may be dispatched. These constraints map the physical operating limits of each unit onto the market dispatch model to ensure technically feasible dispatch solutions. Constraints, such as ramping and rated capacity, can play a major role in determining the optimal solution. Previously we have considered only the demand for reserve as a function of the different reserve prices. In this section, we consider additional technical limits on the dispatch of the units drawn from the constraints depicted in Figure 2.1.

As a base case we utilise the transmission constrained situation as outlined in Table 2.2. We note that the constraints presented here would still apply for the case of a constrained generator. However, in the transmission case, the price differentials are explicit through the divergence in nodal prices which arise. In the generation case, these occur in the divergence between offer prices and final prices which can be difficult to identify[2].

Proportionality Constraints

The proportionality constraint limits the quantity of reserve which may be procured from a generation unit to a proportion of the units generation output. The necessity of this constraint is clear when considering a unit with a reserve dispatch of 100MW and an energy dispatch of 1MW. The likelihood of this unit being able to ramp to the specified reserve dispatch is unlikely in this case. However, from a price perspective such a dispatch configuration may be optimal. In practice, this equation prevents a unit from being dispatched for reserve unless it is also dispatched for energy.

[2]This is especially true for assessing a real market where it can be difficult to identify which unit is both *marginal* and reserve constrained in the generator constrained scenario. This is alleviated for transmission due to the clearly published market prices.

This may have notable effects when an expensive offer tranche must be dispatched in order to obtain reserve. In this situation, to procure an additional MW of energy at the node could be accomplished by dispatching a combination energy from a risk setting unit. Procuring reserve from a proportionality constrained spinning unit and procuring additional energy from this unit in order to relax the reserve constraint. Thus, the optimal dispatch in this point, and subsequently the clearing energy and reserve prices, will lie between the marginal offer prices for energy and reserve. An example of this is shown in Table 2.4.

Table 2.4: Proportionality constraint limiting reserve dispatch for different values of the proportionality constant k. Both marginal energy and reserve prices at n_2 have diverged massively from the offered energy and reserve prices ($p_{g_1}, p_{g_2}, p_{r_1}, p_{r_2}$). Prices are denoted in \$/MWh and quantities in MWh.

	$k = 0.5$	$k = 1.0$	$k = 1.5$
d_1	50	50	50
d_2	300	300	300
p_{g_1}	100	100	100
p_{g_2}	1000	1000	1000
p_{r_1}	0	0	0
p_{r_2}	0	0	0
g_1	150	200	230
g_2	200	150	120
r_1	0	0	0
r_2	100	150	180
f_{1-2}	100	150	180
λ_1	100	100	100
λ_2	700	550	460
μ_1	0	0	0
μ_2	600	450	360

Using the corresponding dual equation and after algebraic manipulations we may obtain an equation for the marginal price of both energy and reserve. We must solve for $\kappa_{g,2}$ simultaneously to determine the appropriate conditions.

$$\lambda_2 = \lambda_1 + \mu_2^T \tag{2.25}$$

$$\mu_2 = p_{r,2} - \kappa_{g,2} \tag{2.26}$$

$$\mu_2 = p_{g,2} + k_{g,2}\kappa_{g,2} - \lambda_1 \tag{2.27}$$

$$\kappa_{g,2} = \frac{p_{r,2} + \lambda_1 - p_{g,2}}{1 + k_{g,2}} \tag{2.28}$$

We substitute $\kappa_{g,2}$ and μ_2 into our original equation for the price λ_2 in order to derive the marginal price for energy at node two.

$$\lambda_2 = \frac{1}{1 + k_{g,2}} p_{g,2} + \frac{k_{g,2}}{1 + k_{g,2}} (p_{g,1} + p_{r,2}) \tag{2.29}$$

For example, using a ratio ($k_{g,2}$) value of 0.5 we see that the marginal MW at the receiving node will be made of $2/3$ energy from the peaking unit, $1/3$ reserve from the peaking unit, and $1/3$ energy from the low cost sending node. For higher values of $k_{g,2}$ this ratio will change accordingly and lead to a decrease in energy and reserve prices at n_2.

Maximum Output Constraints

The maximum generation and reserve dispatch are also subject to constraints for two reasons. The rated capacity of the unit cannot be exceeded and unit may only reach a specific level within the required time limit[3]. These constraints can be observed when a limitation on the total quantity of reserve present in the system exists. The combined energy and reserve dispatch is taken into account in the rated capacity constraint. This refers to the downward sloping line in the inverse bathtub

[3]In the NZEM there are two types of reserve, 6s and 60s. These time limits refer to the time a unit has to ramp up to the required output level to maintain compliance with the dispatch instructions. As such 60s reserve is traditionally easier to supply.

constraint diagram (Figure 2.1)) where the feasible quantity of reserve is limited by the associated energy dispatch.

When the available reserve is limited, more expensive generation units will be dispatched to serve demand. In this situation the energy prices will not incorporate the marginal cost of reserve, and instead will be set by the non security constrained, generation unit offer prices. This situation may be identified when the clearing reserve price has no associated reserve offer price.

An example of this behaviour is considered in Table 2.5 illustrating the capacity constraint upon reserve via a maximum reserve limit, $\hat{r_2}$[4]. Regardless of the reserve offer price the final energy price at each node is set by g_2. In the low priced reserve scenario the final reserve clearing price is equal to the difference between the nodal energy prices:

$$\mu_2 = \lambda_2 - \lambda_1 \tag{2.30}$$

This reflects the gain in social welfare which would result if the capacity limit was relaxed by one MW. In this case a MW of g_1 which is secured by a MW of r_2 on the transmission line would substitute a MW of g_2.

2.4 Empirical Assessment

In practice, the translation of theory to application is necessary to assess the validity of identified mechanisms. Models are useful representations of reality, but they need to be treated as just that. The identification of theoretical mechanisms of constraint binding is of little concern to the

[4] Although there is a third constraint (the combined capacity constraint) this does not bind in a market with no transmission losses as energy units at different nodes become perfect substitutes.

Table 2.5: Impact of reserve capacity constraints binding in a reserve constrained market. In this scenario the final reserve clearing price is set equal to the potential savings which would occur if a substitution between high and (risk constraint) low cost generation units were possible. Prices are denoted in \$/MWh and quantities in MWh.

	Low Priced Reserve	High Priced Reserve
d_1	50	50
d_2	300	300
p_{g_1}	10	10
p_{g_2}	100	100
p_{r_1}	0	0
p_{r_2}	**50***	**150***
$\hat{r_2}$	200	200
g_1	250	50
g_2	100	300
r_1	0	0
r_2	200	0
f_{1-2}	200	0
λ_1	10	10
λ_2	100	100
μ_1	0	0
μ_2	90	150

practical individual. Consider a generator or consumer who must make any decision with a price component. Whilst an improved theoretical understanding of price is useful to this individual, it may not lead to improved outcomes or decision making.

Consider the NZ market which has three notable situations where reserve is important to the final dispatch (The transmission situations are differentiated via direction, as reserve is procured on an island basis in New Zealand):

1. The dispatch of large (risk setting) Combined Cycle Gas Turbines (CCGTs) at Huntly, Stratford and Otahuhu.

2. Northward HVDC transfers from South Island hydro lakes through the HVDC interconnection between the Benmore and Haywards nodes[5].

3. Southward HVDC transfers which occur during "dry" winters.

In this section we identify the occurrence of these constraints for each of the three situations as outlined and assess their effect upon the market. To accomplish this we present an identification heuristic which can be used with final market prices and is drawn from the theoretical mechanisms presented in Section 2.3. Through this aggregated assessment of the NZEM we attempt to understand the total effect on average prices, systemic factors of occurrence, and their role in high spot prices.

Free Governor Response

As a general comment throughout the empirical sections to follow in this Thesis a reference is made to the combined FIR and SIR prices. However, within the NZEM the requirements for FIR and SIR are not equal, there exists a quantity of *Net Free Reserve* (NFR) that is present within the system and offsets the FIR requirement. This NFR is given by the natural inertia of the system and is calculated by Transpower using a MATLAB Simulink model known as the *Reserve Management Tool* (RMT).

The RMT as a model takes as inputs the initial SPD solution run and produces the quantity of expected NFR. This is then fed back into a subsequent SPD solve to determine the optimal response. As such the FIR

[5]Two of the three major reference price nodes. Benmore is the location of a number of hydro stations around the Waitaki Chain which is currently operated by predominately by Meridian Energy (Tekapo stations operated by Genesis Energy). Haywards is the second end of the HVDC interconnection where transfers from the South Island join the North Island AC grid. The final reference node is the CCGT unit located at Otahuhu in the Auckland Region

and SIR requirements are given as:

$$FIR_{requirement} = Risk - NFR \tag{2.31}$$

$$SIR_{requirement} = Risk \tag{2.32}$$

As such whilst the *aggregate* quantities for FIR and SIR dispatched may differ from one another the *marginal* requirement for FIR and SIR for a given increment of Risk are equivalent. As prices in the NZEM are marginal prices, not aggregate prices, the treatment of the Island Reserve Price as the sum of the FIR and SIR prices is applicable during periods of reserve binding upon a marginal risk setting. The NFR is a constant and does not influence this process.

Reserve Constrained CCGT Stations

The hydro-thermal NZ market currently has three large CCGT units which are considered risk setters in the NI. The Otahuhu and Stratford CCGTs (owned by Contact Energy) as well as Huntly E3P (owned by Genesis Energy). Each unit has a rated capacity of approximately 400MW which must be secured by both FIR and SIR reserve. We know from Section 2.3 that if a risk setting generation unit is the marginal energy unit that the nodal energy price, nodal reserve price and marginal unit offer price are intertwined via (2.16). The NZEM has two separate reserve products which are both secured under *N-1* security, as such the nodal reserve price in this case may be taken as the sum of the reserve prices in each market. To identify a reserve constraint we use two boolean conditions. The nodal energy price must exceed the unit offer price by a certain threshold (φ), (2.33) and the difference between the nodal energy price, offer price, and combined reserve prices must be less than a defined tolerance (ν), (2.34). If both conditions are satisfied, then we state that the particular trading period had a reserve constraint binding, η_G as in (2.35).

$$\lambda - p_g \geq \varphi \qquad [A] \qquad (2.33)$$

$$|\lambda - p_g - (\mu_F + \mu_S)| \leq \nu \qquad [B] \qquad (2.34)$$

$$\eta_G = \begin{cases} \text{True} & A \wedge B \\ \text{False} & \text{otherwise} \end{cases} \qquad (2.35)$$

Two tolerance variables, φ and ν are introduced. φ sets a minimum deviation between the energy and offer prices and may be set to any quantity of interest. ν is a maximum tolerance, as we are using nodal energy prices no losses are taken into account in the energy price. As such, theoretically ν should be equal to \$0/MWh. However, for the practical assessment we set $\nu =$ \$1/MWh. A smaller threshold of significant (φ) can lead to additional periods being classified as reserve constrained. Likewise a larger tolerance (ν) will have the same effect. In Figure 2.3 using a $\nu =$ \$1/MWh and $\varphi =$ \$20/MWh, more than 2000 trading periods were identified as having a binding reserve constraint.

Transmission Constraint

The defining feature of the NZ transmission network is the HVDC interconnection between Haywards and Benmore. This interconnection has consisted of multiple configurations over time with the most relevant being: Monopole, Bipole (with Pole Three from 2013/2014 onwards), Bipole (with Pole One in reduced operation due to security considerations, now fully decommissioned). Each of these modes of operation has a different risk profile which can make assessing the impact of the HVDC interconnection on the market difficult.

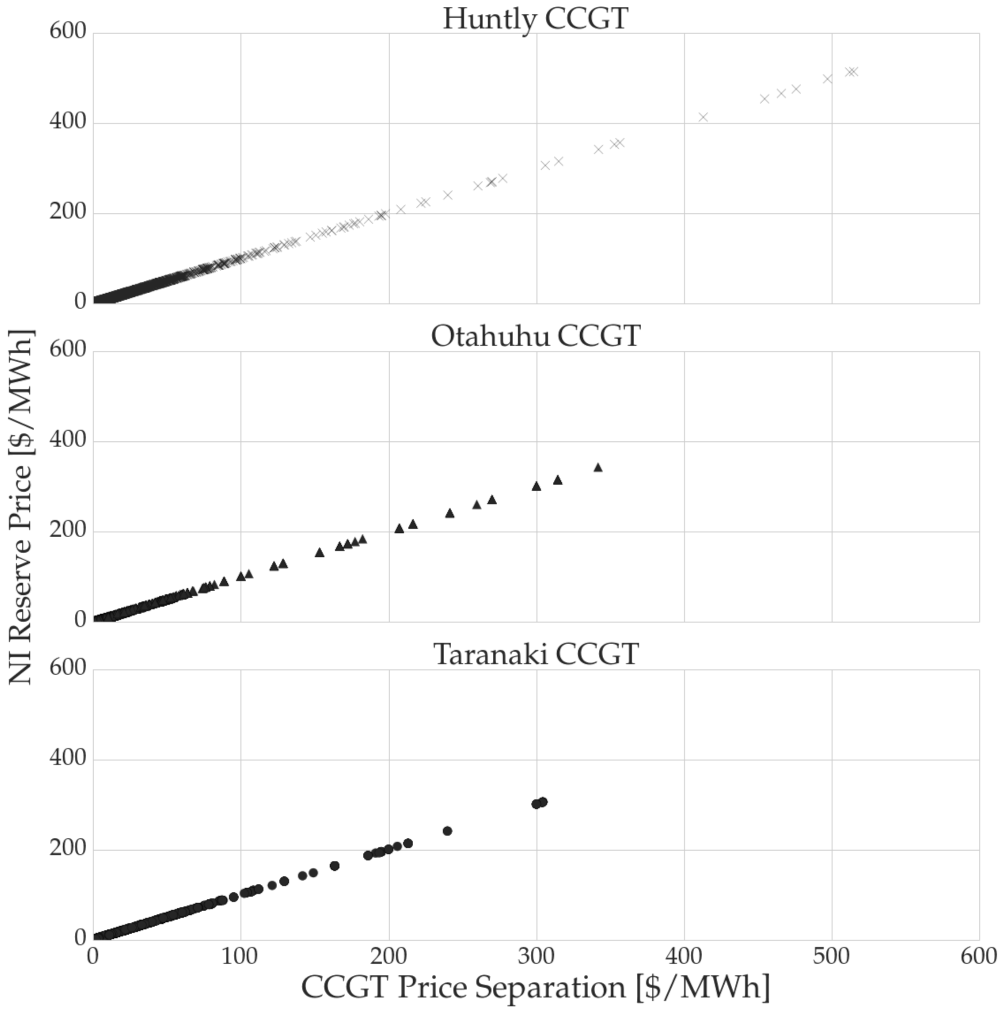

Figure 2.3: Linear relationship between reserve prices and clearing price - offer price separation for each of the large thermal units in the NZEM. Tolerance values of φ = \$20/MWh and ν = \$1/MWh have been used. Points have been offset in the y domain by a normally distributed random variable to enable visualisation of overlapping points.

Consider the Haywards and Benmore nodes as the respective NI and SI reference prices, along with the four separate reserve prices (FIR and SIR prices for each island which we have identified via $\mu_{Island,Type}$. For example the NI FIR price is identified by $\mu_{NI,FIR}$). The HVDC cable may be used to transfer energy in both directions which we have considered as individual scenarios due to the different market structure in each market. During normal operation, due to transmission losses, prices at the receiving node will exceed the sending node by a small margin. In (2.36) we set a minimum price divergence between the two islands of φ as a condition, A. From (2.20) the relationship between island price separation and reserves is known and approximated in (2.37),(2.38) for a given tolerance ν. The goal, in setting φ and ν, is to identify trading periods where price divergence is due to reserve constraints and not due to transmission losses or congestion.

$$|\lambda_{NI} - \lambda_{SI}| \geq \varphi \qquad [A] \tag{2.36}$$

$$|\lambda_{NI} - \lambda_{SI} - (\mu_{NI,FIR} + \mu_{NI,SIR})| \leq \nu \qquad [B] \tag{2.37}$$

$$|\lambda_{SI} - \lambda_{NI} - (\mu_{SI,FIR} + \mu_{SI,SIR})| \leq \nu \qquad [C] \tag{2.38}$$

$$\eta_T = \begin{cases} \text{NI} & A \wedge B \\ \text{SI} & A \wedge C \\ 0 & \text{otherwise} \end{cases} \tag{2.39}$$

To assess a reserve constraint in effect we may apply combinations of A, B and C as indicated in (2.39). Using this methodology approximately $10,000$ separate trading periods were identified in the North Island along with $3,000$ in the South Island from 2008 to 2013. In Figure 2.4 we plot the inter island price difference ($\lambda_{Haywards} - \lambda_{Benmore}$) against the cumulative reserve price for the North Island ($\mu_{NI,FIR} + \mu_{SI,FIR}$). In Figure 2.5 we plot the same measures for the South Island using the appropriate price differential and reserve prices.

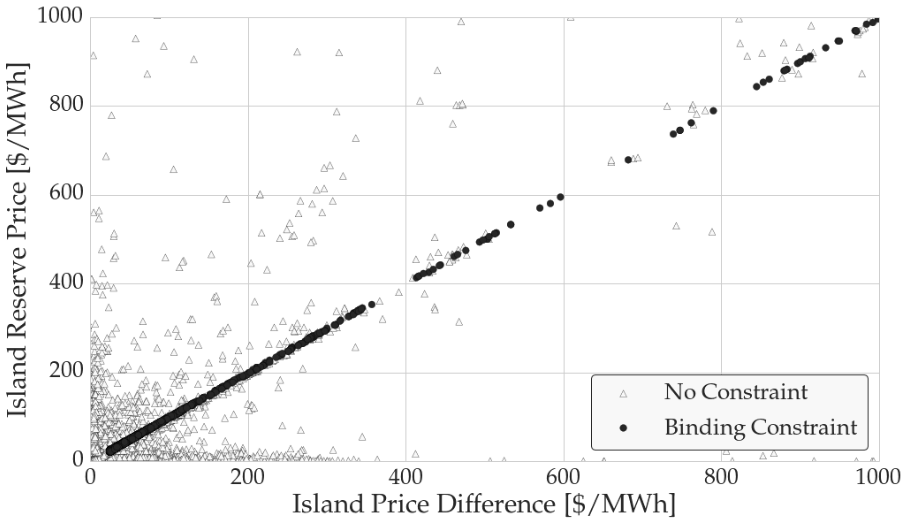

Figure 2.4: Existence of binding reserve constraints upon northward HVDC transfers, a line of slope two appears to exist indicating the potential for multiple risk setters.

Effect of Reserve on High Spot Prices

The second hypothesis is that reserve constraints have a disproportionate effect on the occurrence of high spot energy prices in the NZEM. That is, reserve constraints are a contributor towards high energy prices. Traditionally assessments such as peak demand, capacity shortages, transmission congestion or hydro shortages are thought to be a leading contributor of elevated energy prices. Reserve constraints do not appear to have an effect upon the *average* energy price over the course of a year (although at finer resolutions an effect may be observed). Within the reserve market reserve constraints have a significant impact upon the average reserve price. In Table 2.6 it can be seen that the removal of periods with transmission constraints on HVDC transfers (those periods where

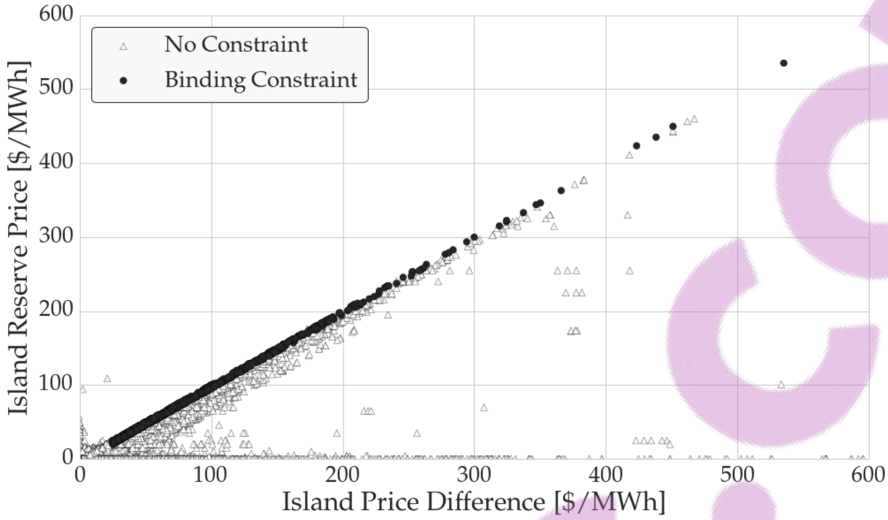

Figure 2.5: Existence of binding reserve constraints upon Southward HVDC transfers, a number of periods appear to be misclassified indicating a greater divergence between NI and SI prices not explained by losses, a lower tolerance may be appropriate.

$\eta_T = 0$) decreases the reserve price with the observable effect largest in 2009. This is to be expected in a tail end distributed electricity market, where just 1% of trading periods resulted in $\geq 35\%$ of the contribution to prices.

Table 2.6: Effect of reserve constraints on average reserve prices for 2008-2014 in the NZEM. Averages have been computed for two populations, the set of all reserve prices in a year and the set of all reserve prices in a year without a transmission reserve constraint.

	NI $\mu(\$/MWh)$	NI $\mu(\$/MWh)$ $\chi_T = 0$	SI $\mu(\$/MWh)$	SI $\mu(\$/MWh)$ $\chi_T = 0$
2008	10.62	10.41	9.59	6.97
2009	18.33	12.29	0.34	0.30
2010	5.80	5.28	2.07	1.68
2011	7.17	5.54	1.42	0.94
2012	6.59	4.65	5.98	4.95
2013	9.66	8.29	0.98	0.62
2014	8.55	7.89	0.72	0.68

What exactly constitutes a high electricity spot price is variable. Some authors have applied shifting values, depending upon a range of market conditions. Others have used fixed cut off values. In New Zealand for example, the *average* energy price is heavily linked to hydrological conditions over a time horizon. We are concerned with constraints and in particular reserve constraints and as such we use a four part characterisation. This enables us to classify a period as unconstrained, NI AC transmission constrained, HVDC congestion constrained and HVDC reserve constrained, from the tests outlined in Section 2.4.

In Figure 2.6, the results of this assessment at different price buckets ranging from $0/MWh to $1000/MWh in $100/MWh increments is shown. At increasing price levels constraints begin to play a larger role and the number of trading periods where no identified constraint had a role decreases. As under our methodology HVDC constraints may be misclassified[6] as not having a reserve constraint we expect that at least 50% of trading periods over $500/MWh have a reserve constraint.

Both the theoretical and empirical work undertaken to date has indicated that there exists a causal link between reserve and high electricity spot prices. Yet, in the understanding so far, the link is incomplete. If reserve constraints are linked to high energy prices, what is causing these reserve constraints to bind? That is, are there any systematic factors?

Periods of reserve constrained pricing appear to occur in clusters. A randomly chosen period has a small chance of being reserve constrained, however this probability greatly increases if the additional information

[6] A strict tolerance value is used in order to classify the trading periods where we are most certain a reserve constraint is in effect. From Figure 2.4 and Figure 2.5 we see that there are a number of periods which visually appear to be reserve constrained although our simple method has not classified them as such. Therefore some periods may be misclassified as being HVDC constrained when in reality they are HVDC reserve constrained.

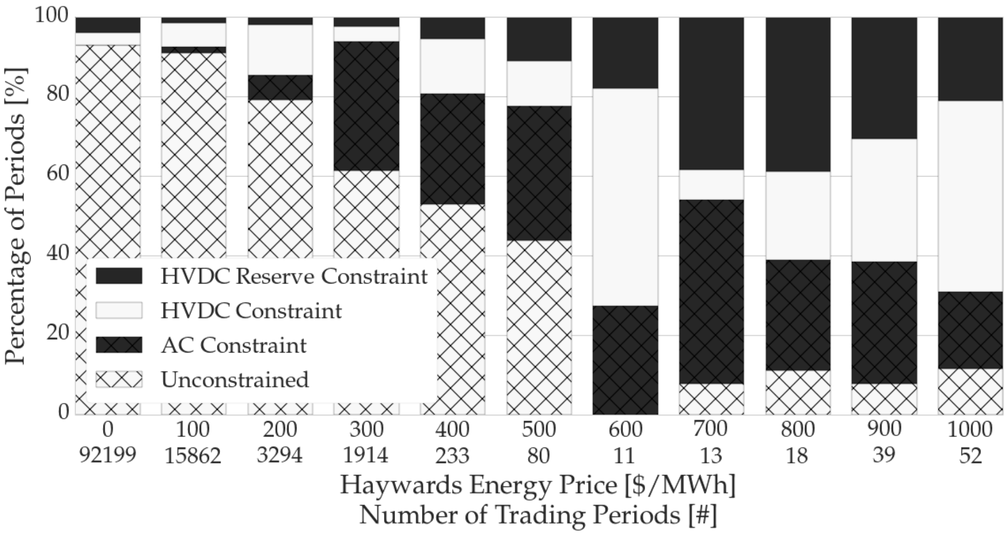

Figure 2.6: Illustration of different pricing phenomena in the NZEM, information is shown as stacked bar charts with the exact percentage of each region within each bar. The total number of periods within a price bucket is shown above each bar.

that a period was reserve constrained in the past twenty four hours is included. Using the assessment of reserve constrained transmission periods we have superimposed periods of both high and low hydro storage levels over time in Figure 2.7. The percentage of periods with reserve constraints (on a month by month basis) are shown indicating that in “wet” years NI reserve constraints are common. In “dry” years SI reserve constraints become a factor.

2.5 Impact upon Decision Making

The conceptual benefit of a deregulated electricity market is that price signals contain valuable information which leads to more efficient decision making. The effect of reserve upon these signals should be understood in terms of the incentives placed upon both the supply and demand side. The effect on contractual considerations and average prices

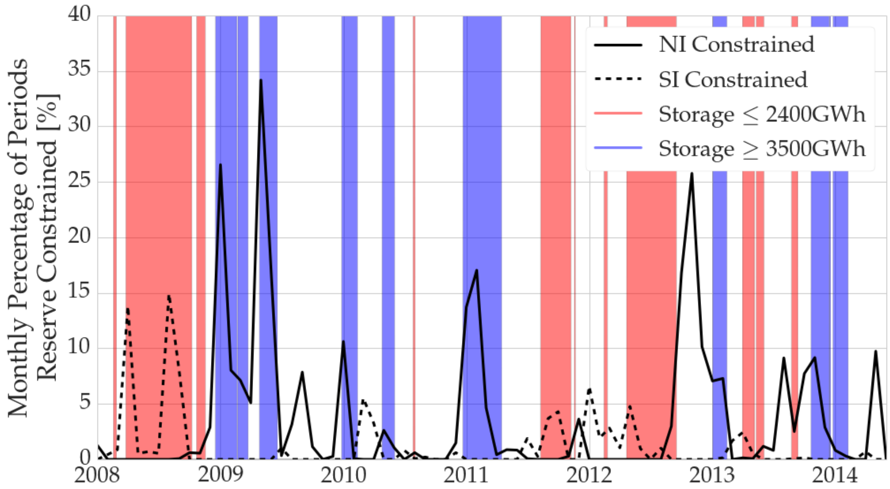

Figure 2.7: Clustering of reserve constrained periods along with periods of relative hydro abundance and shortage in the NZEM.

and finally the effects upon longer term decision making should also be considered.

In a nodal priced market the potential for divergence between locations is of great concern for contractually exposed vertically integrated "gentailers". Consider Meridian Energy, with their vast capacity of SI hydro but limited NI generation presence. For Meridian Energy the price split between islands caused by reserve leads to increased risk. If this occurs, the price Meridian Energy receives for their energy in the South Island is often substantially lower than what they must pay in order to secure their contractual exposure in the North Island (via the spot market).

Meridian Energy has three options to minimise their locational price risk in this case:

1. The purchase of a financial transmission right

2. Purchase a contract with another generator for fixed price supply
3. A reserve market hedge

The third option would protect Meridian Energy from reserve induced spikes in the energy price, although it would accomplish this imperfectly, and options 1. and 2. are of greater value. Alternatively, the simplest option is to minimise their exposure by limiting their contractual position in the North Island. This reduces competition in the North Island retail market to the detriment of consumers.

A positive effect of these reserve constraints is the incentive it sends to consumers of energy. Large scale consumers of energy may also support the safe operation of the grid by offering IL. A site may offer individually or through the services of an aggregation utility. The incentive for participation will vary depending upon the level of exposure each site has towards the spot market and/or what contractual arrangements are in place.

For the spot exposed consumer, IL is a hedge against high spot prices caused by reserve constraints. A fully spot exposed consumer should not consider reserve as a revenue stream as in many cases high reserve prices are also linked to high energy prices. Instead, by offering reserve the site is able to mitigate the effects of these spikes and continue to operate profitably.

For a hedged (energy) consumer reserve may be considered an additional revenue stream. Whether a consumer is hedged, or exposed to the spot market is important when considering new entrance to the reserve market place. As reserve constraints bind due to a shortfall in reserve (as compared to the contingency risk in place) additional supplies of reserve will reduce the frequency of binding reserve constraints and hence revenue.

For the unhedged consumer this effect if of little interest, the principal benefit of reserve for these consumers is reducing their exposure to high electricity spot market prices. Hedged consumers on the other hand see a lack of reserve constraints as a reduction in revenue. In this situation, for an IL consumer the distinction between a fixed (hedged) and a variable (spot exposed) cost base dictates the value of reserve. As reserve markets in NZ typically clear near $0/MWh for the majority of trading periods any new entrance (and subsequent reduction in reserve constraints) negatively impacts hedged consumers over spot exposed consumers first.

For electricity price contracts both the average price and the volatility of this average are taken into account. Consider a market where the volatility is zero. In such a case the risk premium is also zero, as such the hedge price, (H), is essentially the cost of supply, (C_{av}), plus a profit margin, (π):

$$H = C_{av} + \pi \tag{2.40}$$

In markets with considerable volatility participants will also charge a non zero risk premium, rp. This risk premium, (rp), is a function of the volatility, (σ), the hedge supplier expects over the duration of the hedge as well as strategic considerations(Allaz, 1992; Allaz and Vila, 1993). As such the hedge costs seen by the consumer may be approximated as:

$$H = C_{av} + \pi + rp(\sigma) \tag{2.41}$$

As such the cost of integrating reserve into the NZEM via the co-optimised market is not simply the cost of the reserve market (which is nominally small). Instead, the full cost must take into account the increased retail and hedge premiums paid by the majority of consumers. Although new entrance to the reserve market and technological improvements (altered HVDC risk profile due to transmission upgrades) may reduce the reserve induced volatility over time contractual positions for generators change slowly and are downwardly sticky. That is, prices typically do not decrease over time, though their rate of increase may slow.

When assessing an investment an investor must consider information regarding location, size, technology type as well as the expected market return. The reserve market will impact each consideration differently. Consider the case of reserve constrained transmission lines. Due to the requirement for reserve in order to permit transfer between islands investors in NZ will likely favour NI generation sources. This is problematic, the SI has huge potential for both hydrological resources and wind energy. Yet, due to reserve, such investment would exacerbate the occurrence (and price separation) of reserve constraints as the capacity imbalance between islands increases. Likewise, NI generation units are favoured for this (and other) reasons as they will not require additional reserves.

The size of any proposed investment will be impacted by *N-1* reserve co-optimisation. Presently the three largest CCGT units are all approximately 400 MW. If an investor were to build a single plant greater than this such a plant would be the marginal risk setter more frequently. As such, utilisation of this asset would depend upon the provision of reserve from a wide range of suppliers. This procurement can have difficulties, as will be discussed in Chapter 3 and thus investors will favour smaller plants, eschewing economies of scale, to minimise reserve costs.

Chapter Summary and Contribution to the Literature

This chapter has explored the mechanisms through which reserve may influence the optimal energy dispatch. Co-optimised markets with deterministic security requirements have been explored in some depth throughout the literature. However, this prior work has specifically focussed upon the formulation of the market dispatch problem under different conditions.

This chapter represents the first exploration of the pricing mechanisms one of these market designs introduces. The specific pricing mechanism for reserve constrained transmission lines and generation units has been identified, along with an extension of these results to an individual spinning reserve unit which is operating at the cusp of technical feasibility.

Within the literature, studies of co-optimised reserve markets have largely been limited to theoretical approaches. Within this chapter an empirical assessment of one of the world's longest running co-optimised reserve markets (in place since 1996) the NZEM, has been undertaken. A reserve constraint identification procedure, based upon the links between final energy and reserve prices has been developed. Using this procedure more than 10,000 trading periods between 2008 and mid 2014 have been identified. This extension of theoretical results to real market situations has not been significantly explored in the literature before now.

Chapter 3

Equilibrium Models in Co-Optimised Markets

In this chapter, the co-optimised electricity market presented in Chapter 2 has been extended using a Supply Function Equilibrium model. A two participant game has been modelled under reserve constrained generation units and transmission lines. As market participants may be active across both energy and reserve markets, it was hypothesised that reserve market power could be used to influence the energy market. To our knowledge, this work is the first to investigate reserve market power in co-optimised electricity markets.

Results from this model indicate that the optimal supplier strategy is to withhold reserve and thereby limit the dispatch of risk constrained assets. This theoretical result is corroborated by market actions from the 2012 dry year, when a participant took a (contractual) dominant reserve market position in the South Island of NZ.

An initial version of this work was submitted to IEEE Transactions on Power Systems. Comments were received and the work has recently been resubmitted.

3.1 Introduction and Literature Review

The smooth and competitive operation of an electricity market is important to the health of an economy. Uncompetitive markets, those dominated by a few suppliers or with market structures promoting perverse incentives, can decrease social welfare and be detrimental to productivity. Companies who exert market power can have a large effect on economic efficiency in deregulated electricity markets (Tirole, 1988, 2014).

In electricity markets, the study of competition using equilibrium based models has a strong precedent. Nash equilibrium is established when no participant can unilaterally improve their outcomes (Nash, 1950). Equilibrium models are effective methods of studying market competition as they closely reflect real markets with features such as:

1. Participants submit sealed bids to the System Operator which are cleared simultaneously
2. Participants interact frequently with one another (Repeated Game)
3. Participants are assumed rational

Techniques to study electricity markets have arisen using a number of different models of competition. Models of competition, such as Bertrand (Bunn and Oliveira, 2003) or Cournot (Borenstein and Bushnell, 1999) at the two extremes of market power, have a large impact on the participant behaviour forecasted in different situations. More moderate levels of competition in models such as Supply Function Equilibria (SFE), which was first applied by Green (1996) and is based upon the work of Klemperer and Meyer (1989) are often more appropriate. SFE models (Hobbs et al., 2000; Baldick et al., 2000), include the price quantity bid pairs of established electricity markets. An alternative, moderate form of competition, which is recently gaining popularity is the Conjectured Supply Function (CSF) Equilibria model (Diaz et al., 2012).

The principal problem of modelling electricity markets is the temporal and spatial balancing requirement. Most equilibrium models consider simple networks even though it has been shown that transmission has a major effect upon market power (Joskow and Tirole, 2000). Simplified network models are still useful for insight as the real system may be too complex to be modelled within the chosen competitive framework at the full network resolution level. Discussions regarding the depiction of the network and the effect upon equilibrium models can be found in Neuhoff et al. (2005) and Bautista et al. (2007c).

Electricity markets evolved beyond energy only markets to incorporate AS upon deregulation. Historically, AS were procured through the vertically integrated utility companies who had a vested interest in market security. In some deregulated marketplaces this vertical integration has been broken and reserve markets have been introduced. Reserve markets are designed to compensate participants who provide spinning reserve and other essential services. These ancillary service markets also interact with the energy markets and thus, generation company offer structures. At the system level there are different methods of procuring reserve (*N-1*, fixed percentage, manual requirements, probabilistic) which link the reserve requirement to the energy market. In these systems, generators may structure their offers to avoid reserve costs.

At the unit level the decision to provide ancillary services often incurs an opportunity cost as participants are partially constrained from participation in the energy market. Reserve providing generators must therefore optimise their portfolio of energy and reserve offers, not just their energy offers. Although energy offer optimisation has been considered in some depth (Anderson and Philpott, 2002a; Pritchard and Zakeri, 2003; Baillo et al., 2004; Neame et al., 2003; Anderson and Philpott, 2002b), the same level of scrutiny has not been applied to combined energy and reserve market offers.

Consider the model presented in Chapter 2 with *N-1* security requirements. In this model, the reserve requirement is inherently linked to the offers of market participants. If a unit is both the marginal risk setting unit and the marginal energy unit, the reserve price becomes incorporated into the energy price. Unit level considerations can also constrain the electricity market in complex ways.

In this chapter we consider the effect of reserve co-optimisation under an *N-1* market dispatch, based upon the model presented in Chapter 2. We present a SFE implementation across two nodes with a reserve constrained transmission line. The model is general, it may consider reserve constrained generation units and/offer reserve constrained transmission lines, across a number of nodes. In this chapter it is specifically applied to a two node market which is heavily influenced by the transmission network and market structure of the NZEM.

The results of this model are discussed in terms of transmission investment and IL participation. We show that in markets with deterministically procured reserve, a dominant reserve provider has strong incentives to block the dispatch of competitor energy offers by withholding reserve. This result is applied to transmission investment and the Grid Investment Test (GIT) in Section 3.3, and to IL participation in Section 3.5.

Literature Review

This section is not intended as an exhaustive summary of the general equilibrium literature, but instead an introduction to the attempts to incorporate reserve into equilibrium models. The combined energy and reserve offers form a multi product equilibrium. As the supply of reserve can limit the ability of units to generate at high capacity levels, the equilibrium reserve offer is inherently linked to market energy offers (and vice versa). Individual units are also constrained in their combined energy and reserve offers, although we do not consider this special case here. The inverse bathtub constraints, as illustrated in Figure 3.1, constrain the feasible operating region for a unit who offers both energy and reserve.

Whilst there does exist additional, general, literature on the concept of market power in reserve markets the majority of these are not applicable to this Thesis. In particular, we draw attention to the comments made in Chapter 1 where an attempt was made to indicate the usage of the term "Reserve" in this Thesis. The literature cited in the following section contains those pieces of work which align with the definition of reserve as stated in Chapter 1. Other pieces of work do exist which fall outside this definition, though sharing common names.

Two research groups have undertaken the majority of the research into equilibrium models of reserve constrained electricity markets. From 2005-2007 at the University of Waterloo, Guillermo Bautista published four papers focussing upon the formulation of equilibrium models in markets with AC power formulations, an extension from the DC formulations. From 2006-2008 Hossein Haghighat, also from the University of Waterloo considered the effect of market structure on incentives and the effect of different market clearing mechanisms in a competitive framework. We note that both groups were focussed upon the techniques of establishing equilibrium as opposed to market case studies which is the approach we undertake.

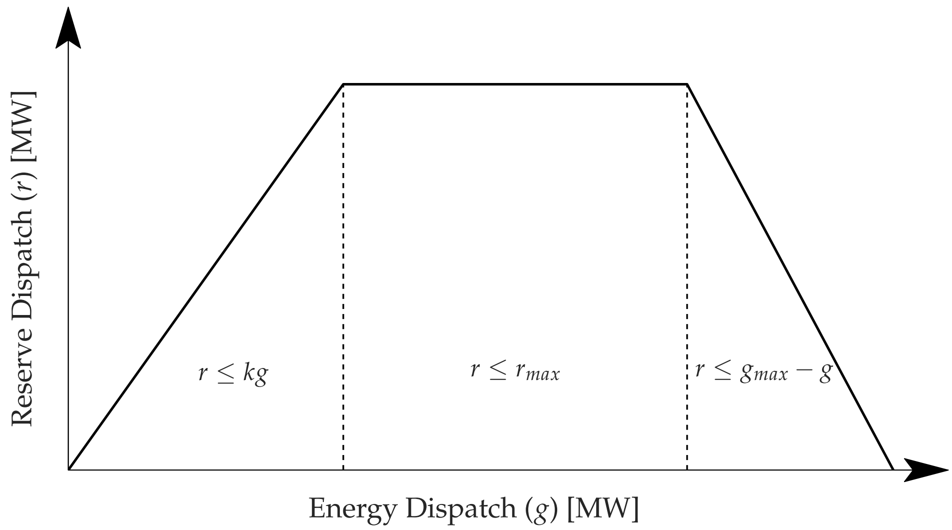

Figure 3.1: The inverse bathtub, a visual explanation showing the three separate feasible regions governed by separate linear programming constraints

The work of Bautista, Anjos, and Vanelli concerns the application of optimisation techniques to electricity markets. The group (along with two separate co authors on a fourth paper) discuss the requirement for detailed transmission networks which incorporate active power, reactive power, and voltage (Bautista et al., 2007c). The paper discusses the challenges faced by researchers who must choose which features to approximate and which to examine accurately and was pitched as a response to an earlier piece of work by Neuhoff et al. (2005).

In Bautista et al. (2006), conjectured supply functions were used to compute the opportunity cost between energy and reserve markets under oligopolistic considerations. Conjectured reserve price functions provide a measure of a generator's ability to influence the spinning reserve price in a theoretical setting. They show that even perfectly competitive spinning reserve markets may have an effect on energy prices. Bautista et al. (2007a) used a non linear programming approach to apply game theory within a reactive power market. They proposed a detailed AC formulation of the power system and use the competitive and Cournot frameworks to model competition. Finally, in Bautista et al. (2007b), the authors proposed an SFE model that extends the active and reactive power formulations to include spinning reserves. Though the reserve market is not the focus of this paper (instead, the wider problem of determining a quantitative equilibrium in a full AC power system is), the authors identify that the presence of spinning reserve markets induces optimising generators to forgo electricity market revenue in order to maximise total profits.

In Haghighat et al. (2007) the authors studied the interaction among suppliers, to develop an optimal bidding strategy for participants active in both energy and reserve markets. An SFE model is developed within a mathematical program with equilibrium constraints using two level optimisation. The authors illustrate that when capacity is fully utilised for energy and spinning reserve the prices of both products increase. However, the model utilised a "pay as bid" (not uniform pricing) approach to assess this. In Haghighat et al. (2008b) the authors appear to utilise the same model in order to understand the effect of market pricing mechanisms. The authors compare the "pay as bid" approach with the uniform pricing (UP) approach and analytically prove that the marginal clearing price is the same for both. We note that "pay as bid" approaches have been compared to "guess the final clearing price" in some discussions and it is unsure how this result applies in a practical setting. Haghighat et al. (2008a) appears to contradict their earlier result and indicates that market clearing prices in joint markets increase after a switching from uniform pricing to "pay as bid" payment mechanisms. The authors indicate that a multi generator game leads to both higher supplier profits and higher market clearing prices.

One of the earliest, albeit shortest, discussions of joint energy and reserve markets is expressed in Ma and Sun (1998). The short letter covers different techniques of reserve dispatch and presents experiences from the NZEM which indicated that the presence of IL leads to decreasing market clearing prices in the reserve markets. A final model as expressed in Chitkara et al. (2009) covers the provision of reactive power. This model is not specific to the co-optimisation of reserves, but is a useful example of a market with multiple competing products. The authors illustrate that in a two person game, prices settle near the market price cap. Different price cap strategies are presented and shown, to help mitigate some of the gaming of the generation participants.

3.2 Model Formulation

A simplified *N-1* security constrained model adapted from Chapter 2 has been adapted to the SFE framework. A simplified two person game with linear marginal energy costs and constant marginal reserve costs is presented in this section. Competitive models under *N-1* reserve constrained transmission are novel in the literature with prior approaches concerned largely with developing AC power formulation models under competition (Bautista et al., 2007b).

The model consists of a game between two profit maximising companies who offer energy and reserve to an independent SO, to satisfy demand subject to reserve constraints. Each company is modelled as a leader with the SO as a follower. The market is nodal (Schweppe et al., 1988) for both energy and reserve, with separate energy and reserve clearing prices. Reserve is modelled as a single product although an extension to a multi product case is possible. All reserve is provisioned through separate units and thus no constraints related to the inverse bathtub constraint are apparent. The model is solved using diagonalisation, with each of the two profit maximising companies taking turns to choose their optimal market offers, under an assumed state of their opponents offers. The following nomenclature is used throughout this chapter.

Nomenclature

n Node with generation and reserve units

i Company consisting of generation and reserve units

$x_{i,n}$ Generation dispatch from a unit located at node n belonging to Company i

$r_{i,n}$ Reserve dispatch from a unit located at node n belonging to Company i

$C_{i,n}$ The total cost of producing revenue and reserve for a company at a specific node

$R_{i,n}$ The total revenue obtained through dispatch for a company at a node

SP Strike price for any CFD contracts in existence

δ Quantity component for any CFD contracts in existence

π_i Total profit for the ith company in the market

$\beta_{i,n}$ Linear cost component of energy dispatch

$\gamma_{i,n}$ Quadratic cost component of energy dispatch

$\alpha_{i,n}$ Linear cost component of reserve dispatch

$\beta^*_{i,n}$ Submitted linear energy bid component to the SO

$\gamma^*_{i,n}$ Submitted quadratic energy bid component to the SO

$\alpha^*_{i,n}$ Submitted linear reserve bid component to the SO

λ_n Clearing energy price at node n

μ_n Clearing reserve price at node n

f Transmission between the nodes

σ_n Binary variable specifying the direction of the transmission flow

χ_n Risk variable specifying the largest risk setting asset

$\nu_{i,n}$ Shadow price of the risk setting generator dispatch

τ_n Shadow price of the risk setting transmission flow

ϕ Relaxation constant to assist in equilibrium convergence

Company Problem

The company problem is to choose submitted bid parameters to the SO in order to maximise their profit which are taken as revenue less cost. Each company has quadratic energy and linear reserve costs. The nodal cost, $C_{i,n}$, of supplying their energy, x, and reserve, r, dispatch at the specific node is thus:

$$C_{i,n} = (\beta_{i,n} + \frac{1}{2}\gamma_{i,n}x_{i,n})x_{i,n} + \alpha_{i,n}r_{i,n} \tag{3.1}$$

Participants receive revenue proportional to their generation output and the Marginal Clearing Price (MCP) for energy and reserve, along with any additional contract revenue. For completeness we assume that a company may have contracts for differences (CFD), with a strike price SP and quantity δ. We include these contracts to study the NZ government forced "virtual asset swaps" between participants in 2010 (Brownlee, 2010) detailed in Section 3.3. As such, the total revenue for each company at a node is thus:

$$R_{i,n} = \lambda_n x_{i,n} + (SP_{i,n} - \lambda_n)\delta_{i,n} + \mu_n r_{i,n} \tag{3.2}$$

The total profit earned by each company is thus the sum of their revenue less their costs across all nodes.

$$\begin{aligned}\pi_i = &\sum_n \{\lambda_n x_{i,n} + (SP_n - \lambda_n)\delta_n\} + \sum_n \{\mu_n r_{i,n}\} \\ &- \sum_n \{(\beta_{i,n} + \frac{1}{2}\gamma_{i,n} x_{i,n}) x_{i,n}\} - \sum_n \{\alpha_{i,n} r_{i,n}\}\end{aligned} \tag{3.3}$$

Under equilibrium conditions each generator attempts to maximise this profit function by changing their bids to the SO. We consider a lightly regulated electricity market where bids are not audited and do not have to equal true costs. Each generator is free to submit the modified parameters $\beta^*_{i,n}, \gamma^*_{i,n}, \alpha^*_{i,n}$ which may differ from their true costs. Prices (energy and reserve), as well as the dispatch instructions for each company, are determined via the SO clearing problem.

SO Clearing Problem

In a pool market the SO is required to ensure the stable operation of the power system. To accomplish this it uses the submitted price functions of the participants to meet an inelastic demand. As this demand is inelastic, prices are set via market offers only. The potential for infinite prices is averted through the introduction of two non-optimising companies who offer at cost. The Primal Optimal Power Flow (POPF) problem satisfies the demand subject to the security requirements, which are specified by the risk variable, χ_n, in each reserve zone. Risk has a locational requirement due to the riskiness of the various transmission lines and must be secured from reserve within its own zone. No maximum capacity constraints are considered, the purpose of the model is to study the effect of reserve constraints only. As such, the presented POPF is incomplete and is not intended to be a full representation of a grid. In particular, the use of $\sigma_n f$ is intended for a two node formulation. It may be extended to a wider grid, however in this form it depicts the balance between the NI and SI of NZ.

The primal problem may be initially written as a quadratic cost minimisation problem with objective function (3.4) and constraints (3.5)-(3.8).

$$
\begin{aligned}
\min \quad & \sum_{i,n} \{\beta^*_{i,n} x_{i,n} + \frac{1}{2}\gamma^*_{i,n} x^2_{i,n}\} + \sum_{i,n} \alpha^*_{i,n} r_{i,n} && && (3.4)\\
\text{s/t} \quad & \sum_{i \in n(i)} x_{i,n} + \sigma_n f = d_n \quad \forall n && [\lambda] && (3.5)\\
& \chi_n \geq x_{i,n} \quad \forall i, n && [\nu] && (3.6)\\
& \chi_n \geq \sigma_n f \quad \forall n && [\tau] && (3.7)\\
& \sum_{i(n)} r_{i,n} \geq \chi_n \quad \forall n && [\mu] && (3.8)\\
& x, r, \chi \geq 0 && && \\
& f \quad \text{free} && &&
\end{aligned}
$$

This is an optimisation problem with a convex objective function but it is not yet in a suitable form for embedding within the company profit maximisation problem. To achieve this we use the methods outlined in Wright (1997) and Mangasarian (1993) [1] for which we require the form:

$$\begin{aligned} \min \quad & \Theta(x) \\ \text{s/t} \quad & x \in X^0 \\ & g(x) \leq 0 \end{aligned}$$

To achieve this form we rewrite (3.4)-(3.8) as follows in (3.9)-(3.13).

$$\min \quad \sum_{i,n}\{\beta^*_{i,n}x_{i,n} + \frac{1}{2}\gamma^*_{i,n}x^2_{i,n}\} + \sum_{i,n}\alpha^*_{i,n}r_{i,n} \tag{3.9}$$

$$\text{s/t} \quad -\sum_{i\in n(i)} x_{i,n} - \sigma_n f + d_n \leq 0 \qquad [\lambda] \tag{3.10}$$

$$x_{i,n} - \chi_n \leq 0 \qquad [\nu] \tag{3.11}$$

$$\sigma_n f - \chi_n \leq 0 \qquad [\tau] \tag{3.12}$$

$$\chi_n - \sum_{i\in n(i)} r_{i,n} \leq 0 \qquad [\mu] \tag{3.13}$$

$$x, r, \chi \geq 0$$

$$f \quad \text{free}$$

[1] We have implemented the model using a slightly different formulation based upon quadratic programming methods found in (Panne, 1975) and the approach to linear complementarity found in (Cottle et al., 2009). In order to achieve equilibrium, the requirement for a zero duality gap at optimisation was also retained as a constraint within the model (Vanderbei, 2014; Bazaraa et al., 2013).

along with the following complementarity conditions:

$$\lambda_n\big(\sum_{i\in n(i)} x_{i,n} - \sigma_n f + d_n\big) = 0 \quad \forall n \tag{3.14}$$

$$\nu_{i,n}\big(x_{i,n} - \chi_n\big) = 0 \quad \forall i, n \tag{3.15}$$

$$\tau_n\big(\sigma_n f - \chi_n\big) = 0 \quad \forall n \tag{3.16}$$

$$\mu_n\big(\chi_n - \sum_{i\in n(i)}\big) = 0 \quad \forall n \tag{3.17}$$

$$\lambda, \nu, \tau, \mu \geq 0$$

These are embedded into each companies maximisation problem and solved for equilibrium. The full maximisation problem is the objective function (3.3) and the primal constraints (3.5)-(3.8), along with the complementarity conditions given by (3.14)-(3.17). In this case, optimality is ensured using the dual conditions (Panne, 1975), complementarity conditions (Cottle et al., 2009), and strong duality theorem (Bazaraa et al., 2013) for quadratic programs.

Technical Implementation

As this is a non linear (bi-linear) program it has been implemented using the LINGO optimisation tool, with the included non-linear global optimisation solver (Schrage, 2006). The solution is obtained by iteratively maximising each company's profits under the assumption of partial knowledge of the opposing company's position (diagonalisation). The assumed position is given by an intermediate position between their opponent's two most recent offers, using the relaxation methods of Contreras et al. (2004). Each offer is weighted by a variable ϕ in (3.18). Relaxation has been used as it can help with convergence issues. Without relaxation the iterative approach of each company is too aggressive, which leads to cyclic oscillations and no stable equilibrium. Iterations are halted once Nash equilibrium is identified by a sequential inability to improve profits for each of the optimising companies.

$$\beta^*_{j+1} = \phi\beta^*_j + (1-\phi)\beta^*_{j-1} \tag{3.18}$$

To ensure the equilibrium obtained is unique we choose multiple starting positions using a random number generator. If each starting location converges to the same final point we consider this to be equilibrium. We have identified an element of path sensitivity to the equilibrium process with potential jumps possible. The use of multiple starting location assists in the identification of these points. We do not require that the same price parameters must be submitted, in the quadratic SFE the company's may choose any combination of the variables β, γ, or α to arrive at the same location. The halting criteria is (3.19) and the full flow chart of the optimisation process is illustrated in Figure 3.2.

$$\begin{cases} \text{Halt}, & |\pi_j - \pi_{j-1}| \leq \Delta \wedge |\pi_j - \pi_{j-2}| \leq \Delta \\ \text{Continue}, & \text{otherwise} \end{cases} \tag{3.19}$$

We note that cyclic behaviour can occur when attempting to reach equilibrium. In this cyclic case each company assumes that they can, simultaneously, monopolise volume within the market at the (stable) final clearing prices. This occurs as the optimisation problem is for a single company only and assigns quantities appropriately. Profits for each company in this case range from zero to a maximum value, yet prices for the consumer are stable. Bautista et al. (2007b) define this situation as a probabilistic equilibrium. They state that since each company cannot improve their outcome under probabilistic considerations, it is still an equilibrium. Within the model as presented, the cyclic behaviour is

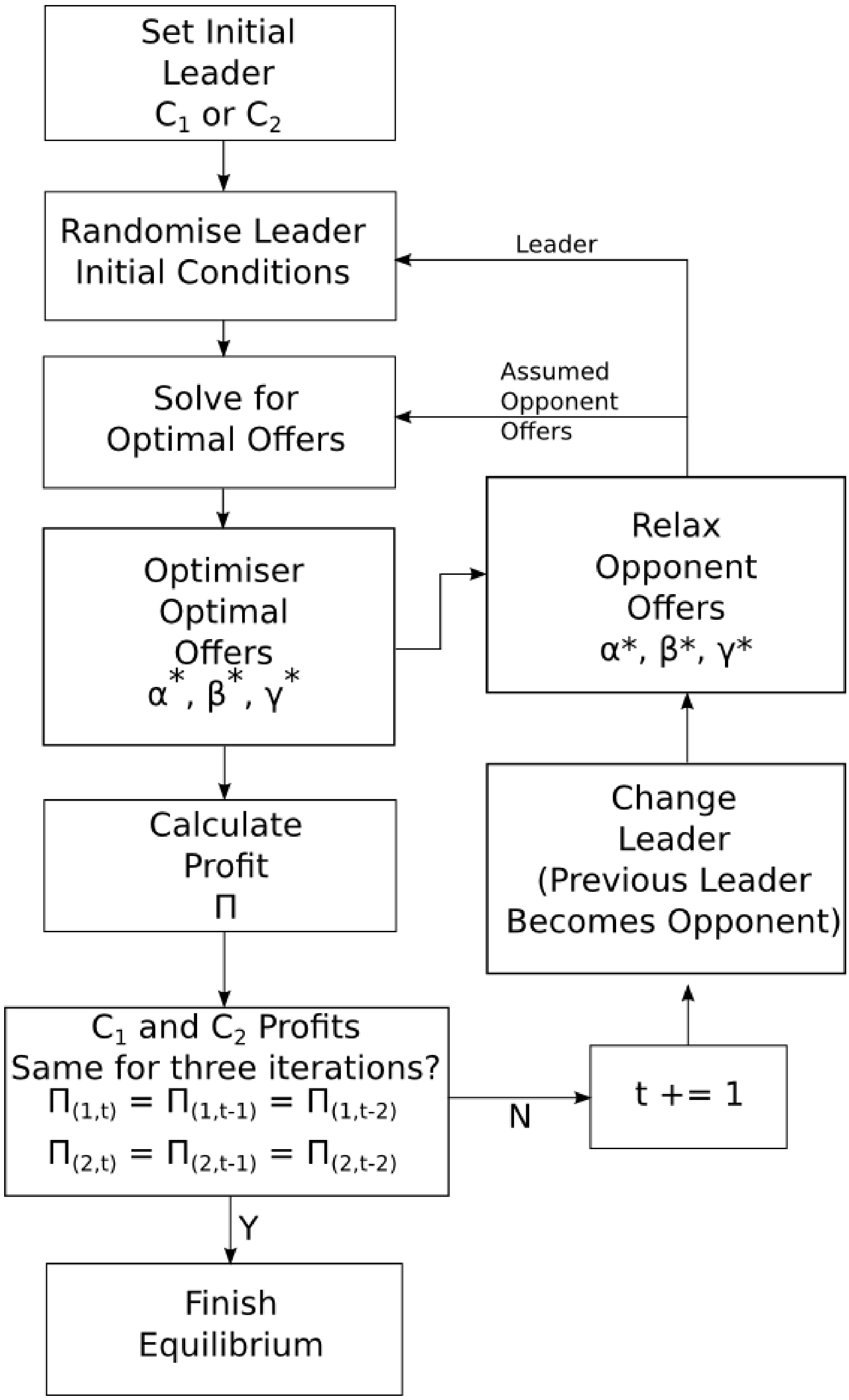

Figure 3.2: Process of arriving at equilibrium, Companies C_1 and C_2 take turns to optimise their offers under the assumed state of their opponents which is calculated by relaxing their opponents previous two offers. When profits remain unchanged for both participants for at least three iterations (both participants have moved twice or more), equilibrium is reached.

partially a function of the lossless formulation, as generation and reserve become pure substitutes for each other. It is most common in the case where reserve is procured to secure both generation units and transmission lines in a nodal reserve market.

3.3 Results

In this section we seek to understand a specific scenario, the effect of the geographical positions of participants at different nodes within markets with reserve constrained transmission lines. In general, transmission lines are seen as a mechanism through which market power may be exerted (Joskow and Tirole, 2000; Borenstein et al., 2000; Bushnell, 1999). A natural method of alleviating the market power has been to invest in transmission capacity. Increased transmission capacity opens an area for competition which improves consumer outcomes, although not necessarily through increased utilisation of transmission lines.

We extend upon the situation outlined by Borenstein et al. (2000) which considers a market with limited transmission capacity between two regions, with large generators acting as near monopolies at each end of the transmission line. In the joined markets, which were modelled under Cournot competition, a transmission line of limited capacity exists. The participants within the market saw incentives to constrain the transmission line, leading to their ability to monopolise the remaining volume (at a significantly higher price).

Borenstein et al. (2000) showed that if an improvement to the transmission line was commissioned, the principal benefits of the line could not be measured by assessing the energy transmitted on the line. Instead, the presence of the line changed the *behaviour* of the market participants in equilibrium. As they were no longer able to withhold and constrain the line, the participants instead competed on quantity in the standard Cournot fashion. This insight improved the understanding of transmission investment between markets. Instead of measuring the technical merits of a proposed asset, the competitive merits and effect on behaviour in the market place should be a primary consideration.

We seek to extend this result in the context of the NZEM. NZ has an electricity network consisting of two islands connected by a reserve constrained transmission line (referred to as the HVDC from now on). The HVDC line enables energy from the South Island hydro generators (owned by Meridian Energy and Contact Energy) to be transferred to the North Island population centres. This is a classic case of the market type studied in Borenstein et al. (2000) - transmission enabling greater competition. However, the NZEM has an *N-1* SCED and requires the Island based procurement of reserve to enable this transmission flow. In the North Island, the three main sources of reserve are: Interruptible Load (from a variety of participants), Hydro PLSR from Mighty River Power and Hydro and Thermal PLSR from Genesis Energy[2].

Consider the example shown in Figure 3.3 with two companies located either side of a reserve constrained transmission line. Reserve from companies at the receiving end of the line must be procured to secure the transfer of energy, reserve that is provided by the transferring companies competitors. Two companies, C_1 and C_2, optimise their offers to the SO in response to each other, with the companies C_3 and C_4 serving as a competitive cap on the market[3]. These competitive companies bid their

[2]A small quantity of PLSR is available from Contact Energy but this is inconsequential as it requires the procurement of expensive OCGT units.

[3]Due to the reserve constraints the participants can (as we will show later) monopolise the dispatch at their respective node. As we have formulated demand as entirely price inelastic this leads to prices being set to high quantities (infinity).

true costs to the market and do not seek to optimise in response to market conditions. We seek to understand the effect of C_2's reserve offers on the actions of C_1, capturing the interplay between the dominant hydro generators in each island. The cost parameters used in the scenarios are shown in Table 3.1. For convenience, all outcomes are specified in per MWh increments (assuming a dispatch period of one hour).

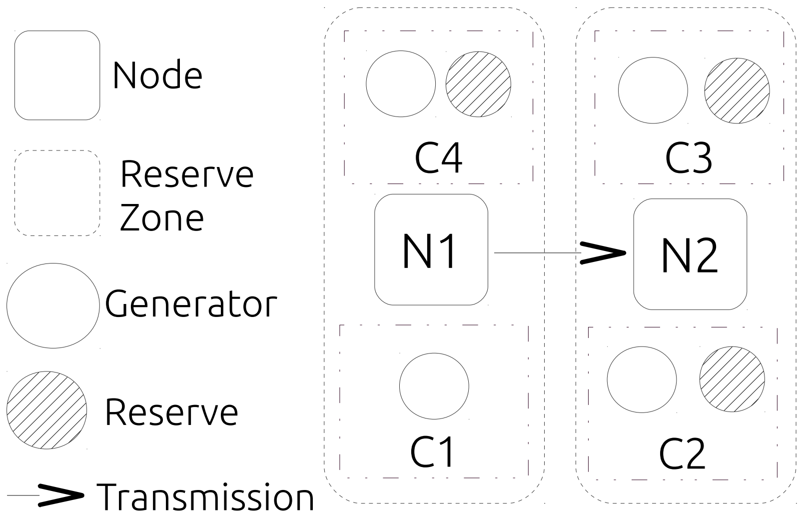

Figure 3.3: Two node market structure where reserve is procured to secure transmission but not generation, resulting in nodal based reserve prices and localised market power.

Table 3.1: Simulation cost parameters for all examples including identification of companies as cost bidders, or optimisers

Company	β	γ	α	node	Optimiser
1	5	1	-	1	Y
2	5	1	5	2	Y
3	150	0.05	40	2	N
4	150	0.05	5	1	N

Considering the result of Borenstein et al. (2000), we see a two node marketplace under three separate transmission regimes; the first, two isolated markets with no possible transmission between the two nodes. The second, an unlimited transmission capacity line which opens up each of the markets to competition from the other participant. In the third case, we use the same transmission line with reserve constraints. We do not consider the effects of reserve on generation at this point. The first two cases are a replication of the earlier result, with the third the reserve constrained extension in an SFE setting, as shown in Table 3.2.

Table 3.2: Effect of introducing non-reserve-constrained transmission and reserve-constrained transmission between prior monopoly controlled nodes

	No Transmission	Free Transmission	Reserve Constrained Transmission
λ_1	150	55.1	150
λ_2	150	55.1	150
μ_1	-	-	5
μ_2	-	-	58.7
g_{11}	10	9.5	10
g_{22}	10	10.5	10
r_{14}	-	-	0
r_{22}	-	-	0
f	-	-0.5	0
π_1	1350	384	1350
π_2	1350	416	1350

As expected, the introduction of the transmission line removes the monopoly situation. Prices are reduced from the competitive caps imposed by the two non-optimising generators. In this case, the line is arguably unused, transmission flows are just 0.5MW across the unconstrained line. As both generators are identical it is expected that a symmetric duopoly should arise with equal profits and flows. This does not occur in this case due to the iterative computational procedure followed. In a purely analytical case, such as Borenstein et al. (2000), the symmetric situation would resolve. Prices are still substantially reduced due to the increased competition, with generator profits reduced accordingly (although volumes remain similar). The competition benefits of the transmission line leads to increased consumer welfare.

The introduction of the reserve requirement in the third case study serves to return the monopoly state. The optimising participant, C_2, withholds reserve in order to prevent C_1 from being able to compete at n_2, retaining its monopoly. This returns the monopoly situation from the first case at n_2. Seeing that it is unable to compete at n_2, the optimising company at C_1 increases their offer prices until the cap is reached once more. By being blocked from competing at n_2 it is in their own best interests to monopolise quantity at n_1.

Thus, the optimal behaviour is for the lower cost generator to self withhold from the market. Any attempt to increase volume (by reducing prices) is ineffective due to the reserve constraint leading to self restriction. Placing this result in the context of the NZEM, the South Island generator Meridian Energy is at times blocked from competing in the North Island. Meridian with its vast hydro schemes has sufficient capacity to generate substantially more than they currently do. Yet, to do so would reduce their generation selling prices and thus, expose themselves to locational price risk for any contractual obligations they have.

The reserve price at n_2, (μ_2) is set by C_2 and is very high. Yet, at n_1 the reserve price (set by C_4) is just 5$/MWh. C_2 could attempt to increase volume by pricing at $144.9/MWh. However, this leads to a response by C_1 to prevent this occurrence. As such, profits for C_2 are reduced if they attempt to compete at n_1 as C_1 will respond, reducing energy prices. C_2

thus exerts market power in the reserve market (by withholding reserve) which leads to increased energy prices as they monopolise the energy dispatch at n_2.

We know from Cleland et al. (2014a) and Chapter 2 that energy and reserve prices become linked in the presence of a binding reserve constraint on transmission as (3.20). For transfer from n_1 to n_2, the energy prices (λ) between the nodes become linked by the nodal reserve price (μ) at n_2.

$$\lambda_2 = \lambda_1 + \mu_2 \tag{3.20}$$

If a participant has retail or contractual obligations at the receiving node, this price discrepancy and associated inability to increase volume is a source of risk. The appropriate response for the blocked generators is to limit their exposure at the nodes, where they are blocked from directly competing. This reflects the view of Figure 2.4, where large inter island price differences occur.

For the retail market in the NZEM this has the effect of theoretically reducing the willingness of participants to compete. New Zealand companies are vertically integrated "gentailers" who both own generation facilities and have large retail contractual obligations. During most trading periods the effect of reserve on electricity prices is negligible, however from Figure 2.6 we see that the effect on high spot market prices is substantial. For the spot exposed "gentailer" who sells in the South Island and buys in the North Island, this implies exposure in a significant number of trading periods. A natural response is to limit participation in the opposing island retail market without sufficient contractual cover. This forces the participant to undertake a pure retailer strategy, as opposed to a "gentailer" strategy. The presence of reserve constraints on transmission lines prevents them from securing their contractual exposure through their own generation facilities.

In other circumstances, for example a cap introduced to the reserve market, a non stable equilibrium results. The two participants drive up price or volume until the cap is reached, at which point the optimal response is to undercut the other generator. This patterns continues indefinitely in a stable series of steps. Introducing nodal reserve requirements upon both generation and reserve did not result in a stable equilibrium either. If the same reserve required to enable generation may also enable transmission the generator is placed at an inherent disadvantage. If C_2 prices their offer above the competitive reserve provider C_3 they forgo all potential reserve revenue and their energy offers may be undercut by lower cost offers from C_1 at the opposing node. In this case, C_2 seeks to retain control via the reserve market whilst also blocking C_1 to a certain extent, an impossible conundrum which has no stable equilibrium result.

Generation Case Results

We have also considered a variant of the transmission case where generation units at separate nodes are secured under *N-1* with reserve procured from that node. In this case, we vary the nodal reserve price at n_1 through modification of the reserve offer price of C_4. This explores the effect of reserve offers (and prices, as C_4 sets the reserve price at n_1) in one market upon the behaviour of geographically separate market participants. As the reserve offer price is increased at n_1 the competing generators respond by adjusting their energy offer prices. For the risk setting generator at n_1 this has two effects: Energy offer price decreases towards zero in order to remain competitive with transfers from n_2. Other generators at n_1 are able to capitalise upon the constrained generation output to capture market share. In particular, if reserve prices at n_1 are high enough the multiple risk setting pricing behaviour outlined in Section 2.3 occurs. In this situation, the output from the two energy units at n_1 are equivalent and the competing unit at n_2 is able to capitalise to gain volume to a certain extent. For example, when μ_1 is set to \$70/MWh *and* energy offers from C_4 are fixed at \$15/MWh, the final energy prices are \$44/MWh at each node. However, unlike in the free transmission line case C_2 monopolises the majority of the volume (75%) with the remaining volume split equally between C_1 and C_4. Companies with risk setting generator who are dependent upon the reserve market to enable their generation are thus at great risk.

The implications of these effects are most apparent for markets where generation units are *N-1* risk setters. Companies in these markets are discouraged from building plants with significantly greater capacity than other existing plants, as any shortfall in the reserve market will severely limit potential output. In these markets, generation plants will tend towards a standard upper capacity limit, as to exceed this point leads to uncertainty about the utilisation of this asset. Offer prices must also take into account the reserve market dynamics in place. Risk setting generation units who are competing at the price making end of the offer curve must price their offers after taking the clearing reserve price into account. Peaking generation unit may also be able price higher in the energy offer stack. These units have no risk setting component and are therefore not subject to reserve market limitations.

The net effect is to discourage investment in a generation unit whose capacity is a significant outlier within the market. Non-competitive reserve markets limit the ability of risk setting generators to behave competitively in the energy market as they must price their offers lower in order to be dispatched. This can lead to inefficient dispatches, as higher cost energy units without a reserve requirement may be utilised instead of a highly efficient (but high risk) base load unit.

In the NZEM this may partially explain why the three large CCGT units are of similar sizes (in this case 400 MW). To build a larger unit, for example the 600 MW units common in some other markets, would greatly increase the reserve market requirements. In many situations reserve constraints would be binding upon this enlarged unit. Thus, the offers for this unit would be explicitly linked to the reserve market provision. An assessment of the reserve offer stacks indicates that beyond 500 MW the availability of reserve is heavily linked to the presence of spinning reserve hydro units. At current prices, it is difficult to justify additional investment in reserve (either through IL or spinning reserve given that prices are near zero for the majority of trading periods) therefore, it is unlikely that large generation units will ever be a feature of the NZEM. Smaller units are favourable from a security constrained point of view, which reduces the consequences of a unit tripping, at the expense of potential (economic and operational) economies of scale.

As such, uncompetitive reserve markets don't just modify the optimal offer strategies of risk constrained generators. Instead, they also modify the incentives for building different forms of generation regardless of their expected utility within the energy market. This inefficient outcome is not due to the non cost based competitiveness of reserve constrained generation. That is, risky generation by design has an additional cost to secure. Instead, the inefficient outcome is due to the reserve supply cliff which tends towards an infinite marginal cost once the reserve supply is exhausted.

3.4 Grid Investment

In liberalised electricity markets, transmission is a regulated monopoly. The transmission infrastructure has significant economies of scale due to network effects and is therefore an instance of a natural monopoly. In return for the sole exclusive right to operate transmission lines within an area, grid owners are heavily regulated. For many, there exists limits upon how they may charge, which is often linked to the cost of the installed capital base. For market participants extensions to this capital base are a potential bone of contention and participants are prone to disputing the necessity of transmission assets. Regulators will only permit lines to be built if the grid owner can show definitive economic (or security) improvements as a result. These improvements may be direct, or related to competition (Rosellon, 2003). Alternatively, some grid owners have begun to invest in transmission projects to enable renewable energy projects (Parsons-Brinckerhoff, 2007) which is reliant upon transmission to be competitive with thermal units located near population centres.

In markets with security constrained dispatches, the risk profile of generation and transmission assets is a factor in decision making. Linearly increasing an assets capability leads to significant reserve requirements in these situations and is thus largely fruitless. As such, in *N-1* markets the tendency for investments is towards many smaller investments, rather than singular large ones. This is also true for transmission investments. Under *N-1*, only a single line must be secured with reserve and therefore multiple parallel lines are advantageous.

The HVDC interconnection in the NZEM has recently been upgraded from a monopole arrangement with a 700MW capacity to a bipole with an upper capacity limit of between 1240MW and 1400MW. Before the upgrade transmission flows were rarely near the thermal limit of the single line as security considerations limited transfers. Under the new configuration the risk profiles of the HVDC interconnection have been modified as shown in Figure 3.4. This figure illustrates the frequency of different HVDC flow conditions under the two different risk profiles. The risk profiles were obtained from the GDX files[4] that the Electricity Authority releases for which the HVDC pole capacity levels may be obtained.

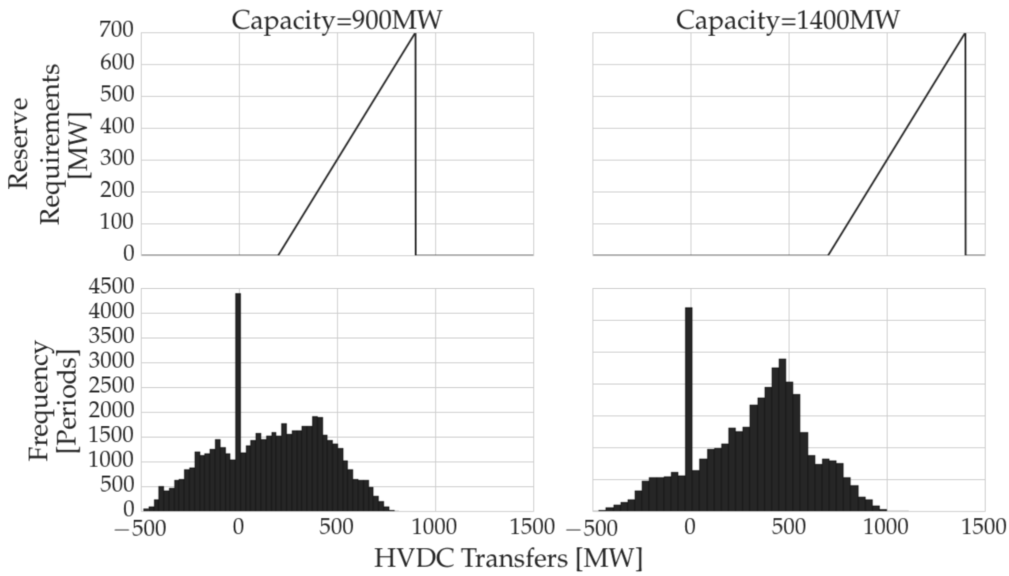

Figure 3.4: Risk profile of the HVDC interconnection with frequency distributions of operation for two different modes of operation. Note that transfers did not significantly increase in the second case near the total capacity as it is unneeded. Instead, the reserve requirements are significantly reduced. What is not represented in this diagram is the seasonal component to HVDC transfers which we have not adjusted for.

In the context of the equilibrium model presented in this chapter we see the primary benefit of the upgraded HVDC interconnection as the modified risk profile, not the thermal increase in capacity. To obtain high

[4]A GDX file can be used to resolve the complete market dispatch using an the regulator developed replica of SPD, vSPD. As such a GDX file contains information about transmission outages, line limits, ramping constraints and nodal demand. This resolution is significantly higher than what may be obtained through other sources, at the expense of being in a format which is difficult to work with.

levels of HVDC transfers requires a particular combination of factors; SI capacity must be high, SI load must be low, NI demand must be high, and the *"right"* NI generation units must be operating in order to provide the requisite reserve[5]. The modification of the risk profile alleviates the ability of generators to withhold strategically and should enable greater competition. SI generators will be able to take larger contractual positions and inter island price separation should be reduced.

In the NZEM (and some other markets) Grid Investment Tests (GITs) (Boyle et al., 2006) are regulator applied assessments of the usefulness of a regulated transmission investment. Traditionally these assessments have assessed the usefulness of transmission investments on the basis of competition in the energy market. This chapter indicates that such assessments may be incomplete. As the reserve market can influence the optimal energy solution it must be accounted for when considering the investment of risk setting transmission assets.

3.5 Interruptible Load Participation

Reserve markets are often less competitive than energy markets due to the greater technical barrier to market entry (as well being significantly less lucrative). To participate in the energy market a unit must only provide a stable source of energy to the grid, indeed there is also provision in energy markets for units who cannot follow dispatch instructions such

[5]This is an interesting problem in itself. How to configure a group of power stations in order to maximise the transfer of energy between two islands under a *N-1* reserve constrained transmission line. Station capacity, the availability of spinning reserve, and the relative distribution of demand between the two islands (relative to the total island generation capacity) are all important considerations. Partially due to the rarity of this combination of factors in a market (as opposed to internalising the problem within a centrally owned monopoly), it is unlikely that HVDC transfers will reach maximum levels in the NZEM.

as wind and solar. Reserves, due to their critical security function within the grid, have reliability and technical standards which must be maintained. As the reserve market is significantly less lucrative than the energy market and due to the technical requirements for market entrance, many markets, such as Spain, have retained mandatory provision for some services (Lobato Miguelez et al., 2008) in order to ensure sufficient supply.

In most markets there will be more than one participant who is able to provide the marginal MW of reserve. However, the equilibrium model presented here predicts that a provider will withhold reserve if they are in a monopoly position. For example, in the NZEM when reserve requirements begin to exceed 450MW, only a single participant must withhold reserve for the *N-1* security constraint to bind.

A natural market experiment occurred in 2012, a "dry" year in the NZEM. During "dry" year conditions HVDC transfers are southward and energy flows from NI thermal units are used to serve SI demand and retain water in the hydro reservoirs. The SI FIR and SIR reserve markets are significantly less liquid than the NI market, consisting of just two generation companies, Meridian and Contact Energy, and one IL provider, the Tiwai Point aluminium smelter. In 2012 Meridian Energy purchased the rights to offer the IL from Tiwai Point as they saw fit. They proceeded to use this dominant market position (at that point controlling over 50% of the SI reserve) to limit HVDC flows by pricing reserve in the hundreds of dollars. This is the result that is predicted in Section 3.3 if a participant is able to take a dominant reserve market position. The supply stacks in the SI FIR market for a specific period in this situation are shown in Figure 3.5. Meridian Energy was reprimanded by the Electricity Authority (NZ regulator) for this action (Hall, 2012).

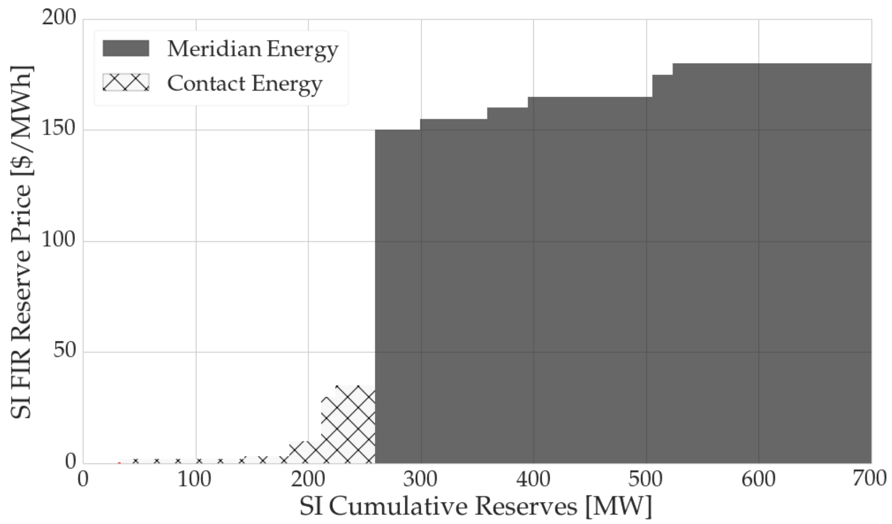

Figure 3.5: Supply Stacks of the SI FIR market during the 2012 dry year, noticed how Meridian controlled reserve (Blue) is priced significantly higher than Contact controlled reserve (green). In this situation Meridian had purchased the rights to offer the Comalco Smelters IL reserve and priced it significantly higher than normal leading to high reserve prices (and limited HVDC transfers).

The introduction of additional IL to the market can alleviate these market power issues. IL can be considered the CR equivalent of base load and unlike spinning reserve, has no opportunity cost in the energy market. Increased IL availability in a market increases the threshold at which spinning reserve units are required to supply reserve. This has two effects:

1. It reduces market power in the Instantaneous Reserve markets
2. It releases generation units from spinning reserve duties and therefore increases the capacity available for energy whilst alleviating the co-optimisation constraints.

These co-optimisation constraints are not negligible. To illustrate their effect upon the electricity market we have developed a software tool for the NZEM known as Tessen (Nigel Cleland, 2014). Tessen (a form of Japanese Fan), produces a visual representation of the fan curve approximation (Drayton-Bright, 1997) to assess the feasibility of energy and reserve offers (with price). Figure 3.6 visualises the combined energy and reserve offers for the Maraetai Station, owned by Mighty River Power.

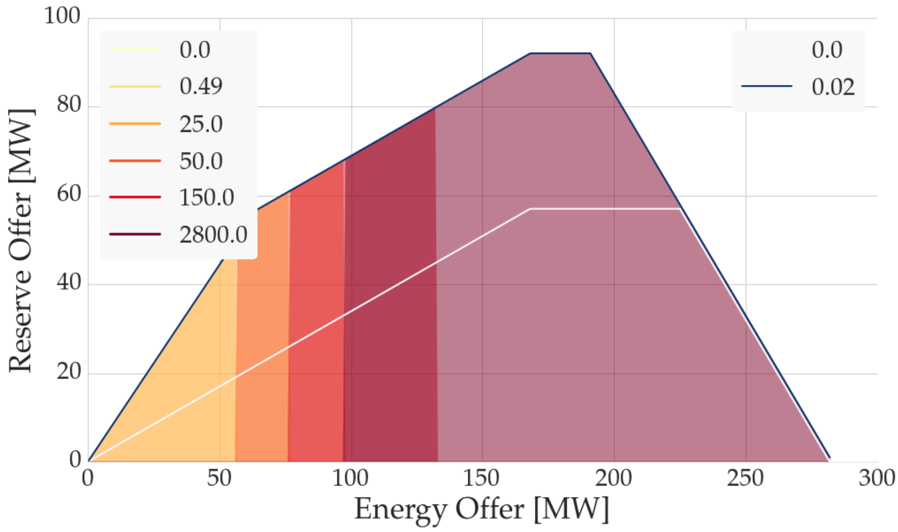

Figure 3.6: Combined energy and reserve "Tessen" diagram for Maraetai on October 3^{rd}, 2013, for Trading Period 19. To obtain the "low cost" reserve the associated energy offer tranche ($2800/MWh) must be dispatched. The upper left legend refers to energy offer prices and the upper right legend refers to reserve offer prices.

For this trading period the Maraetai station had two reserve offers at 0c and 2c, respectively. Energy was offered in five tranches, up to a maximum of $2800/MWh for the final tranche. The area under each of the contours represents the the feasible combinations of energy and reserve, at each reserve and energy price level. As seen in the later part of the graph, to obtain the full contingent of reserve offered at both required the dispatch of the $2800/MWh energy tranche. This situation was examined theoretically in Section 2.3.

We do not see this situation as an attempt to manipulate the energy market through the manipulation of reserve market offers (however, we do note that Maraetai was marginal for both energy and reserve). Prices for both products reached \$1600/MWh during the period. We recognise that a substantial amount of contracting activity was occurring due to HVDC testing. Given the shape of the offer stack, it is more likely that the company in question did not fully verify the technical feasibility of their offers, given the contractual position they were taking. The occurrence of such periods indicates that spinning reserve can be used to exert market power in subtle ways. In this situation, the reserve at 2c was offered at low cost to the market, but was physically unobtainable without energy prices reaching into the thousands of dollars.

A question arises, given the rarity of this situation are there any conclusions to be drawn as to the effect on the total market? The question is a subtle one which is linked to the readers framing. We have raised it to illustrate the true *potential* of such a situation in an electricity market. In chapter 2 we identified the potential for such a situation to arise through enumerating the mechanisms. In this piece of work we have identified a real trading period with the theoretical behaviour. As such, researchers and regulators (not to mention competing generators and spot market exposed consumers) must be aware of the consequential effect on both electricity and reserve prices.

Finally, the identification of market power exertion has always been difficult in electricity markets. Identifying when participants are have both the *means* and the *motive* to unilaterally influence the energy market is difficult. The mechanism illustrated here is a subtle manifestation through which spinning reserve may be offered to the energy market at a low *nominal* price and a high *effective* price due to the energy dispatch link and the proportionality constraint.

IL providers do not have the same constraints upon dispatch and thus, the introduction of unit level reserve constraints to the energy price cannot occur. Unfortunately, for IL participants the benefit they obtain from the market is sensitive to the total quantity of reserve supplied. Binding constraints make up a significant portion of reserve revenues and alleviating them decreases prices substantially. Direct Connect IL consumers see a partial hedging mechanism to IL provision, which helps to protect them against a particular class of high spot prices. Aggregated IL providers see no such benefit. For these participants, revenue obtained from the market must outweigh the costs of participation. In the medium to long term, hedge premiums (and retail contracts) may be reduced as generators are exposed to less reserve risk, although whether this benefit will be passed to the consumer is a different consideration entirely. In electricity markets prices are downward sticky.

3.6 Discussion

An overview of papers in the field of competition study in electricity markets has shown that limited literature exists on competition in co-optimised reserve markets. Energy markets are much larger in size than reserve markets and researchers are often predisposed towards targeting the biggest objectives first. This approach is logical in large North American and European markets where reserve requirements are low relative to generation capacity. This does limit the applicability of the large models to countries with small grids. In these countries reserve requirements can be large and the introduction of co-optimised reserve can have a significant impact upon participant behaviour. An energy only assessment loses validity in the case where participants may influence the energy market through secondary concerns.

We have shown in Chapter 2 that the reserve market influences the energy prices and we have identified empirical situations of the relationship between energy and reserve prices. This chapter covers the influence of these constraints upon the competitive incentives seen by consumers. In a theoretical SFE setting, the participants withhold reserve in order to restore monopoly profits. A participant in the NZEM attempted a similar strategy by seeking to control a dominant reserve market position in 2012. The reserve withholding strategy is most effective in situations where reserve has a locational requirement. Locational reserve markets will be less competitive than a locational energy market if reserve cannot be transferred between nodes due to a transmission line acting as the risk setting asset. Thus, participants may have situational market power which they can use to influence the final clearing dispatch.

To alleviate this market power two potential strategies exist:

1. Modify the procurement method of reserve
2. Increase the aggregate supply of reserve within the constrained zone

The competitive effects identified in this chapter are specific for *N-1* procurement of reserve and we note that this is not the only method available. A different procurement methodology will not have identical mechanisms through which reserve may bind in the electricity market. Methods based upon a fixed percentage of demand, a manual risk, or a probabilistic method, should not have such competitive problems. In these cases, the link between the dispatch of generation and transmission assets is not as tightly coupled with the reserve dispatch. Breaking this tightly coupled link removes a mechanism through which participants may exert market power.

Chapter Summary and Contribution to the Literature

This chapter has extended the assessment of co-optimised reserve markets under a competitive setting. A Supply Function Equilibrium model has been developed in a two player setting. The model predicts that reserve withholding will occur in order to limit the dispatch of risk constrained assets. Observations from the NZEM corroborate this theoretical result.

Within the literature the inclusion of reserve co-optimisation in equilibrium models has been covered by two major research groups. The first of these sought to develop a series of models to cover the implementation of full AC power flow models under competition. A brief section in Bautista et al. (2007b) discussed spinning reserve generators, although this was not explored in depth. This chapter represents a novel extension to this earlier work by directly exploring a reserve market participant who seeks to control energy prices by changing their reserve offers. Furthermore, while allusions to competition in co-optimised reserve markets under *N-1* security have been presented within the literature, this work represents the first significant undertaking to focus on the specifics of spinning reserve generator dispatch under equilibrium.

Part II

Application to IL Consumers

Chapter 4

Optimising Load Curtailment for IL Consumers using kNN

In this chapter, load curtailment for an Interruptible Load (IL) consumer is considered. This form of consumer may be compensated by reserve revenue in periods with high electricity prices - when non IL consumers would ordinarily curtail. A kNN model has been presented to classify trading periods ex ante. The model assesses the likelihood of sufficient reserve revenue occurring during a trading period which has high energy prices, for the consumer to continue operation.

The model uses publicly available information on hydrology, thermal availability, demand, as well as temporal information about a specific trading period (including time of day, season and recent occurrences). A number of trading periods which are mathematically similar are identified. These are used to estimate the optimal curtailment response for an IL consumer. The kNN model is able to correctly classify 95% of trading periods under some configurations and a profitable demand response strategy has been developed based upon this model.

4.1 Introduction

Motivation and Hypothesis

Electricity prices are complex time series which contain information on weather patterns, demand, hydrological levels, market power, and technical outages. They are obtained by solving large mathematical programs across distributed networks. Large prices spikes at isolated nodes are possible, as shown in Figure 4.1, where the price spread across four separate nodes is over \$2000/MWh. For large electricity consumers who are exposed to spot market prices, these price spike imply short term financial risk which can be hedged.

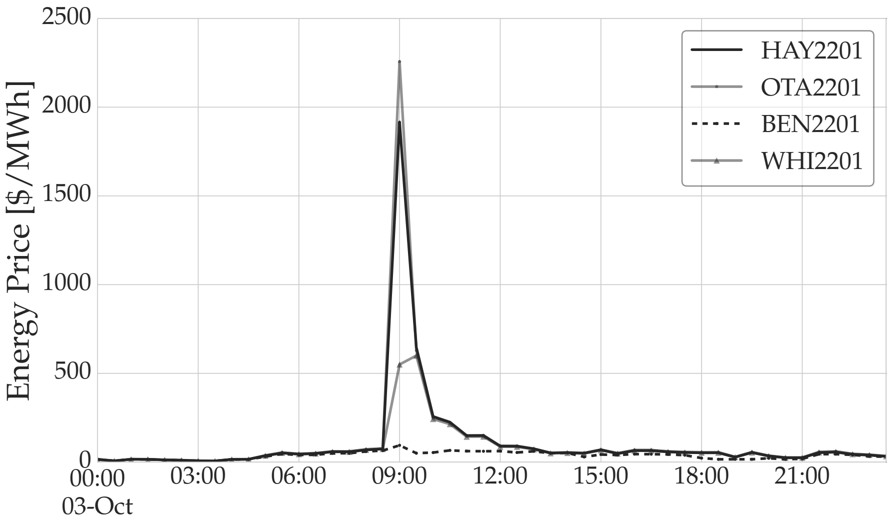

Figure 4.1: Electricity spot price for four New Zealand nodes, Benmore (SI), Otahuhu (NI), Haywards (NI) and Whirinaki (NI) on October 3rd 2013. Note the temporal and spatial variance which occurs during the energy price spike.

The practical insights from theoretical models, such as the exploratory linear program presented in Chapter 2, are limited. Capturing the complexity of an electricity market requires simplifications and assumptions about how participants will act towards one another. The network itself becomes simplified, a shadow of its former self in the attempt to reach a degree of mathematical convenience.

By taking advantage of the net participant positions in co-optimised electricity markets and assessing how reserve constraints link into high energy spot prices, an alternative strategy is possible. Demand Response for IL consumers in co-optimised markets has an additional layer of complexity. Instead of responding solely to energy prices, the IL consumers must also take into account reserve market revenue in a trading period. As prices between markets are linked (Chapter 2) and are not known *ex ante* the net participant position is difficult to forecast. Forecasting models that assess when reserve market constraints are binding during periods of high spot prices are valuable to these companies. In this chapter, a method to forecast when reserve constraints are binding based upon the k nearest neighbours technique is developed and explored for a company in the NZEM.

It is not possible to obtain the full set of information surrounding an energy price, for one, the contractual positions of energy companies are not publicly disclosed. Models therefore must make assumptions about participant behaviour and their effect on market prices. This knowledge gap is a disadvantage for small companies and consumers. Large companies hire and maintain dedicated teams of individuals who analyse market positions and energy prices, an advantage over smaller entities. For consumers, the economies of scale to support this expenditure are not present - introducing an asymmetry in available information and sophistication (Ramos et al., 2013). Consumers instead have rudimentary processes in place, simple decision heuristics hard won over time from often bitter practical experience. These are often reactionary and may not be optimal in the current market environment.

This asymmetry has led to many consumers hedging and therefore opting out of full spot market participation in return for price surety. Electricity markets need demand elasticity and time of use pricing in order to operate efficiently. This self withdrawal therefore impacts all consumers and the wider market efficiency, as it limits the pool of available responsive consumers (Kirschen, 2003; Cramton, 2003; Borenstein et al., 2002b). Tools which enable consumer participation within the spot market can have wide systemic benefits. However, as these systemic benefits are external, the tools must first show an internal advantage before implementation.

Review of Available Literature

Electricity prices have long been studied by researchers, as it is an attractive field due to the sheer volume of information available which facilitates the application of numerous analytical techniques (Aggarwal et al., 2009). These include time series approaches (Lora et al., 2004; Tipping et al., 2004), statistical approaches (Benth et al., 2007; Li and Flynn, 2006; Guthrie and Videbeck, 2007, 2002; Weron, 2007), Neural Networks (Lora et al., 2002; Amjady and Keynia, 2010; Szkuta et al., 1999; Catalao et al., 2007, 2011), Nearest Neighbours (Lora et al., 2007; Zhao et al., 2005), Clustering and Classification (Martinez-Alvarez et al., 2008; Zareipour et al., 2011), as well as Agent Based methods (Young et al., 2012; Zhou et al., 2009), and Support Vector Regressions (Gao et al., 2007).

Although a significant amount of literature has been produced, two clear gaps are apparent; price spike forecasting models and reserve price forecasting models in co-optimised markets. Electricity price spikes have a clear effect on volatility within electricity markets which can influence hedge premiums. In Zhao et al. (2005) the authors attempt to develop a generalised framework for assessing electricity price spikes. The authors use a Naive Bayes classifier to assess electricity price spikes and present a number of factors that influence electricity prices, such as demand and availability of interchanges. In Amjady and Keynia (2010) a neural network model is presented. A key feature of the model is the assumed knowledge of the price two time steps before, $P(t-2)$. This feature explains a substantial degree of model accuracy. Commonalities between both models include the selection of appropriate features and classification of trading periods.

The co-optimisation of electricity markets and the relationship between energy and reserve prices has not been explored in the forecasting literature. As such, the current energy only price forecasting models are insufficient for IL consumers to optimise their actions under uncertainty. Co-optimised markets have unique features which may be exploited by the IL consumer. In particular, as indicated in Chapter 2 a (causal) relationship between high energy prices and reserve constraints exists. Consider Figure 4.2, which illustrates the link between energy and reserve prices for specific trading periods. All points below the slope of 1 indicate periods where reserve revenue is offsetting the energy consumption cost. For these periods, a simple energy price forecasting model would be insufficient for the site to optimise their consumption level.

Methodology Used

In this chapter, a tool is developed to assist in the decision making process for a large industrial consumer with an associated IL offer. This tool is a form of Decision Support Tool (DST) and is designed to work in con-

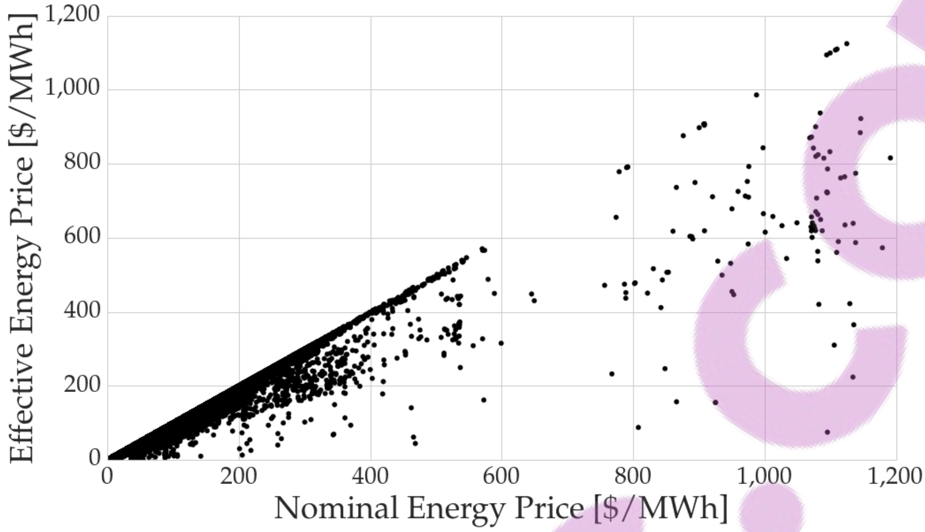

Figure 4.2: The effective energy price for a consumer in terms of the nominal electricity price, less the potential for reserve market revenue. This price assuming an equal relationship between consumption levels and reserve offers in the New Zealand electricity market from 2008 to mid 2014 and is given by $\lambda_{effective} = \lambda_{nominal} - (\mu^{FIR} + \mu^{SIR})$.

cert with decision makers, not instead of them. DSTs differ from other tools as they produce information which is designed to be used by people. Other tools may produce information designed to be used in automated software. For an example, consider the difference between Value Investing and High Frequency Trading. Both may use similar input to their tools but the former produces information used by an individual decision maker, whereas the latter produces automated machine usable actions.

We have developed a DST which uses the k nearest neighbours (kNN) technique. kNN is a relatively simple method of undertaking a non parametric regression to relate a large source of input data to a specific output. Consider a single output data point. This point has an associated vector of information about it which contains all of the *ex ante* known data points. The kNN technique uses this *ex ante* vector to find a selection of output data points which closely resemble the target situation. This selection (consisting of k points) is used to predict the value for the unknown output point through a weighted (or linear) combination.

Other models, such as multivariate regressions and other statistical techniques, have been considered and discarded. These models which map a collection of inputs to a defined output are powerful, but can be limited in their ability to adjust to major market shifts such as regulatory changes. The kNN technique can handle such situations by comparing recent data points which are mathematically similar, to predict the *ex post* component. The kNN points used in the prediction are the set of vectors which minimise a distance metric across all of the considered information. This is illustrated mathematically as follows.

Consider a vector v_{t+1} with features $x_1, x_2 \cdots x_N$ and a desired target y_{t+1}. Assume there is a set of vectors V containing inputs $v_1, v_2 \cdots v_t$ for which we have information of the desired target y_t. This set of vectors represents our training database of points with the latest vector, v_{t+1} representing the point for which we are trying to make a prediction.

We compute a distance metric, for example the Euclidean distance (4.1), to rank each of the vectors in V according to their closeness to our test vector v_{t+1}. For a vector, v_i, the distance metric is thus:

$$d(v_{t+1}, v_i) = \sqrt{(x_{t+1,1} - x_{i,1})^2 + \cdots (x_{t+1,N} - x_{i,N})^2} \tag{4.1}$$

The k closest points are determined by computing the distance metric for all such points and ranking the metrics by minimum distance. Each of these points has a value for y_i attached to it, which is then used to predict the value of y_{t+1} for the new data point v_{t+1}. This typically occurs through simple aggregations, (4.2), which may be weighted or non weighted accordingly. In the non weighted case, $w = 1/k$. Alternative schemes may weight the contributions by the associated distance metric, d_j (4.1).

$$y_{t+1} = \sum_{j=1}^{k} w_j \times y_j \tag{4.2}$$

The technique is simple to understand conceptually and is not a black box to the end user. Other techniques, such as neural networks, may produce difficult to grasp networks of non-linear aggregations. As these networks may lack first principle knowledge, they are less suited as DSTs due to the break in the relationship between contextual information and outputs. DSTs are often required to support decision making not to make the actual decision themselves and thus a clear relationship between input information and output advice is required.

The remainder of this chapter is separated into two parts. In Section 4.2 the relationship between electricity prices and different factors such as load and hydrology is explored. Based upon these factors, a modified approach to kNN modelling is developed in Section 4.3, to take advantage of the relationship between price spikes and reserve prices. The results presented in Section 4.4.

4.2 Prices in the NZEM

Electricity prices may be modelled using a large number of factors. The classical view of electricity prices is that they increase with demand, through the relationship between the load duration and price duration curves. As the demand for electricity increases, more expensive generation units are dispatched, leading to increased prices under the marginal pricing system. In a thermal dominated market this framework can work well. Generation capacity is a scarce commodity and prices increase with demand, up to the Value of Lost Load (VoLL) at which point it becomes economically efficient to shed demand as opposed to serving it.

Markets with significant reservoir hydro or intermittent renewable generation break this pattern. Intermittent generation sources are often treated as a negative source of demand. In Wind-Thermal markets the relationship between energy prices and net demand (not total demand) is relevant[1]. As wind varies, prices in turn will vary for different total consumption levels. The thermal only orientation is less appropriate for hydro dominated markets such as New Zealand (NZ) or Norway. The fuel cost for hydro units is the *economic opportunity cost* of releasing water from the reservoir (Halliburton, 2004). This water cannot be used to serve a unit of demand at an unspecified point in the future (potentially at higher prices) if it is released today. As such, the marginal cost of hydro units is sensitive to system conditions. Two trading periods, which are equivalent from the point of view of demand, may have different energy prices due to changes in hydrology.

Consider Figure 4.3, which depicts the distribution of energy prices in 10% bands, ranging from 10-90% for total NZ demand at the Otahuhu reference price node. In general, electricity prices increase with demand, although a wide distribution of prices at each demand level exists. At peak demand levels electricity prices range from \$100 to \$400/MWh.

The NZEM is a hydro dominated electricity market and lake levels have an effect upon energy prices, as shown in Figure 4.4. Periods of low inflows (and therefore reduced reservoir levels) are important to market

[1] This assumes a low penetration of intermittent generation into the market. Thermal units cannot ramp instantaneously and must be dispatched for extended durations. In markets with high intermittent generation penetration excess energy (wind or solar) must often be shed in order to enable stable thermal operation.

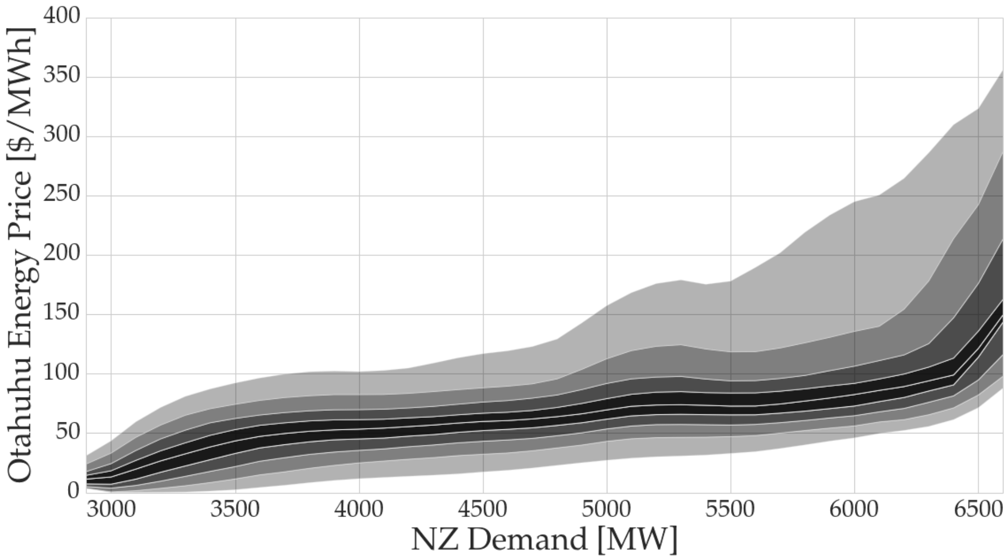

Figure 4.3: Relationship between nodal energy prices at Otahuhu and total New Zealand electricity demand for all periods from January 2008 to July 2014. Prices are presented in distribution bands of 10% ranging from 10-20% in the first band, to 80-90% in the last. The darkest bands refer to the median bands.

participants. During these periods, the average electricity price significantly increases for a sustained period of time (such as the 2008 and 2012 dry winter months where energy prices were many times the average) (Goodwin, 2006). Participants must mitigate their exposure to weather conditions through careful management of generation and contractual portfolios. Planning models such as SPECTRA and SDDP have been developed to estimate the opportunity cost (fuel cost) of water for hydro units (Miller, 2009; Halliburton, 2004; Pereira and Pinto, 1991).

A natural seasonal component to hydro reservoir levels exists in the NZEM (for example, see the lower decile component of Figure 4.4). Market participants recognise that low lake levels in Autumn, as demand increases up to the winter peak, is a greater concern than low lake levels post winter as demand decreases and spring inflows are expected to occur. To account for the temporal nature of lake levels, we adjust

Figure 4.4: Monthly average energy spot prices at the Benmore (South Island) node from January 2008 to March 2014. Lake levels are for all New Zealand lakes using data from NIWA and are taken as the monthly average. The lower decile hydro demand was calculated daily from the past 88 years of data and is a common reference point in the NZEM, for example in hydro risk curves.

the hydrological storage level by the lower decile figure and present distributions of price compared to the relative hydro storage level in Figure 4.5. Variants of this approach have been used to incorporate hydrology within market spot prices (Tipping et al., 2004; Young et al., 2012). In this case we have used (4.3) to represent hydro storage levels. Where L is the current hydro storage level, $L_{Relative}$ is the relative amount and $L_{10\%}$ is the bottom decile storage level for the specific day of the year, taken from a dataset of the past 88 years of hydro storage data.

$$L_{Relative} = L - L_{10\%} \tag{4.3}$$

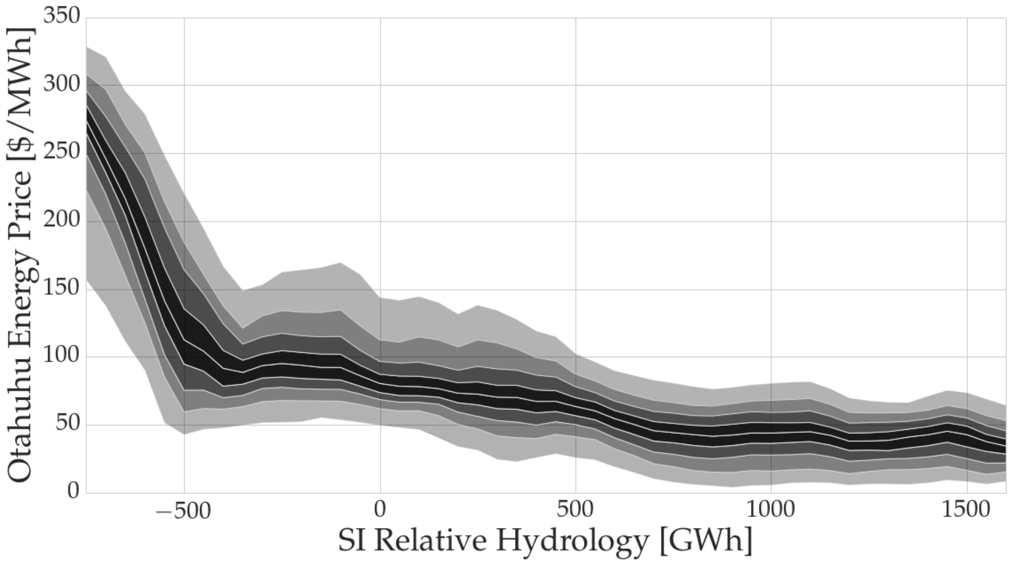

Figure 4.5: Relationship between South Island energy prices at Benmore and relative South Island hydrology. The relative hydro level is calculated using (4.3).

High Spot Prices

A hydro-demand based model is often sufficient to forecast average electricity spot prices in the NZEM. However, they do not explain the variability which can occur in trading periods which leads to high spot market prices. A spike in the electricity price may be considered as a period which falls outside the mean. The precise definition of a price spike may vary from market to market. In this chapter, we will later define a high energy price spike in terms of the curtailment condition for a consumer of energy.

To understand high electricity prices it is useful to assess the conditions associated with a high energy price. Not the prices associated with a specific set of conditions, which was shown for demand in Figure 4.3 and relative lake storage levels in Figure 4.5. Consider Figure 4.6, where the inverse of Figure 4.5 is shown. From $0 to $300/MWh a fairly uncontroversial result occurs, as price increases; hydro reservoir storage levels decrease. At prices above \$300/MWh, the level of the storage reservoirs associated with a particular energy price point increase. In trading periods where prices exceeded \$600/MWh, the hydro storage level was 1000 GWh above the long term lower decile. In Figure 4.5 ,this storage level was linked to low electricity prices. In the NZEM, *wet* hydrology conditions where abundant hydro generation is present, are associated with both the lowest average energy prices and a significant portion of energy price spikes.

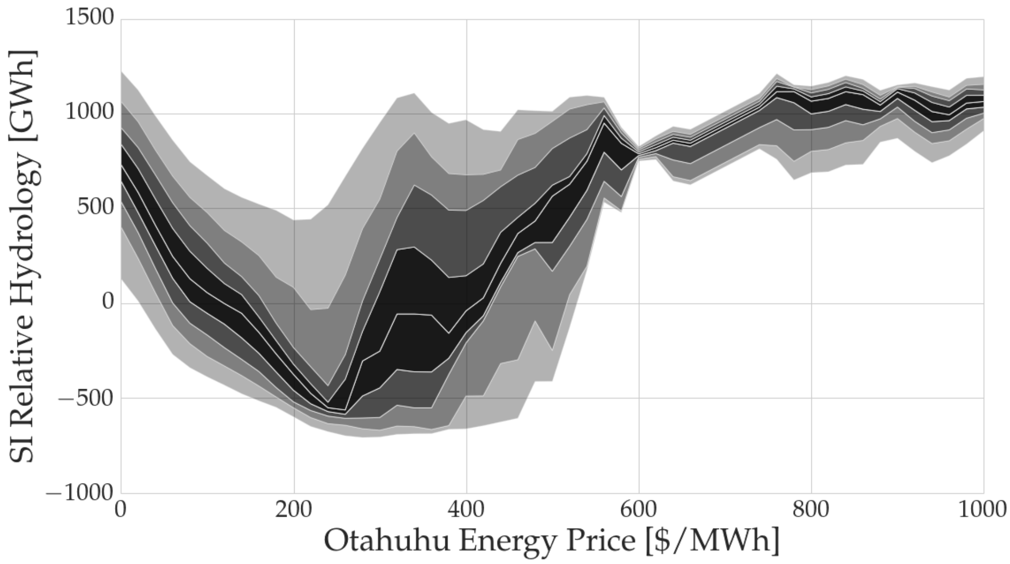

Figure 4.6: Range of hydrology levels for energy price bands ranging from \$0 to \$1000 in increments of \$50/MWh for January 2008 to mid 2014 in the NZEM. The relationship between scarce water and energy prices begins to disassociate at high prices.

High reserve prices are also linked to periods with high energy prices. In Figure 4.7, the distribution of reserve prices for different tranches of energy prices is shown. Most periods with a very high energy price also have high North Island reserve prices. Chapter 2 examined the mechanisms through which energy and reserve prices interact with one another in the NZEM. Figure 4.7 indicates that this interaction may be linked to very high energy (and reserve) spot market prices.

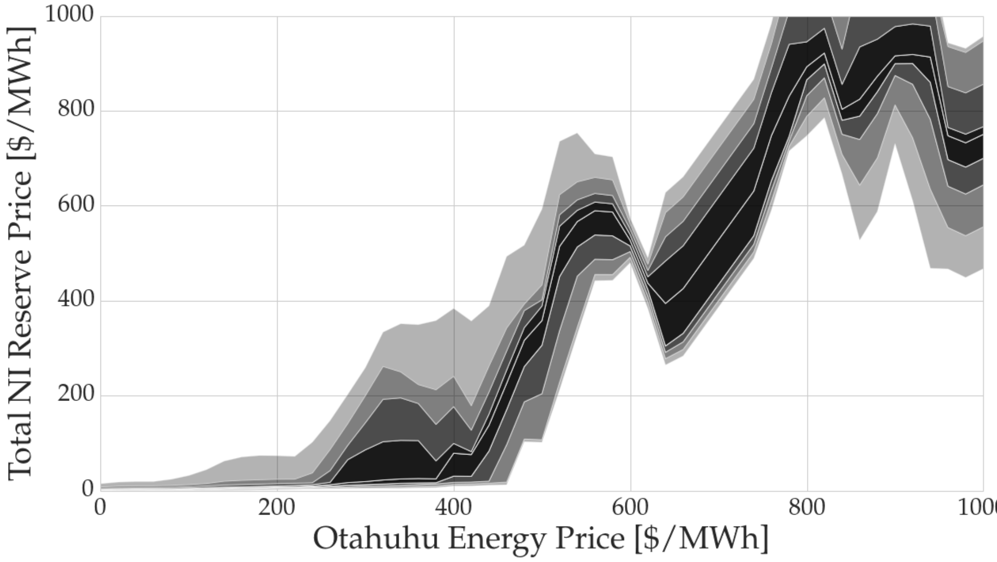

Figure 4.7: Distribution ranging from 10% to 90% in 10% increments of total North Island reserve prices (FIR + SIR), for each energy price band ranging from $0 to $1000/MWh in $50/MWh increments.

4.3 kNN Model Development

For an energy intensive production site (industrial consumer) energy is a significant cost. Unlike residential or commercial consumers who purchase energy to facilitate general activities (for example lighting and heating), consumption by an industrial consumer is directly linked to output (and therefore profit). Consider the simple example of a consumer who has fixed costs, C, in all trading periods along with variable electricity costs, $\lambda_t L_t$, variable reserve revenue, $\mu_t R_t$, and proportional production sales revenue, $S_L L_t$. The single trading period profit, π_t, for this consumer is thus:

$$\pi_t = S_L L_t + \mu_t R_t - \lambda_t L_t - C \tag{4.4}$$

In a simplified example, the consumer can participate in the electricity market by curtailing operations if profit (π_t) is negative. Otherwise, assuming that the consumer is price taking, they will wish to operate at full production in order to maximise profit[2]. If the site curtails, all production for the trading period is lost (but is limited to the single period), then $L_t = R_t = 0$ and site profit simplifies to $\pi_t = -C$. For simplicity, we may determine a threshold energy price, λ^T at which the site should curtail operation. An IL consumer will be profitable if and only if (4.5) holds true[3].

$$\lambda L - \mu R \leq \lambda^T L \tag{4.5}$$

A simple IL consumer has a discontinuous demand curve. At all points where (4.5) is true, the optimal response is maximum consumption. For all other periods, any non zero consumption will decrease total site profit and therefore, full curtailment is the optimal response. This binary response profile is given by a response criteria, τ.

$$\tau = \begin{cases} \text{Curtail} & \text{if } \lambda L - \mu R \geq \lambda^T L \\ \text{Operate} & \text{otherwise} \end{cases} \tag{4.6}$$

Under a simple demand response scheme, an IL consumer must decide if they are willing to continue consumption at a given energy price.

[2]In this case the site will choose to operate for all periods where $\pi_t \geq -C$ as curtailment still incurs a fixed cost. For some facilities, those with multiple products or long running processing schedules, which are not easily interrupted, a more complex approach to incorporate this information is necessary.

[3]We note that there exists a simple case for (4.5) for a non IL providing consumer where $R = 0$. In this case, the site is profitable if $\lambda \leq \lambda^T$ and decisions solely on the basis of energy price may be made. The method presented in this chapter takes advantage of reserve revenue to maximise production in periods where energy prices may exceed the given threshold, but compensation exists in the reserve market.

This simplistic form of bidding is insufficient for consumers with reserve revenue who seek to operate on the basis of their net position. Under a binary response profile, the decision to curtail on the basis of energy price alone can reduce profit, as needless curtailment occurs. It is possible to improve decision making by incorporating additional contextual information for a specific trading period. The curtailment heuristic is thus modified to: *Given what we know about a trading period, should we curtail if a high energy price were to occur?* This may be expressed in terms of the probability of τ, which we call $Pr(\tau)$. A kNN model has been presented to estimate $Pr(\tau)$ on the basis of mathematically similar trading periods.

Consider the kNN approach to this problem. We may draw from a training set, M, which consists of vectors of information linked to a specific trading period. Each vector contains the available hydrology, H, season, S, trading period, P, IL availability, I, and thermal availability, T, information. For each period, the *ex post* prices can be used to compute the known optimal response, τ, for that trading period. Using a distance metric (for example the Euclidean distance, (4.1)), we may select the k most relevant trading periods which can be used to estimate $Pr(\tau)$, given what has occurred historically.

A naive implementation of this approach performs poorly. Only 1% of trading periods meet our definition of a price spike and thus the default action in most trading periods is to continue operation[4]. The strategy may be improved by modifying the set of training data with additional information and taking advantage of demand side offers. In general, the profitability (and choice of operation status) of the site is

[4]Note that here, we use the definition of λ^T as the basis for a price spike. In this case, a price spike is a trading period where the consumer has to make a decision as to whether to continue operation. This varies on a site by site basis and is not necessarily constant over time.

a ternary criteria relating to the energy price threshold, λ^T and the profitability criterion (τ), which can be represented as:

$$\begin{cases} \text{Operate} & \lambda < \lambda^T \\ \text{Curtail} & (\lambda \geq \lambda^T) \wedge (\tau = \text{Curtail}) \\ \text{Operate} & (\lambda \geq \lambda^T) \wedge (\tau = \text{Operate}) \end{cases} \tag{4.7}$$

For all prices where $\lambda < \lambda^T$, the optimal decision is to operate. Hence, we are only concerned with high priced trading periods, $\lambda \geq \lambda^T$, where the site must consider curtailment. We determine $Pr(\tau)$ conditional upon a highly priced trading period occurring. In this situation, we take a subset of the training data, M, and exclude all trading periods below λ^T. We then use the kNN approach to calculate $Pr(\tau)$ for this subset, using the process illustrated in Figure 4.8. In this case, $Pr(\tau)$ is predicted through the linear (or weighted) combination of τ from each of the *k* trading periods using (4.2). The site can then use this probability, $Pr(\tau)$ in place of τ in (4.7), to determine the optimal choice of action.

In the distance function, (4.1), we note that the range of values for a single parameter may have a large effect upon the overall distance calculated. The parameters must be normalised to ensure they have an equal effect upon the distance metric. A simple method to achieve this is to normalise via the standard deviation of each parameter.

Parameters may also be weighted to increase their effect on the distance metric. This places more emphasis on finding trading periods which minimise the distance between a specific parameter (for example, in NZ hydro lake levels may be considered significant). The parameters are weighted through multiplication of each (normalised) parameter by a defined value. In this situation we have utilised user defined weights, drawn from familiarity with the New Zealand market, to emphasise both

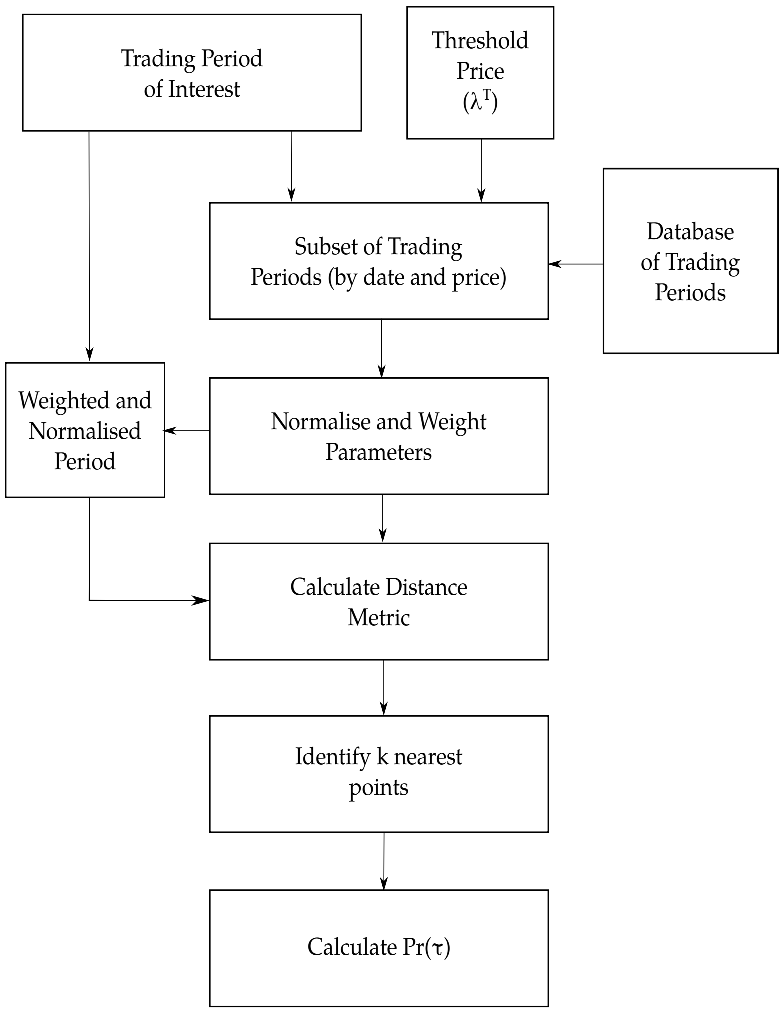

Figure 4.8: Determination of the optimal curtailment response for a site in an individual trading period. This may be used by the facility to decide whether to submit a curtailment offer of $L = 0, p = \lambda^T$ to the SO which is based upon the estimation of their optimal response in the period, $Pr(\tau)$. This diagram represents the determination of $Pr(\tau)$ for a single trading period, where the requisite input information is known.

recent trading periods, as well as relative hydro lake levels. Other authors have proposed methods such as Genetic Algorithms (GA) (Yang and Honavar, 1998) to determine the optimal features and weights to include in the kNN technique. We have neglected this approach as GAs can add significant computational complexity without significantly improving the output result.

In the Euclidean distance, each parameter contributes to the distance metric through the absolute distance between points:

$$\sqrt{(x_i - x_j)^2} \tag{4.8}$$

If we linearly weight each of these parameters, deviations within that parameter are "punished" to a greater extent. For example:

$$\sqrt{(wx_i - wx_j)^2} = \sqrt{w^2(x_i - x_j)^2} \tag{4.9}$$

In general, the weights chosen are small (close to 1) due to their large effect upon the final result. Different weightings reflect differences in opinions regarding the most important contributors to high electricity prices.

A decision support tool should provide information which assists in the decision making process. For a consumer of energy, information about the trading periods which have been used to calculate $Pr(\tau)$, is often useful. These points reflect the trading periods which were mathematically similar across a range of factors. Information from these periods can be used in other models, or as the basis for a qualitative assessment of the likelihood of a price spike in the current period. For example, consider a situation where the trading periods returned for a particular input are highly dissimilar. In this case, the user may conclude that high energy price spikes are unlikely given the current state of the market. Alternatively, if the returned periods are similar, then pre-emptive measures to prepare the site for possible curtailment. This could include increasing capacity in intermediate processing stage buffers to minimise the cost of disruption.

Specific Model Development

The model has been implemented using the Python programming language and heavily utilises open source packages[5]. A database of information about seven years of trading periods (beginning in 2008) has been accumulated. Each trading period within this database contains information on; final energy and reserve prices for the North Island (Haywards) and South Island (Benmore), daily national hydrological storage levels, along with the lower decile storage level for the particular day of the year, season information for the particular trading date using the standard four season year (represented by integers) where Summer ranges from December to February, time of day information, as sorted into three buckets (off peak, shoulder, and peak trading periods (represented by integers)). A recency parameter is determined by subtracting 2008 from the calendar year of each trading period to leave an integer remainder (0-6).

Each parameter in the database is normalised by scaling each value by the standard deviation of the parameter. At this stage, each point of information has been scaled to roughly equivalent levels and consists solely of numerical information. Parameters are then weighted by scaling factors. For example, we have applied a weighting of three to the hydrological values in Section 4.4. Hydrological conditions are a significant contributor to high electricity prices in the NZEM and thus, we have weighted

[5]In particular the scientific Python "stack" which consists of Numpy, Scipy, Pandas, Scikit-Learn and matplotlib.

them heavily. At this stage, the database has been weighted and scaled in preparation for the determination of the distance metrics for each period.

For a given input, the database is culled to remove all periods from the trading day of the period in question onwards. As such only historic information, from the day before the trading period of interest is assumed to be available to the model. A chosen energy price threshold, which is of interest to the user, is selected and all periods within the database below this point are removed. Typically values include \$200/MWh or \$300/MWh, although values as high as \$500/MWh have been used. Different values are appropriate for different energy price ranges. As Figure 4.6 and Figure 4.7 show, the periods with the highest energy prices are often unlike lower priced trading periods.

The kNN technique is then applied to this final subset of information to calculate the distance metric, d, for each trading period, relative to the current trading period. The k nearest trading periods are identified on the basis of the distance metric, d. For each of these trading periods the optimal curtailment condition, τ, can be calculated on the basis of consumption, reserve offers, energy prices and reserve prices. The estimation of τ in the current trading period, $Pr(\tau)$, is calculated by linearly aggregating the occurrences of τ in the k nearest periods. This $Pr(\tau)$ forms the basis of the optimal decision choice for a consumer if a high energy price is to occur.

The model is sensitive to the choice of k as well as the energy price threshold cut off. In Section 4.4 we have chosen $k = 10$. A smaller value of k does not introduce sufficient variability into the trading periods which are used to calculate $Pr(\tau)$. Likewise, a very large value of k may incorporate a large number of periods which are less valuable.

Thus, the choice of k value may be optimised by the user as required, subject to their personal needs.

Likewise, a low energy price threshold introduces additional periods which may be of low predictive value. For example, a trading period where the price is $200/MWh is of less relevance to one where the price is $1000/MWh, than a period where the price is $500/MWh. This recognises that different pricing regimes can exist in an electricity market. In particular, beyond $300-400/MWh in the NZEM, the relationship between unit offer prices and final pricing begins to devolve. Above $400/MWh the presence of constraints is a significant contributor to the final prices seen and regular modelling procedures are less applicable.

Potential Model Extensions

Replacement Periods due to Dataset Pollution

One issue in applying response models over time is the eventual pollution of the dataset. The model as proposed has assumed a *naive* IL consumer, that is one who is not already responding to trading periods. Over time as the consumer uses the model this assumption is no longer valid and thus the sites decision becomes a factor in the selection of the nearest neighbours. That is, a site may *fail* inclusion in the selection set because the sites action reduced prices. Without this action the period would be included.

One mechanism of including this could be to include the IL providers response, however, the exact specification through which this could be done is fraught with difficulties. An alternative approach is to use vSPD, the audited recreation of the NZ power system. the Electricity Authority releases data files *ex post* which can recreate electricity prices. If the site were to respond, subsequently polluting the data for that period, vSPD may be used to simulate the price outcome of the trading period without the site response by modifying the input file. In this situation the kNN dataset becomes a hybrid dataset with both *true* trading periods based upon the actual site information and *simulated* periods from vSPD for any periods when the site curtailed.

This approach is *first order* in behaviour. That is, we assume that all other market participants will offer the same regardless of the IL consumers behaviour. The *second order* situation is difficult to enumerate at all and thus there remains a risk that market participants will begin to take the IL consumers strategy into account when they structure their energy and reserve offers. Identifying second order behaviour is an open problem in many domains but nears impossibility in this situation as highly granular data is required for vSPD, down to the individual offer tranche level. The risk of modifying these is infeasible or unrealistic dispatches.

Multi Time Period Models

The model as presented here within has been a *single period model* with no reference given to extensions to the multi period case. In the case of the given kNN model this is simple. In the case of extending this to the specific model of the consumer it is difficult.

The kNN model prepares the optimal response for the IL consumer *if* high energy prices were to occur. The model can be run using any set of inputs for an extended time resolution. From this, a set of optimal decisions for an extended period of trading periods, for example 72 hours (144 periods) may be made on the basis of forecasted information. Thus, the problem domain changes somewhat to the following:

> Given the information known about the upcoming set of trading periods including the forecasted energy prices and the forecasted optimal response to high energy prices what is the optimal strategy for the site.

The site optimisation problem may thus have two inputs. The kNN model as proposed here provides one of them. Whilst a set of forecasted prices (one option is to use predispatch prices, day ahead prices, forecasting models or historical periods) provide the remainder. Given these two inputs a multi time period model arises naturally.

4.4 Results

The model as described in Figure 4.8 has been implemented in a simulated, online manner. Trading periods are assessed iteratively with information updated daily. Thus, the model does not assume information about the previous trading period, but it does about the previous day. There is a strong temporal basis to electricity markets. In NZ, a new price occurs every thirty minutes and general market information is typically released daily. These are incorporated into the model through a batch extension of the set of training data used.

We consider a consumer who purchases energy from the spot market (no contractual hedges, variable electricity cost) with an equivalent reserve dispatch. The site has been modelled as a price taking unit with their individual consumer level decision having no impact upon the final marginal energy price. For larger consumers this assumption is less appropriate. We consider three metrics to assess the model:

1. Case studies (intended to replicate the functionality the user may see from such a model).

2. An aggregated assessment of model accuracy and consistency over time.

3. The profitability of a simplified strategy undertaken using the model as a basis.

Case Studies

Case studies are important as they reflect how the model might be used in practice and act as a useful "sanity check". By assessing specific trading periods a manual check of the model can be undertaken. We consider seven periods, one for each of the years from 2008 to 2014. We have chosen a large range of years due to the systemic changes which have occurred in the NZEM over this time frame. In modelling, this is known as concept drift, or the tendency for underlying assumptions to change over time. The kNN approach as implemented, partially circumvents this as new information is continuously incorporated and recent information is weighted heavily. In particular, 2008 saw one of the worst dry years on record, 2009, global financial difficulties, 2010-2013 the rise of geothermal energy in the face of stagnant demand, and in 2013/2014 a new HVDC interconnection was commissioned. There were also changes in government policies such as the forced sales of generation assets and the partial privatisation of state owned (SOE) generation companies.

Table 4.1 contains an overview of the trading periods used in the case studies. The actual optimal decision as to whether to operate, τ, is given by a binary yes/no condition. The kNN model predicted optimal decision, as indicated by $Pr(\tau)$, is included as a percentage for each trading period. The predicted optimal response, $Pr(\tau)$, for each of the trading periods has been calculated *ex ante*. This optimal response uses a linear contribution from the ten ($k = 10$) most similar trading periods as identified using the kNN model. The model is able to clearly predict which periods the site should continue to operate in, in the face of high electricity prices. The information the model has used to identify similar trading periods has also been included. Periods were chosen to be similar across the years, in terms of similar time windows, hydrology conditions, demand, and prices.

Five simple comparative methods have been included in Table 4.1 to show the range of expected prices using simple 1 or 2 variable models. These methods are simple aggregations, not full models and are based on the distribution plots in Section 4.2. For example, the expectation of prices for the Hydro-Demand-Time (HDT) method attempts to take into account the current level of hydrology, demand, and the trading period. For the periods which meet these conditions the lower and upper quantile of prices for these conditions are shown. In each case, the energy price for the trading period exceeded the likely range of prices based upon the available information.

In Figure 4.9, the daily and average monthly energy prices for each of the case study days is presented. The kNN model was able to correctly identify the correct response to the two price spikes in 2011 and 2012, as well as the heightened (sustained) period of pricing in 2009 and 2010. This indicates that it is robust in a range of different scenarios. An aggregated assessment of the overall model performance over time has been completed. Though this assessment does not reflect how the model would be used in practice, it is a useful metric to assess the utility of the model over time.

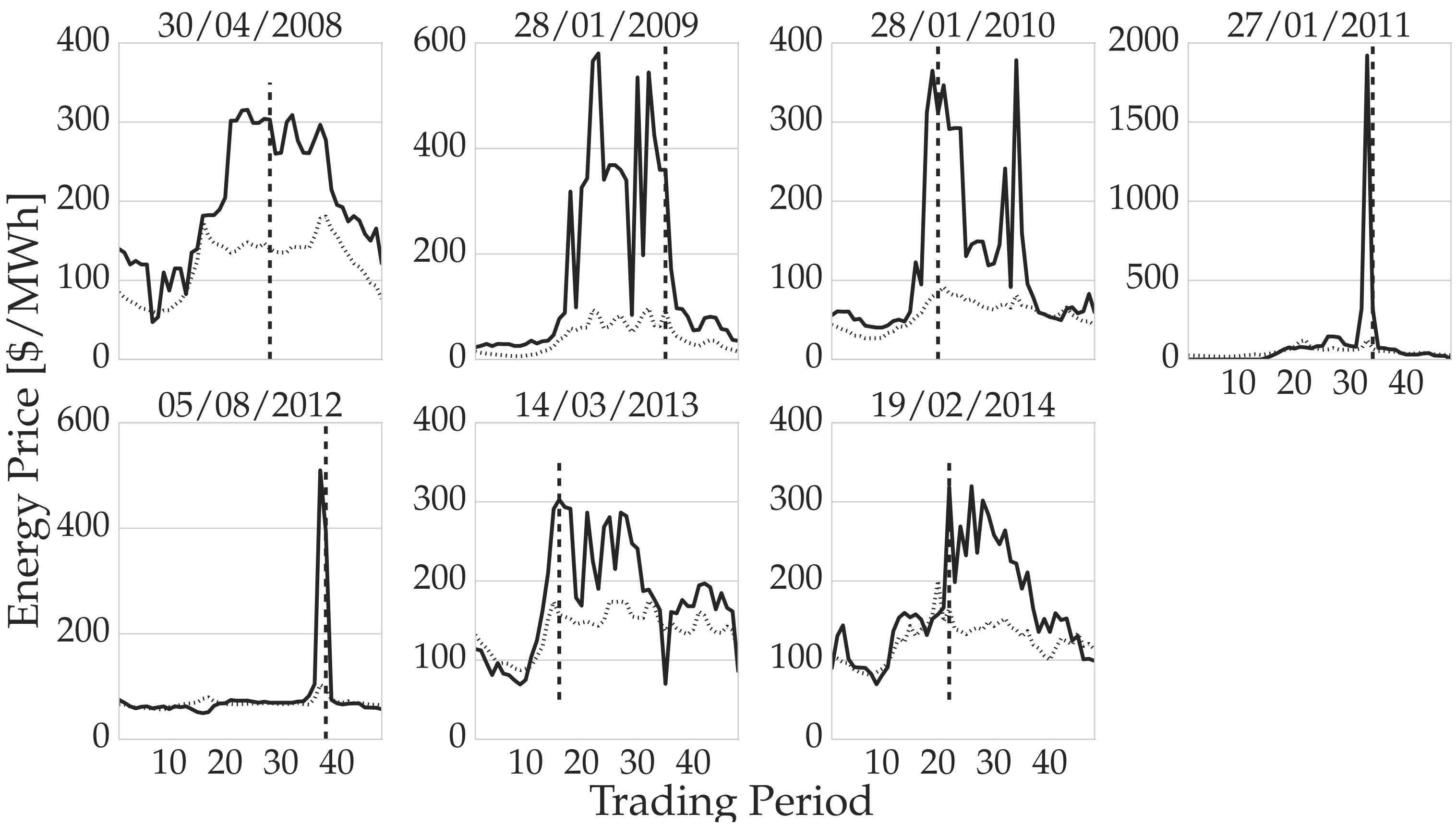

Figure 4.9: Price time series for the seven case studies analysed. Note the occurrence of both persistent price increases as well as short duration price spikes. The lighter grey line indicates the monthly average energy price for the specific trading period. The vertical line represents the trading period for which the case study was presented.

Table 4.1: kNN classification technique case studies from 2008-2014. Additional information regarding market conditions have been included for the reader as well as five simple aggregation based models which reflect likely ranges of energy prices given those conditions.

	2008	2009	2010	2011	2012	2013	2014
Date (day/mon)	30 Apr	28 Jan	28 Jan	27 Jan	05 Aug	14 Mar	19 Feb
Period	28	35	20	34	38	16	22
NI λ [$/MWh]	303	359	311	319	394	302	318
SI λ [$/MWh]	345.6	44	41	29	55	314	284
NI μ [$/MWh]	4	285	214	242	256	12	9
SI Lakes [GWh]	1518	2863	2853	2912	1461	2283	2497
NZ Demand [MW]	4850	4862	4978	4993	5583	5102	5122
Thermal [MW]	2107	1664	1869	1385	1510	1270	968
SI Rel Storage [GWh]	-476	963	953	1020	253	165	464
τ	No	Yes	Yes	Yes	Yes	No	No
$Pr(\tau)$ [%]	0	100	100	70	100	10	0
Hydro [$/MWh]	39-267	5-78	5-78	2-73	53-135	43-159	31-151
Demand [$/MWh]	30-191	30-191	31-191	31-191	38-232	31-175	31-175
Time [$/MWh]	37-196	35-156	35-156	35-156	30-176	30-188	35-156
HD [$/MWh]	56-280	17-121	18-90	25-98	65-146	66-213	41-254
HDT [$/MWh]	213-300	37-339	34-291	61-145	60-187	89-294	131-285

Overall Performance

A model concerned with electricity price spikes must be both *consistent* and *accurate*. There are four possible responses for the site relating to a 2x2 grid of optimal responses and actual responses. We assess Positive and Negative responses as the decision to either operate or curtail and attach the moniker True or False relating to the appropriateness of this decision. In this scheme, a True Positive is a trading period where the site was correctly recommended to operate during a high priced trading period. A False Negative is when the site was recommended to curtail but should have remained in operation. Profit is increased for True Positives, zero for False Negatives and True Negatives, and negative for False Positives. In this section we define accuracy as the number of identified periods and consistency as the appropriateness of the indicated response:

$$\text{Accuracy} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \tag{4.10}$$

$$\text{Consistency} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} \tag{4.11}$$

For a given trading period, the site must choose whether to submit a load reduction offer to the SO, typically at price λ^T. We assume that the site is dispatched on the basis of energy offers only and the effect of the site's reserve is discounted in the decision process. For the site, two default strategies exist; full curtailment or zero curtailment. A third option is introduced - strategic curtailment - where the site chooses to submit a curtailment offer to the SO, on the basis of $Pr(\tau)$. The site can choose different threshold values at which to act upon. A high threshold implies increased conservativeness as the site will reduce load more often, minimising the impact of False Positives and their negative effect on profit.

A perfect response strategy has also been included to assess how close to the theoretical optimal solution we are achieving.

From 2008 to 2014 approximately 1100 trading periods exceeded \$300/MWh, which we have chosen to be the threshold energy price, λ^T. Data is updated daily (e.g. trading period 24 assumes no information about trading periods 23 on the same day). The rates of True and False Positives, as well as False Negatives, are shown in Figure 4.10. In total, approximately 300 trading periods satisfied the True Positive condition over this time period. We have excluded True Negatives from the plot as curtailment is the default choice of operation and we wish to examine when we should deviate from this.

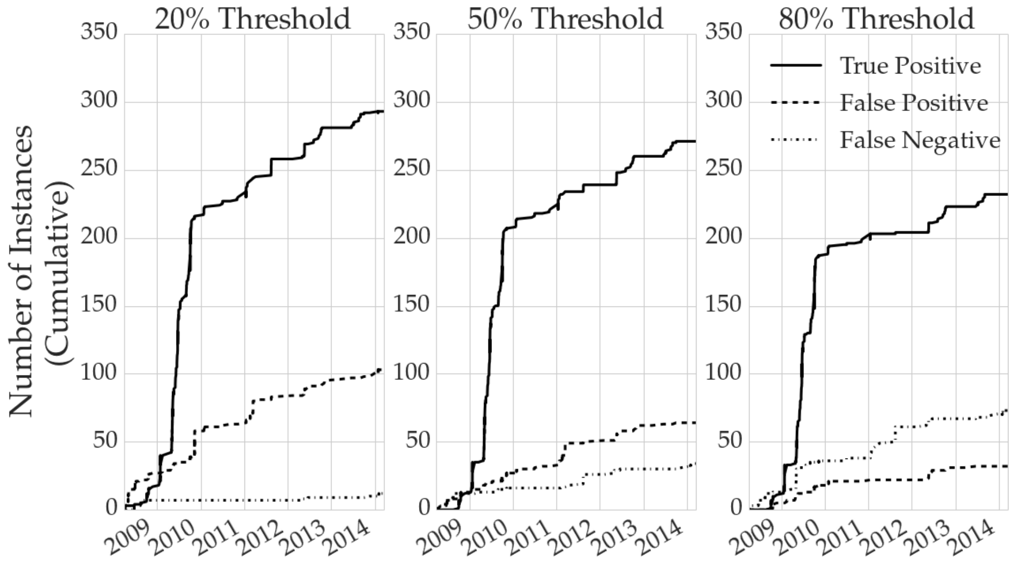

Figure 4.10: Classification accuracy at different threshold rates in the NZEM for trading periods where prices exceeded \$300/MWh in terms of the absolute rates of True Positives, False Positives, and False Negatives over time. In 2009 a large number of True Positives appeared to occur with the rate slowing to a more consistent level in latter years.

Under a conservative approach using a threshold of 80% (8 of the 10 most similar trading periods having an optimal response to continue operation) the accuracy level was 75%, with a consistency of 82%. At a lower threshold of 20% for the site to continue operation, accuracy was increased to 95% at the expense of a reduction in consistency to 75%. The optimal decision threshold varies on a site by site basis as well as on the quantitative values of the incorrectly classified situations. For example, False Positives lead to negative profits for the period, not just zero profits. As such, a high consistency is desirable at the expense of accuracy to a certain extent. This effect is illustrated by assessing the monetary performance of a strategy over time, using a hypothetical production value and the operate-curtail decision making of the kNN model.

Strategy Profitability

Consider a production site who consumes 1 MW of energy in every trading period and is dispatched for 1 MW of reserve if it is consuming. Currently this site has two potential strategies in response to the spot price; full curtailment in periods where price exceeds $300/MWh and zero curtailment otherwise. Alternatively, this may be considered a form of demand side bidding to the SO. Instead of seeking to respond to price the consumer instead offers a consumption curve which is 0MW after $300/MWh and 1MW otherwise. The site receives a fixed value for production in terms of consumption, S_L. In general, for this site the total trading period profit, π_i is given by (4.12).

$$\pi_i = \begin{cases} S_L L_i + \mu R_i - \lambda_i L & \text{if operating} \\ 0 & \text{if curtailed} \end{cases} \tag{4.12}$$

For a number of trading periods the response of the site is contained within a strategy vector, N_k. N_k has elements of 0 or 1 relating to curtailment or operation, respectively. Thus, the total strategy profit is the sum of π_i for the given strategy vector N_k over time:

$$\Pi = \sum_{i \in N_k} \pi_i \tag{4.13}$$

For the two simple strategies, full curtailment and zero curtailment, the vector N_k will consist of either all ones or all zeroes. Alternatively, in the strategic kNN based strategy, N_k consists of the predicted optimal response for the trading period given the known information for a specific decision threshold. We may also compare this result against the theoretically optimal strategy. The optimal strategy is a function of the value a site obtained from consumption, S_L. For three different consumption values the kNN strategy profit as a function of the curtailment threshold is shown in Figure 4.11. This is used to determine the optimal response threshold which is the point where profits are maximised. For $k = 10$ the optimal threshold is 70%. At higher values of k, the optimal value changes as dissimilar trading periods are included in the forecast of $Pr(\tau)$. In particular, the choice of k must be large enough to obtain sufficient variety of trading periods yet small enough that dissimilar trading periods, are not introduced. Dissimilar periods have low predictive power for the trading period at hand and may be identified through the distance metric. An inherently conservative strategy, $Pr(\tau) = 70\%$ or more, is favoured at low site values. This indicates that it is of the greatest concern to avoid highly priced trading periods at the expense of losing a small quantity of production. At high site values more aggressive strategies are desirable. In these periods, the lost profit associated with curtailing is higher than reduced profits due to continued operation during periods with high prices.

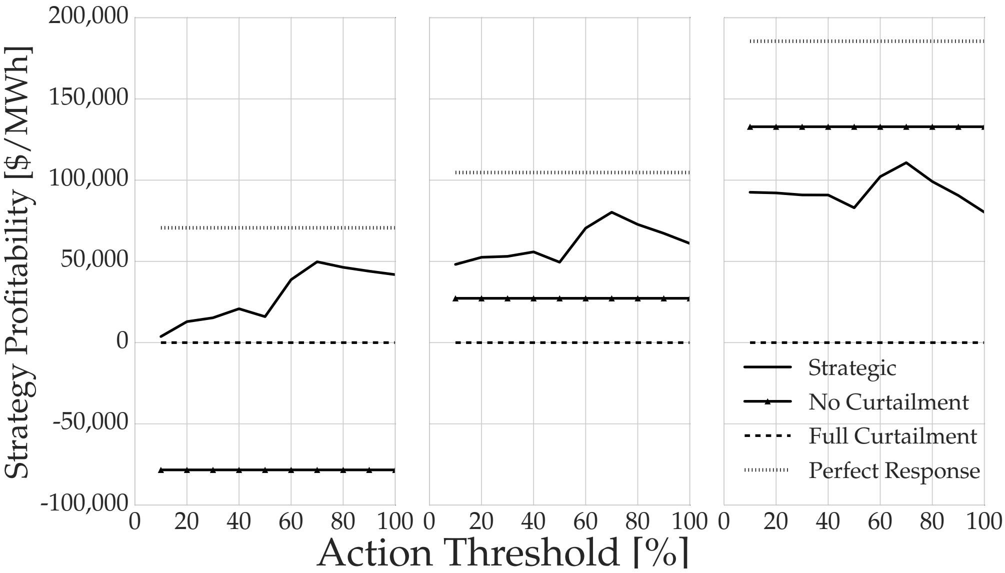

Figure 4.11: Strategy profitability at different action thresholds and consumption values, $k = 10$, $V \in (200, 300, 400)$. Profitability is assessed across the full time horizon from 2008 to mid 2014. The perfect strategy is the theoretical upper limit for any of the strategies, assuming the site has perfect information about the trading period and may respond to maximise profit.

4.5 Discussion

The current implementation of electricity markets treats many consumers as passive entities who are not price responsive. This has had an overall negative effect upon the efficient operation of the power system. Many consumers are both willing and able to reduce consumption in response to high electricity prices. This reduction has numerous benefits, not the least of which is the reduced need for expensive peaking plants which can increase overall energy efficiency (and reduce greenhouse gases). Peak shaving was historically practised in some centralised regimes through schemes such as hot water ripple control. However, the transition to decentralised markets has led to the decay of such systems, as the benefits and costs have been spread amongst many system participants.

Many production sites who are exposed to the spot electricity market have sufficient capability to reduce consumption. Unlike some forms of residential load consumption, industrial consumers do not typically inflict energy rebound effects[6] upon the grid, as they operate near their maximum capacity levels in most trading periods. The corollary to this is that industrial load curtailment is significantly more disruptive to the consumer, as the lost production may not be recovered. To encourage these consumers to reduce load, energy prices must reach a level where continued operation is unprofitable.

Understanding prices within electricity markets requires an understanding of hydrology, demand, outages, ancillary services, and the underlying transmission network. Predicting spikes in electricity prices is difficult, although prior attempts in the literature have been made (Amjady and Keynia, 2010; Zhao et al., 2005). An IL consumer is naturally hedged against some spikes due to reserve market revenue. This complicates demand response for the consumer as they wish to act upon their net position, not just the electricity price (the format in which they must submit bids to the SO).

Consider Figure 4.2, which indicates the effective price paid by an IL consumer of energy after considering reserve revenue. For points where

[6] An energy rebound effect occurs following a demand response callout when the load is restored to the grid. For example, consider a group of 100 refrigeration units with a peak consumption of 100MW and a load factor of 20%. When the demand response window is initialised on average approximately 20MW will be reduced from the system. However, as the window continues ever greater numbers of refrigeration units must be *prevented* from consuming load in order to maintain the initial reduction. Once the window ends a greater number of the units are not at the point in their cycle where they wish to consume energy and hence (unless controlled properly) will turn on en masse. This leads to an *energy rebound* as a preliminary spike, greater than the initial quantity of demand response, will be imposed on the system. Furthermore, the size of this spike is proportional to the length of the window. Energy rebound effects can exacerbate the initial problem (peak shaving) that demand response was meant to solve.

the *effective* price of energy was below the *nominal* price, the consumer must consider reserve when choosing their response. We have developed a k nearest neighbours approach to forecast the optimal response to an electricity price spike (after taking into account the likelihood of reserve revenue), *ex ante*. We considered a simple example, that of a consumer who wishes to curtail at electricity prices in excess of \$300/MWh. In formulating their demand bid to the SO, the site could utilise the kNN model as described. If $Pr(\tau)$ exceeds a particular threshold this site could offer a flat demand curve to the market, indicating a willingness to continue consumption at all prices. They may offer this in confidence that in the event of a high energy price, sufficient reserve revenue to retain profitable operation will occur. This approach, in the simplified demand response scheme (which eliminates the need to forecast when the electricity price will spike as the site offers a curtailment demand curve) would lead to increased profitability as shown in Figure 4.11.

The kNN technique was chosen partially due to its simplicity and ease of explanation to non technical stakeholders. As a tool, a model must be understood by those who use them, who in this case are managers and analysts at IL consumers. For these consumers, energy is just one of a number of costs, albeit one which varies significantly over time. Other techniques such as ARIMA (Autoregressive Integrated Moving Average) models, neural networks, and SVM (Support Vector Machine) were considered. The kNN technique was chosen as it is not a black box. As such, the presented kNN model helps to support the analyst, not replace him. The participation of consumers in electricity markets has been hampered by a lack of tooling (Kirschen, 2003). This model, and others like it, can assist in increasing participation and therefore improving the elasticity of demand. Increased demand elasticity will improve the operation of the power system both operationally in the short term, as well as strategically in the long term, as the requirement for expensive peaking generation plants is reduced. A caveat is that a diverse range of models will be required. If all consumers seek to optimise their consumption profiles using the same model a circular effect begins, nullifying any potential benefits.

Chapter Summary and Contribution to the Literature

This chapter has presented a kNN model which has been used to optimise the curtailment strategy for an Interruptible Load consumer. The chapter presents a novel assessment of electricity prices in the NZEM which recognises that electricity price spikes are associated with periods where energy prices are low on average and are linked to reserve constraints.

The presented kNN model capitalises upon the reserve co-optimisation in place to optimise consumer operation during periods of high prices. The study of high electricity prices in the literature is limited. A few models have attempted to forecast the occurrence of these high priced periods, with mixed results. This model represents an alternative strategy to the problem. Recognising that consumers who try to forecast high energy prices do so in order to maximise profit. Revenue from reserve markets may be used to compensate consumers for operating throughout high energy prices. This approach is a novel contribution to the literature as it suggests an alternative approach to price response for IL consumers, which takes advantage of their natural cross market position.

Chapter 5

Integrating Demand Side Participation with Energy and Reserve Markets

In this chapter a stochastic optimisation model for an Interruptible Load (IL) offering consumer is presented. This model optimises the combined consumption level and reserve offer stack for a large (price making) energy consumer. Numerical simulations have been performed to determine energy prices under uncertainty. A dynamic program is used to calculate an optimal reserve offer for each consumption level.

The model has been implemented in three phases. First, the effect of the site's consumption level under uncertainty, for a range of load levels, is simulated. For each load level, an optimal reserve offer is calculated. Finally, the optimal site consumption level is calculated by simulating energy and reserve prices, for each consumption level, with the associated optimal reserve offer in place.

This model has been called Boomer-Consumer. It uses an audited representation of the NZEM market dispatch model, within the simulation process, to produce accurate prices. Uncertainty has been introduced by sampling from a *demand distribution and simulating the resulting energy prices, under assumed market offers.*

The material in this chapter was first presented at CMS Lisbon 2014 in a short conference paper (Cleland et al., 2014b) with an extended edition submitted to a special issue of CMS for which comments were received and incorporated into a revised article.

5.1 Introduction

Motivation and Hypothesis

To integrate demand side loads into the electricity market requires careful thought and optimisation. Poorly integrated loads may do more harm than good as energy payback can exacerbate situations (Strbac et al., 1996; Strbac, 2008). Consider an aggregated portfolio of refrigeration units, currently operating (net) at 50% of their combined energy capacity. A demand response call out occurs and the load is curtailed, all units are idle regardless of their point in the refrigeration cycle. Following the end of this event the refrigeration units may all begin their cooling cycles. The combined load from these units rises to 100% of their energy capacity and a substantial ramp occurs which places additional stress on the system.

Hence, the integration of demand side response into the electricity grid requires optimisation at both the individual consumer and system level. Here a delineation is made between Demand Response (DR) and Demand Side Participation (DSP). As defined in Chapter 1, DR requires an active response from the consumer, for example, demand side offers and price responsive curtailment (Albadi and El-Saadany, 2007) are forms of DR. Whereas DPS may be controlled at the utility level through automated action. Many researchers have turned their attention to the problem of system level optimisation, neglecting to a certain extent the individual consumer level optimisation problems which exist. Partially, this is due to the asymmetry of information present in the system which renders many consumers unable to act efficiently (Ramos et al., 2013). This is also due to the negligible impact the average consumer has upon the electricity price. Though demand response, in aggregate, leads to greater elasticity and improved social welfare, the benefits for individual consumers are small. Efficient Demand Response promises a reduction in capital investments over a period of many years, in effect, slightly reducing the electricity price at some point in the future. To obtain this benefit many consumers are asked to suffer real inconvenience now, a difficult proposition to tackle. To rectify this divergence of incentives, many researchers have been studying the design of demand response schemes to encourage consumers to participate.

An alternative approach is to consider the potential for large scale demand response from a single, industrial, consumer. Industrial consumers (who directly connect to the transmission grid), may choose to purchase energy from the spot market and are thus exposed to time of use pricing. Time of use pricing has been identified as a key requirement for effective demand response schemes (Barbose et al., 2004). Industrial consumers have a real impact upon the electric power system. A brief study of a reduction of 10% from the four largest industrial consumers in the NZEM for 20 days a year led to a systemic saving of $27 million NZD per year[1]. The value of a single MW in a given trading period was calculated

[1]This investigation was completed using vSPD. The days with the twenty highest trading periods were identified. The four large consumers, Norske Skoge, New Zealand Steel, Pan Pac Pulp and Winstone Pulp (Three wood processing facilities and one steel mill) were reduced in their consumption by 10% by overriding their nodal consumption levels. This total reduction was 30 MW on average for each of the trading periods. From 2008 to 2013 (inclusive) a total systemic saving of $160 million NZD was identified, equating to $27 million per year on average. This saving was calculated by assessing the difference between the energy prices in each trading period. This difference was multiplied by the total load (as determined on an island basis using Otahuhu and Benmore as the island reference nodes) to determine the reduction in cost to consumers. Whilst simplistic, this method is a useful ballpark figure for the utility of demand response. Whilst not a perfect example, market conditions have changed considerably over this time period with dry years in 2008 and 2012, wet years in 2009 and regulatory and government changes over the whole period it does serve as a baseline example. The quick study indicates the potential value a well orchestrated demand response scheme could have if targeted at consumers large enough to shift final prices. That is, a sufficiently large load block to form a price *making* not just price *taking* consortium.

at approximately \$1000/MW/period *to the system*. However, individual consumers see a fraction of this and may even have lost money due to reduction in production.

The optimisation of large consumer load profiles has numerous benefits compared to a portfolio of aggregated smaller consumers. Large consumers typically have 24/7 control rooms, are connected directly to the transmission network, and pay the wholesale electricity price (time of use pricing). These consumers also have existing energy efficiency protocols in place and have a strong incentive to reduce consumption if it leads to increased profits. On the other hand, smaller consumers with less energy intensive usage requirements place a significantly greater utility upon their (minor) consumption[2].

To optimise consumption for large users requires a full appreciation of the underlying transmission network, as well as the market offers for both energy and reserve within it. In this chapter we present a model we have called *Boomer-Consumer*, to optimise the consumption of a single large consumer within the NZEM. We present two variants; a single load only case to optimise the level of consumption for an individual site and an extension, integrating optimal Interruptible Load (IL) offers for the site. *Boomer-Consumer* is a stochastic optimisation model which utilises a full representation of the underlying electricity network. The approach presented in this chapter is broadly an extension of the identification method presented in Chapter 4. Here, we attempt to optimise demand response for a price making consumer who participates in the IR markets of NZ by offering IL. This extends the previous chapter, from

[2]Consider a firm who primarily uses energy for light computing requirements. The value this firm obtains on a per MWh basis from consumption is substantially larger than a processing facility in primary industry.

the "price taking" scenario, to the "price making" capabilities of a large consumer.

Background

Consumers are (largely) untapped resources, their integration can increase the operational and investment efficiency of electricity markets. Load in an electricity market must be continuously satisfied at all times. Any imbalance leads to variance in the system operating frequency. If this imbalance exceeds safe operating ranges, damage to generation facilities is possible. In the worst case scenario this can lead to power system failure. Two options exist to prevent this scenario; curtail load or increase generation.

A simple example can be used to highlight the aggregate benefit of load shifting[3] as a method of balancing system demand. In the load duration curve, shown in Figure 5.1, the effect of peak shifting is illustrated. Load has been curtailed in high demand periods and increased in low demand periods. This leads to a flattening of the load duration curve and thus the level of peak capacity required is reduced. In the first "unshaved" case, a substantial portion of generation capacity is only dispatch infrequently. In the second example, the highest load peaks have been "shaved". The difference between the two scenarios is the level of peaking generation required (and therefore the capacity utilisation rate of base and mid range units). This helps to reduce the highest spot market electricity prices within these periods (Cramton and Stoft, 2006).

The optimal level of demand response from a consumer has two (interconnected) criteria; the individual optimal level and the systemic op-

[3]An idealised form of load shedding where shed load may be rescheduled from high demand to low demand periods.

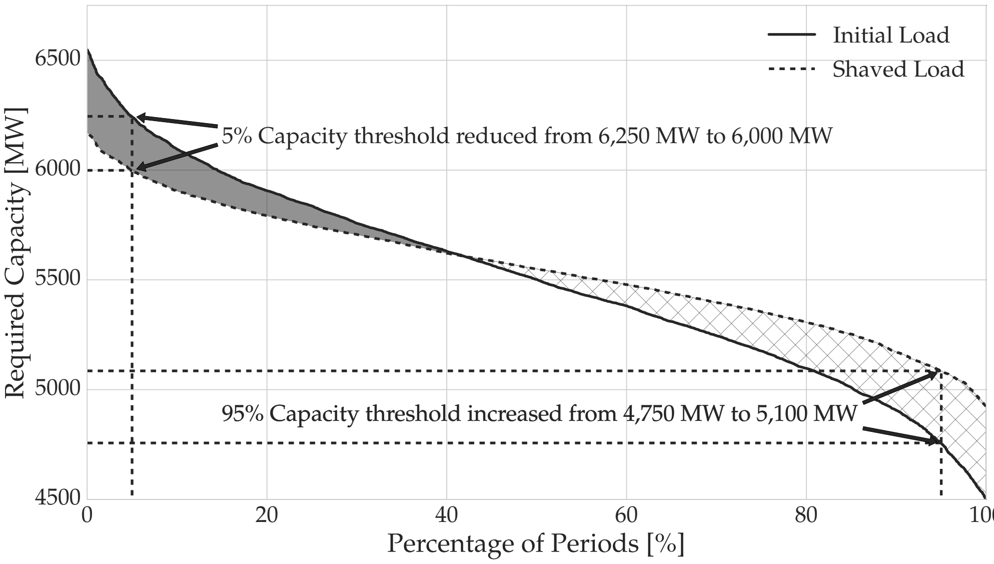

Figure 5.1: Load Duration Curve illustrating the different requirements for capital investment in an electricity market under peak shifting. The curtailed consumption during peak periods has been shifted to non peak periods. In the example shown, a 1:1 relationship does not exist which indicates the presence of energy payback (Strbac, 2008).

timal level. These two levels may be in conflict with one another. For a SO, the optimal criteria is when total social welfare is maximised. On the other hand, an individual consumer wishes to maximise their total profits. In the Uniform Price auction the consumer's load decision can influence the final clearing price. Sophisticated (large) consumers can therefore reduce their total energy cost by if partial curtailment reduces final energy prices.

Many large scale consumers current participate in electricity markets. These consumers pay spot market electricity prices and some participate in AS markets. IL is an excellent source of primary contingency reserve (CR) in an electricity market. Not only is IL typically faster than equivalent generation reserve, it can also relieve reserve capacity, which permits a higher utilisation of existing assets. This is particularly important in markets with large reserve requirements relative to total capacity. Four classes of consumers may be defined based upon their size and participation with the electricity market:

Retail Consumer: A retail consumer consumes their load under the umbrella of a retail company. They traditionally pay a constant per kWh price, as well as fixed charges for distribution. These consumers are inactive in the wider electricity market.

Small Consumer: A consumer who purchases their electricity from the spot market but has no (individual) effect on the spot market price. This consumer's contribution to total load is too small to justify a full optimisation model. This class of consumer can be considered a pure price taker.

Large Consumer: A consumer of sufficient size to have price making characteristics in many trading periods. Upon partial or full curtailment of the consumer's load, the marginal clearing price will be reduced. As such, they must optimise their consumption with respect to the wider market.

Large IL Consumer: A consumer with price making characteristics who is active in multiple markets, specifically reserve markets. This consumer must consider their consumption profile and reserve market offers in the context of the full market dispatch.

Large consumers must also consider their position within the electricity network. Consider Figure 5.2, which depicts an overview of the generation and transmission assets in the NZEM. The NZEM has been classified as a "long and skinny" transmission grid and is dependent upon the transfer of hydro energy originating in the SI to the NI load centres (Read, 1997). A consumer located in an isolated region, for example Whirinaki, will have a different optimal consumption level to the equivalent consumer located at Tiwai Point or around the Auckland region.

The remainder of this chapter presents a theoretical overview of load reduction, in both the deterministic and stochastic cases in Section 5.2. In Section 5.3 an overview of *Boomer-Consumer* is presented and the model is extended in Section 5.5 to incorporate IL offers, as well as choosing appropriate market offers.

5.2 Theoretical Load Reduction

Under LMP (Schweppe et al., 1988), the price of electricity at a specific node and time in the grid represents the marginal price of electricity at that node. The network flow linear programs (Bazaraa et al., 2013) used to model power systems, typically seek to maximise total social welfare or minimise costs. In these systems the objective function and the nodal balance constraint are used to optimally dispatch a number of generators. In a lossless system, the following is sufficient to create a rudimentary grid dispatch, where A and B are mapping matrices aligning generation and transmission flows with particular nodes, and all remaining variables are vectors.

$$\begin{aligned} \min \quad & p_g^T g \\ \text{subject to} \quad & Ag + Bf = d \qquad [\lambda] \end{aligned} \tag{5.1}$$

In practice, clearing an electricity market is often conceptualised through the illustration of an offer stack. The offer stack consists of tranches arranged in order of increasing price which are considered the trading period supply curve. In most electricity markets, demand is not explicitly

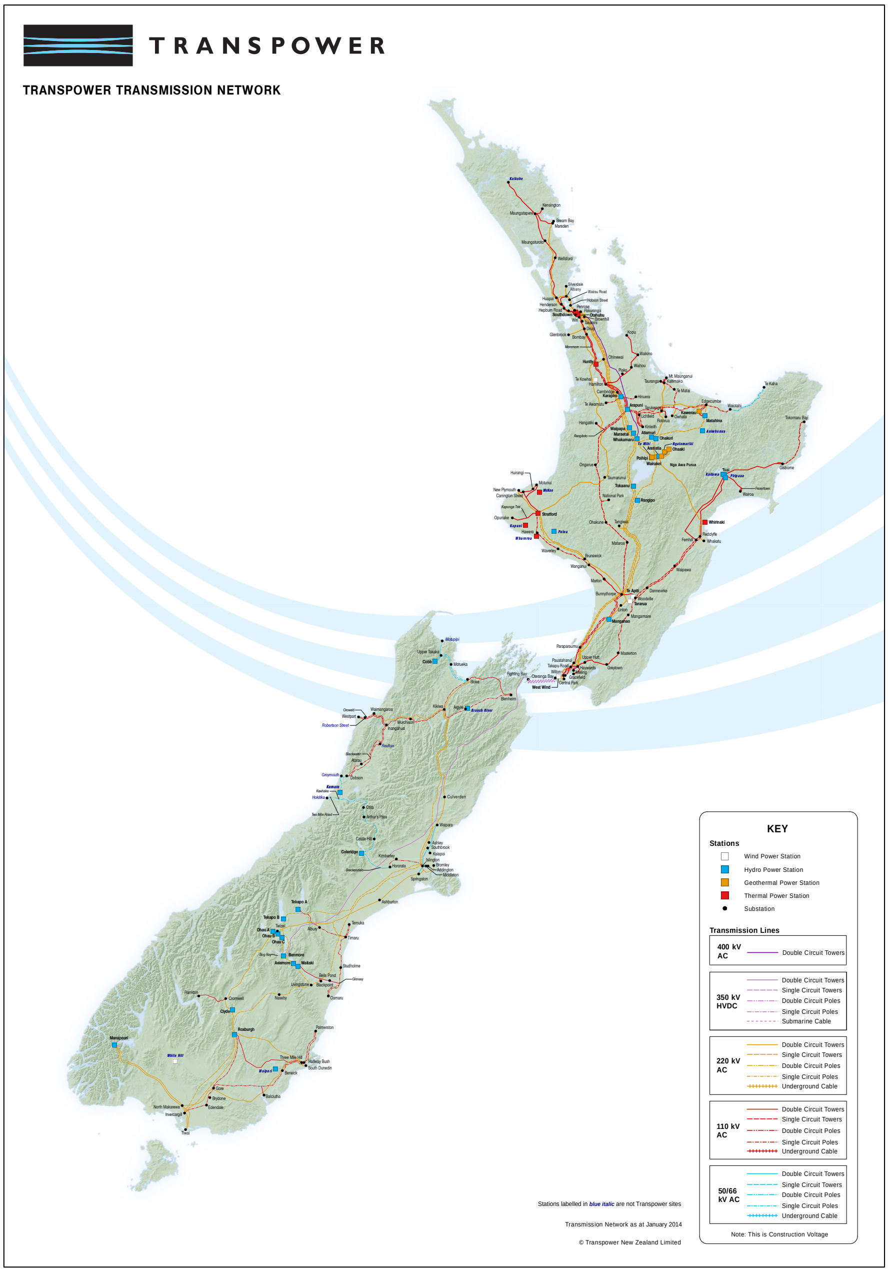

Figure 5.2: Overview of generation assets and transmission lines in the NZEM. The system is fundamentally linear with two primary clusters of generation assets in the Lower SI on the Waitaki hydro chain and around the Taupo region. Thermal assets exist at New Plymouth, Huntly and around the Auckland region. Source Transpower New Zealand, retrieved November 2014 (Transpower, 2014b).

co-optimised. Instead it is taken as a fixed exogenous parameter. Consider Figure 5.3, which is an example of a real offer stack from the NZEM. The offer curve in this case resembles a "hockey stick" (Hurlbut et al., 2004), where electricity prices steeply increase at the margin. In this trading period, a 40MW reduction in consumption is sufficient to shift the marginal electricity price, leading to a systemic reduction in the energy price. In this supply stack, the submitted price components increased from \$100/MWh to almost \$1000/MWh in less than 200 MW.

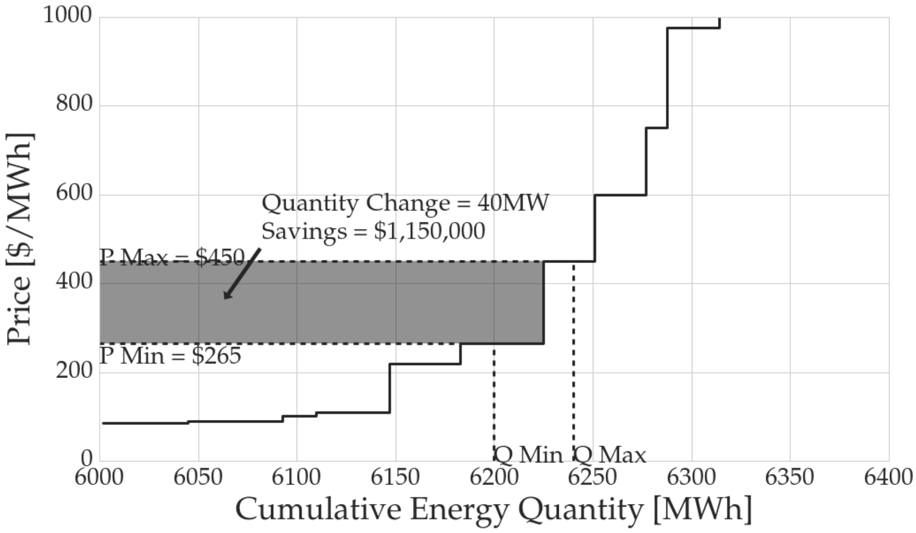

Figure 5.3: System level savings and price reduction achieved via a small reduction in total consumption. The offer stack is for the 15^{th} June 2014, trading period 36. The majority of the savings are realised systemically due to the reduction in electricity price.

The savings from the demand reduction are shared system wide. All consumers benefit from the decline in the electricity price, either directly in the case of spot market exposure, or indirectly through reductions in retail or hedging costs in the future[4]. If we continue the deterministic

[4]Clearly we assume here that the generation and retail companies will eventually pass on this saving, in an effort to obtain an advantage over competing retailers or generation companies.

case study, we see that the site has a large instantaneous marginal cost of consumption (Figure 5.4). This jump in the energy cost represents an opportunity for the site to influence the energy price. It also demonstrates the ineffectiveness of price only heuristics as a method of optimising the site consumption profile.

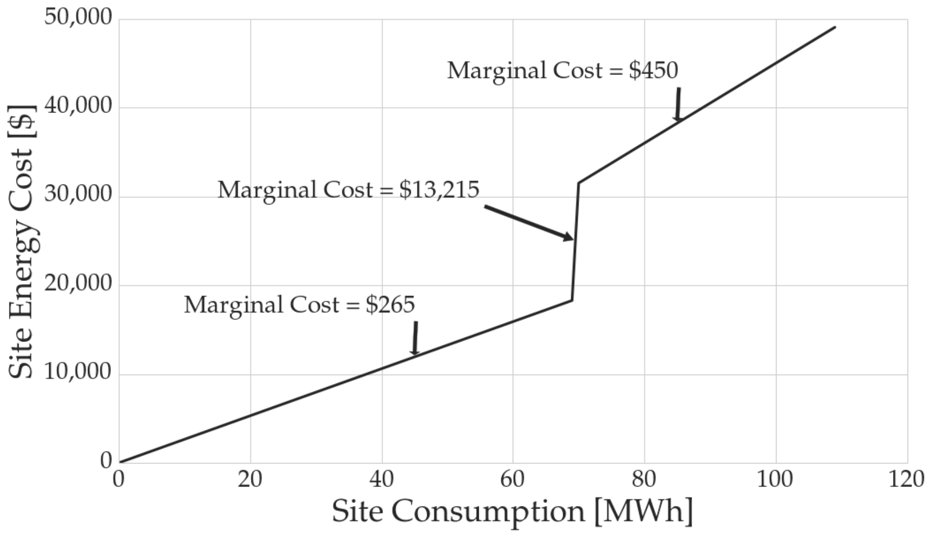

Figure 5.4: Marginal and total costs observed by the site at different levels of consumption, using the offer stack from Figure 5.3

In the deterministic environment, the optimisation of an individual consumer's consumption is a simple matter, as all information is known. This deterministic model has two key assumptions; perfect knowledge of the final demand and perfect knowledge of the supply stack. In this case, the final energy price (λ) is a direct function of the sites consumption level (δ_l) and total load (L):

$$\lambda = f(L + \delta_l) \tag{5.2}$$

As these assumptions are clearly not reasonable, a stochastic process should be applied to incorporate uncertainty about assumptions. In reality, we have a number of possible demand options, as well as potential supply stacks. Consider the supply stack shown in Figure 5.3, for a site that wishes to optimise their consumption in the face of uncertain total load (L). For different total consumption levels, assuming a fixed supply stack, we plot the resulting site energy cost as a function of site specific consumption, δ_L, in Figure 5.5. The site energy costs are inherently linked to the overall demand level, as well as the market offers. Under uncertainty, many possible prices exist for each level of consumption.

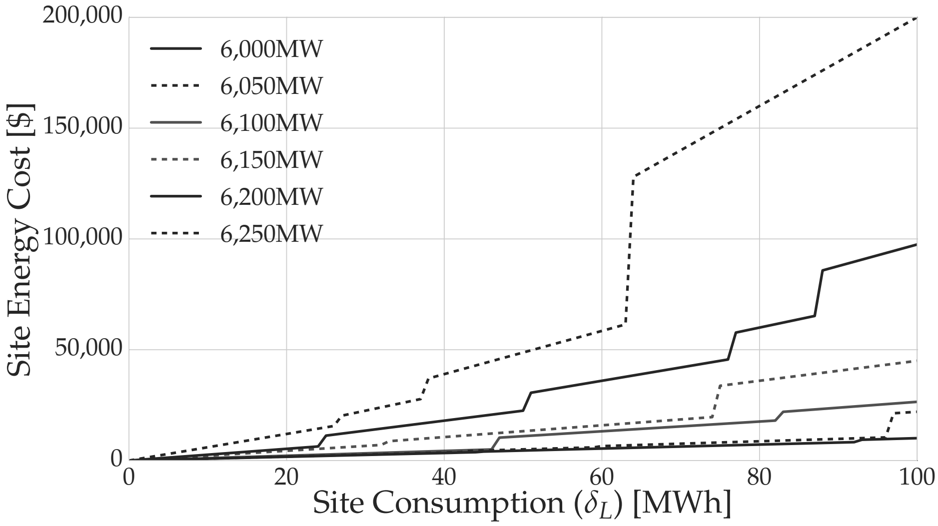

Figure 5.5: Site energy costs at different levels of consumption, assuming a stochastic representation of demand and a fixed supply stack modelled after Figure 5.3. Each jump represents a moment where the site's consumption level influences the final energy price. Increasing stacks represent increasing demand levels in an alternating fashion.

This is a stochastic representation of the energy costs seen by the site, which assumes full knowledge of the market supply function. In the real world context, the site does not have full information about the offer stacks submitted by each generator *ex ante*[5]. Hence, the site must take into account uncertainty regarding total load, as well as uncertainty in the market offer stacks. There also exists a repeated game element to their

[5] Although published offers for historic trading periods do exist.

decision making. If the site continues to curtail in a consistent manner, suppliers will eventually take this action into account.

The example presented in Figure 5.5 represents an energy only case. No revenue from IL has been considered. IL introduces a third source of uncertainty as the participant must also take into account their effect upon the IR markets, as their reserve offers are implicitly linked to their consumption levels[6]. Within SPD, the marginal reserve price can, and often does, become integrated with the marginal energy price under *N-1* reserve constraints. As such, the simplified offer stack visualisation of the effect of different consumptions levels on energy prices is no longer relevant. In the co-optimised setting, no simple visual representation of the influence of combined energy and reserve offers on the energy and reserve prices exists. This is due to the lack of an *ex ante* relationship between energy offers, reserve offers, and price which may be obtained without resolving the full market dispatch. We have therefore integrated IL offer optimisation into *Boomer-Consumer*. This is accomplished in a simplified fashion in order to minimise the level of market dispatch solves which must be conducted.

It is widely known in electricity markets that one node models are insufficient to accurately capture prices. For example, consider Figure 5.6 which compares a single node offer model, under assumed losses of 3%, with the final prices at a non-core node in the NZEM. Models without transmission networks are unable to accurately price trading periods, even given perfect information about demand and market offers. This problem is compounded for co-optimised markets when a consumer is offering IL as well. IL providing consumers must also model their im-

[6] A curtailed load cannot offer IL and therefore, forgoes all reserve revenue. Total supply to the reserve market is also reduced which can have an impact upon the configuration of generation units.

pact upon risk setting generators, which requires a full market dispatch model. Any divergence between reality and the model will lead to inherent inaccuracies, especially when attempting to solve at the high resolution which is required to assess the impact of different consumption levels.

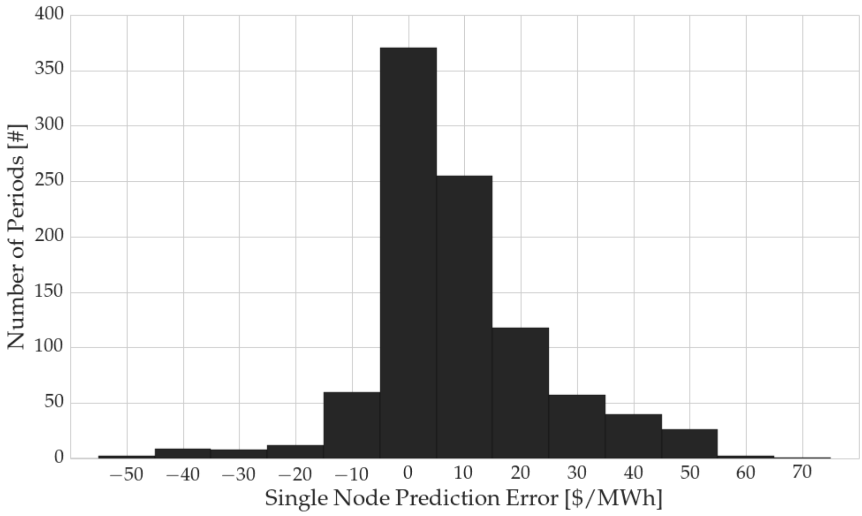

Figure 5.6: Difference between a simple offer stack model, assuming perfect information of market offers and demand, against the final prices in a trading period. Losses in this case are assumed to be 3% of total demand and all trading periods in the month of July 2011 have been considered.

Assumption of Fair Play

This chapter assumes that a market participant will act *within* the market offer structure as a non spoiling entity. During periods where reserve margins are tight there does exist a strategy for an IL consumer to withdraw all of their reserve market offers. That is, to offer zero volume. This can often send the system into infeasibility *penalty* prices which are subsequently cleared off market. In these periods, a consumer in response to a high energy price will withdraw their reserve offers, constrain the period and the final market clearing will occur under relaxed conditions.

In these relaxed conditions there are two options for the Market Clearing Manager. They may either *zero the RAF* (Reserve Adjustment Factor), that is, to turn off the reserve requirement element of the co-optimisation and in essence solve the system as a pure energy market. Or they may (in steps) reduce the reserve requirements until a feasible solution occurs. In both of these situations generation plant that was previously dedicated to reserves may be redispatched into the energy market leading to reduced clearing prices.

However, this strategy is beyond the scope of the Boomer Consumer model. In this chapter we restrict ourselves to investigating periods where the consumer may influence the price within the confines of the full co-optimisation.

5.3 Development of *Boomer-Consumer*

Boomer-Consumer is a stochastic optimisation model designed to be used by large consumers of electricity in the NZEM, which has been developed in conjunction with Golbon Zakeri and Geoff Pritchard. These consumers are either large consumers or large IL consumers (according to our definitions in Section 5.2). *Boomer-Consumer* is not appropriate for small consumers with a negligible impact on the marginal energy price. It is appropriate for consumers who offer reserve and wish to take into account any reserve revenue in their decision making process. Large consumers may take advantage of "hockey stick" supply offer stacks and can impact the final energy price through variations in their consumption level.

In a generalised setting we assume that a consumer may participate in the electricity market. At this point, we have not linked the operation of *Boomer-Consumer* to specific mechanisms. Instead we note that some form of discretion regarding choosing the optimal consumption level and reserve offer must exist. This may be through demand side offers or *ex ante* curtailment in expectation of high prices. For our purposes we may classify trading periods into two regimes; those with reserve constraints where the optimal consumption level includes reserve, and a simpler energy only case where reserve is irrelevant. The model presented in Chapter 4 can be used to determine *ex ante* the trading periods where reserve has a significant impact on the site's decision making process. In the energy only case, the problem is simpler and decomposes to the determination of the optimal consumption level under uncertainty.

In both situations, a key requirement for the optimisation of large scale consumers is an accurate depiction of the network and the participants' supply offers. Consider the difference in resolution between one node, two nodes, n nodes, and the full representation of the grid. Whilst the simpler cases may be easier to conceptualise and analyse, they fail to accurately represent electricity prices, especially in markets with transmission constraints. The accurate optimisation of a consumer's load profile and reserve offer strategy requires greater depth of representation.

The NZ market regulator, the Electricity Authority (EA), has developed and released an audited replica of the underlying dispatch model (SPD), which has been written in GAMS and is known by the name vSPD (Naidoo, 2013). vSPD (vectorised SPD), features the full detailed representation of the participant offers for energy, IL, PLSR, and TWDSR. The full transmission network is contained within vSPD, consisting of approximately 11,800km of high voltage lines across 178 substations, 250 nodes, and 450 links. Transpower, the Grid Owner, has provided a loss model to accurately represent losses along key assets such as the HVDC interconnection. The full cooptimisation with the entire set of security constraints for *N-1* reserve dispatch is included.

vSPD can be modified in order to override key parameters, such as demand or individual market offers. Hence, we utilise it as the base representation of the NZEM transmission network, along with the predefined market offers released daily by the EA. This substantially simplifies the modelling problem. vSPD has been audited by the EA in order to accurately recreate final market prices, subject to the market offers included. Hence, for small changes in system conditions, vSPD can be considered an accurate representation of the NZEM under uncertainty. The consequence of the extensiveness and accuracy of vSPD is that a single trading period can take several seconds to solve. This limits the number of iterations (and scenarios) which can be completed quickly.

There are two forms of uncertainty in the optimisation process; demand and market offers. To account for market offers we utilise the previous offers submitted by generation companies, which are provided in accompanying GDX files[7]. Any complete set of market offers may be used as a base case. However, we limit ourselves to situations similar to the expected period. Extended coverage of this procedure is outlined in Section 5.5. At this stage we have not attempted to create hybrid market offers drawn from multiple situations. Participant offers occur as a result of the natural competitive trading and contractual process in each period. Creating offer chimeras breaks this relationship and the resulting prices may bear little relation to reality.

[7]A GDX file contains all of the information required to solve the GAMS model in a compressed format.

We account for uncertainty in demand through a stochastic sampling procedure. We begin with a distribution, for example a log-normal distribution of total NZ demand, or alternatively a joint SI-NI distribution. The SI-NI distribution can be desirable due to the presence of the HVDC interconnection and its role as a risk setter in the NZEM. These distributions are stochastically sampled to determine a scaling factor for demand which we apply in the base scenario situation.

At this stage a fully defined system exists with a single optimisation variable - the consumption level of the site. Predefined site operating levels are specified according to feasible operating conditions. Or, linear consumption levels may be considered to determine the full effect of the site on the market (at the cost of increased computation time). Using this consumption level, we resolve vSPD with the updated (stochastic) total demand and chosen site operating level, resolving vSPD for each possible operating level. The full process of the optimisation procedure is outlined in Figure 5.7. Our problem becomes the determination of the optimal site consumption level, given a range of possible market offer or demand scenarios. For each solution run, a distribution of energy prices is determined.

This approach is computationally expensive. The full grid dispatch is solved for a large number of iterations. Considering a site with ten consumption levels and ten demand samples for a single state of market offers, 100 iterations must be solved. This scales linearly with the number of potential market states which are chosen. To partially alleviate computational requirements, a full market (dispatch) solution is performed for the first iteration only, with the remainder considered as "hot" solutions. A "hot" solution begins with the solution from the previous iteration as the starting point and therefore converges much quicker. This approach

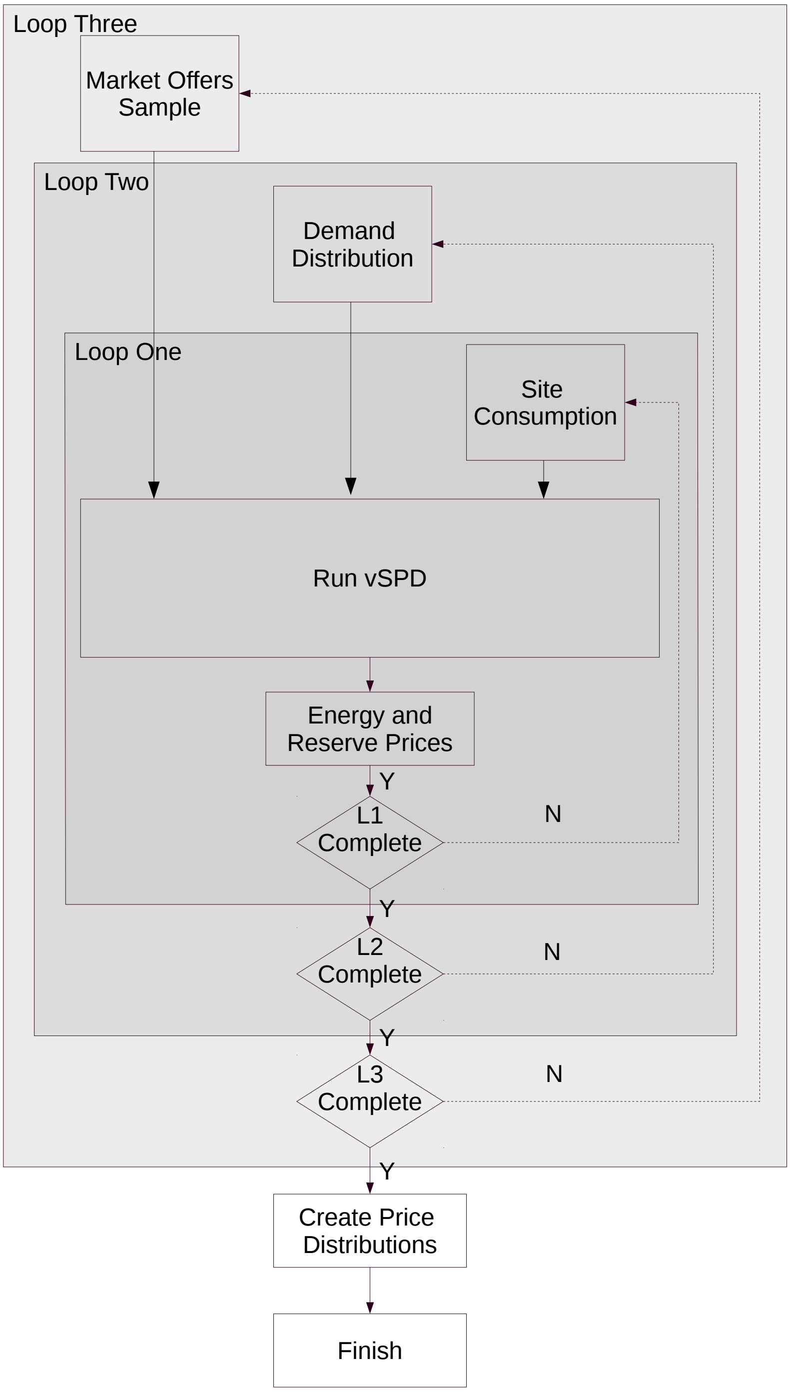

Figure 5.7: The process through which Boomer-Consumer is solved consists of three loops. For each set of market offers a demand distribution is sampled. Within this distribution, different levels of consumption are solved in order to resolve energy and reserve prices.

is valid for small changes in the system, such as small changes in demand or consumption level, but not for large scale changes. By utilising "hot" solutions the time required for each iteration is significantly decreased.

The prices produced by *Boomer-Consumer* are a form of forecasting, given uncertainty. For example, the site may not be able to submit consumption bids (the functionality may not exist). In this case, the site must determine their consumption level before the market gate closure. The site therefore cannot respond in real time to electricity prices or they may face non-compliance costs imposed by the SO. Many models exist to forecast price in electricity markets. An overview of some of these models have been presented in Chapter 4. A key assumption of these models is that of independence from the underlying market dispatch. That is, the models are valid for price-takers, not price-makers in the electricity market. As such, *Boomer-Consumer* may be considered a method to improve upon these models and extend them to the price making situation.

5.4 Model Results

The implementation of *Boomer-Consumer* has been tested for a major consumer in the NZEM, using the previous day's offers as the base for the load optimisation process. Thirteen months from the 2008-2013 calendar years were selected for analysis[8] Within each month, weekdays were assessed due to the limitations of a "following day" assessment for days when load profiles are substantially different. Hence, Monday to Thursday were used as a base for the optimisation decisions to be taken on Tuesday to Friday. Load profiles for the NZEM are shown in Figure 5.8.

[8]These months were chosen due to the number of highly priced trading periods within them, where a high price was defined as one above $200/MWh. This level was chosen after discussions with large consumers as to their greatest cause for concern when exposed to spot market prices.

We note that Mondays and Tuesdays have lower morning peaks, Friday has a reduced evening peak, and Wednesday has the highest daily consumption level. These load profiles are all susceptible to seasonal patterns and changes in weather.

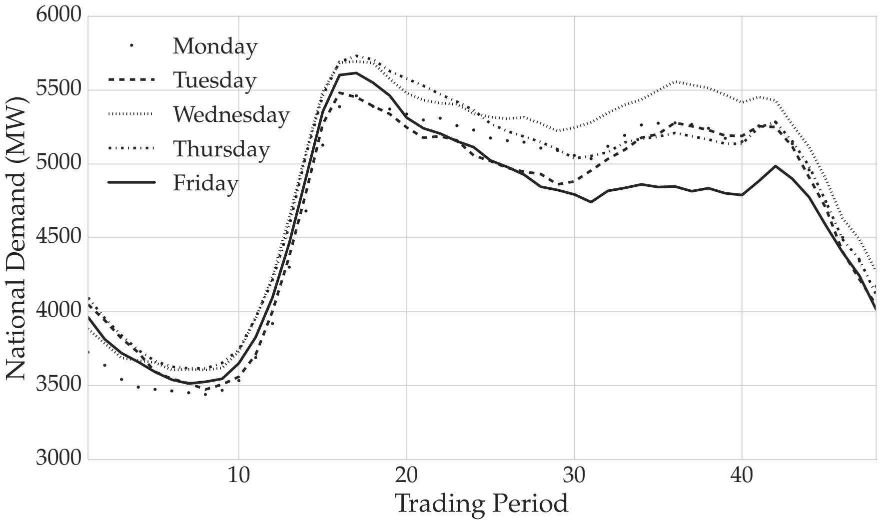

Figure 5.8: Illustration of weekday load profiles. We note the difference across the week, with Monday and Friday in particular having dissimilar load patterns. Weekends have been excluded as both Saturday and Sunday exhibit unique consumption profiles.

We have assessed the viability of *Boomer-Consumer* under five different scenarios:

1. As a spot price prediction tool
2. As a qualitative daily price profile predictor
3. As a predictor of high trading period spot prices
4. As a predictor of high spot prices over the course of a day
5. As a load reduction strategy (measured in $ per MW)

Boomer also contains additional functionality to produce the optimal IL and consumption offer for a trading period. We have not directly assessed this, as "optimal" depends upon specific plant operating conditions which are not in the public domain.

Spot Price Prediction

Ten different load scenarios were simulated for each trading period across a large number of possible plant configurations. In order to compare the stochastic prediction to the final price, some form of aggregation is required. As outliers can arise during peak trading periods, when the simulated load variation may shift prices into the infeasible region, a truncated average was utilised. This excluded the two lowest and two highest energy prices. More complex methods, such as CRPS (Continuous Rank Probability Score), were assessed with a similar overall distribution of errors as the results from simpler method. That is, the distribution of errors (or CRPS scores) was similar to the results shown in Figure 5.9 indicating periods of high accuracy along with extreme inaccuracy at the margins. The simplified error has been used as it indicates the relationship between an aggregate and the final price, which can be used in practice.

The errors in this case follow a power law distribution, not a normal distribution. For 50% of trading periods, *Boomer-Consumer* is accurate to within \$20/MWh and 80% of periods are within \$50/MWh. For the final 5%, errors reach extreme levels ranging into the hundreds and thousands of dollars. A percentage error approach has also been undertaken, with results following a similar power law distribution. We have chosen not to present the percentage results, as low price predictions (e.g. low single digit energy prices) overwhelm the results. Many of the errors occur

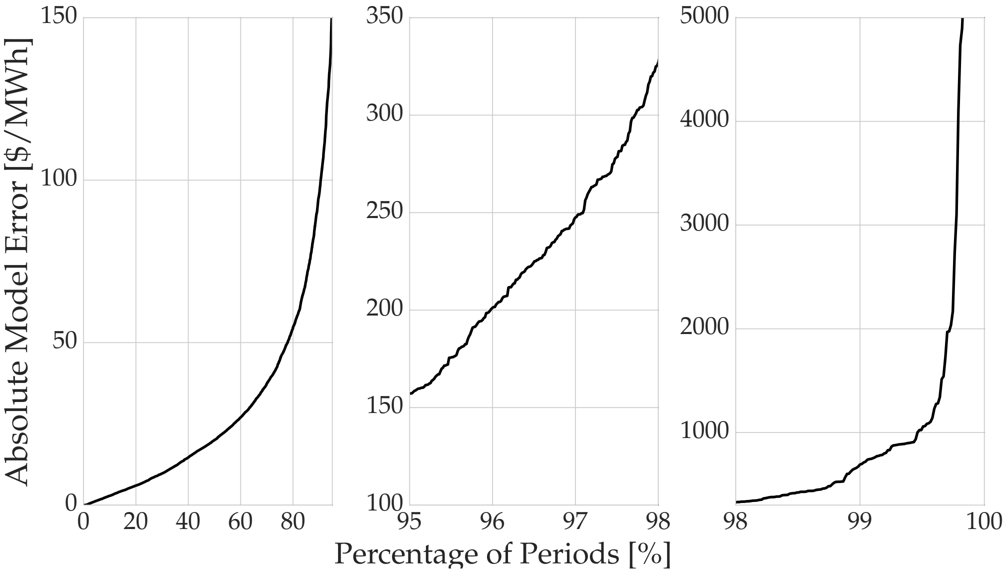

Figure 5.9: Triptych of absolute errors for Boomer-Consumer, indicating different error categories. The majority of periods have small errors, although these errors rapidly grow in size at the margins. The x axis represents the percentage of periods with a model error below the y axis quantity. For example, 98% of trading periods have an absolute model error below $325/MWh.

due to an unexpected event (transmission outages or extreme weather conditions), which are not represented in the base scenario used. These could be (but have not been) inserted into the scenarios. As other market participants are aware of these scenarios, the second order response must also be taken into account. This would require a full simulation of competitor offers.

The most extreme errors occur due to penalty pricing situations. Penalty pricing has been introduced to vSPD to indicate a priority order for violating the feasible dispatch solution. For example, the model will attempt to solve for energy and violate reserve constraints before it seeks to shed load. In reality these prices are not expected to occur, as pre gate closure energy trading between large generation companies typically alleviates these pressures[9].

Qualitative Assessment

A secondary usage for *Boomer-Consumer* is to create qualitative forecasts of the price profiles expected over the upcoming day. A qualitative forecast includes information, such as "peaks" and "troughs" in the energy price, which is valuable information. The results for this assessment are mixed. Three days where the model was particularly well suited to predicting prices, along with three days with poor results are presented in Figure 5.10. The worst days are identified by missing large one off energy price spikes.

Identification of High Priced Periods

The previous sections illustrate the difficulties in forecasting spot prices, even when using a full representation of the transmission network. There are alternative methods of using *Boomer-Consumer*. The model produces a distribution of prices which can be used as a measure of the risk a period will have high spot prices. For example, numerous forecasts of high energy prices are an indicator that management should closely assess the plant operating status in preparation for curtailment. In this case, the model is used as a forecasting tool to determine if prices will exceed a particular threshold. This assessment can be either for a specific trading period, or for a number of trading periods over a trading day (days are preferred due to the release schedule of information within the NZEM).

[9] These can still occur during five minute real time dispatches due to unforeseen fluctuations in load, for example a sudden cold snap. In many cases these prices do not eventuate to the final pricing solution which uses an average for the load values across the trading period.

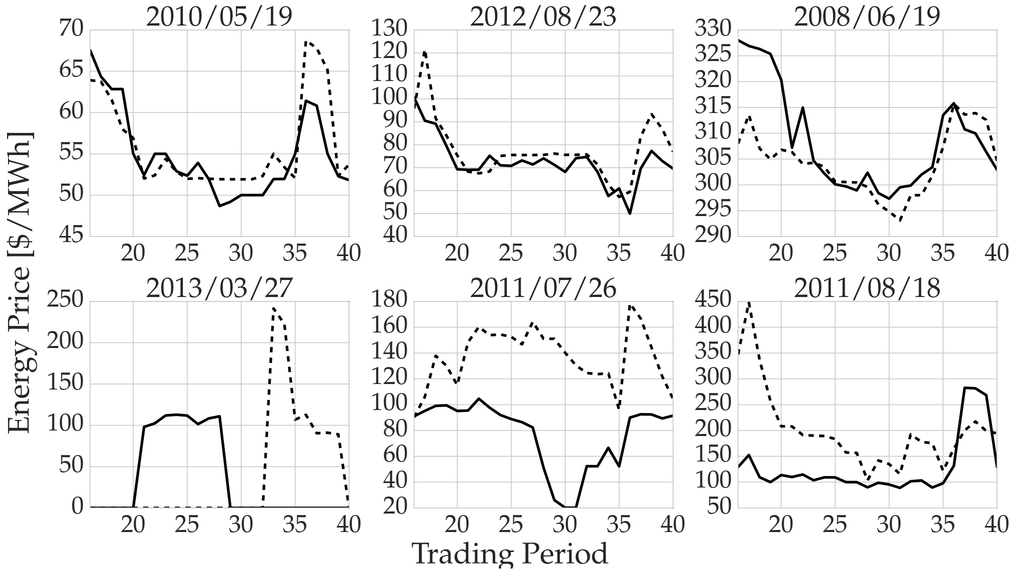

Figure 5.10: Qualitative price profiles as predicted by Boomer-Consumer (dotted line), compared to the actual price profiles (solid line). The top row represents a selection of days where Boomer was particularly accurate, whilst the bottom row represents the opposite.

The daily assessment recognises that for consumers, the cost of responding to a singular trading period where prices are high has repercussions on the overall production profile. As such, there is a bias towards responding to a succession of periods where prices are high.

If 50% of the distribution exceeds an energy price we assess the event as likely to occur. In this situation two metrics are important; Consistency (5.3) and Accuracy (5.4). The consistency of a prediction relates to the number of high priced periods accurately identified. Accuracy is the number of predictions which were correct compared to the total number of predictions made. These may be defined using n_a, the number of periods where an accurate prediction was made, n_m, the number of periods where the price exceeded the threshold but *Boomer-Consumer* did not recognise this (missed periods), and n_i, the number of periods where

Boomer-Consumer predicted high prices which did not eventuate (inaccurate). Our metrics are thus:

$$\text{Consistency} = \frac{n_a}{n_a + n_m} \tag{5.3}$$

$$\text{Accuracy} = \frac{n_a}{n_a + n_i} \tag{5.4}$$

A model should be both consistent and accurate. A trivial case of a model which predicts every period will have 100% consistency but very low accuracy. Likewise, correctly making just one prediction results in 100% accuracy, but very low consistency. Accuracy is the trust that the prediction is right, consistency is the trust that the model is not missing situations of interest.

In Table 5.1, *Boomer-Consumer* has been assessed on both a trading period by trading periods basis, as well as on a daily basis. It is most important to assess when prices will be high for a consistent number of periods, as opposed to a single trading period (although the daily prediction is a collection of individual trading periods). In a dry year, energy prices typically reach high levels for a sustained period of time (1-3 months) and as such, forecasts of high energy prices during these periods is less useful as managers are typically aware they would be occurring anyway.

The daily assessment is most important. For a consumer of energy, the ability to understand when a sustained period of high energy prices is likely to occur is valuable. A day with high spot prices is identified as one where more than 10 trading periods exceed \$200/MWh from 9am to 8pm. Over the days assessed there were 40 days that satisfied this condition. *Boomer-Consumer* predicted that 50 such days would occur, with an overall consistency of 75% and accuracy of 60%. That is, twenty of the predictions were erroneous whilst ten of the days with high spot prices were also missed.

Table 5.1: Ability of Boomer-Consumer to accurately and consistently assess trading periods with high spot prices on both a period by period basis as well as a daily basis where more than 10 trading periods exceeded the threshold energy price.

	Inclusive 2008 Dry Year (Period)	Exclusive 2008 Dry Year (Period)	Daily Assessment
Total Predictions	1262	701	50
Periods over $200	1063	546	40
Consistency	69%	50%	75%
Accuracy	58%	39%	60%

Strategy Profit

Boomer-Consumer has been compared in a practical setting against a continuous operation strategy and the theoretically perfect response strategy. This comparison is used to determine how profitable *Boomer-Consumer* is over the trading periods considered in an aggregated assessment for different values of site load. The production value is inherently linked to the optimal response a site may take, as it influences at what level the site should respond to energy prices. In Figure 5.11 we assume that unprofitable operation occurs at $200/MWh, which is used as the cut off decision threshold (when *Boomer-Consumer* predicts the energy price will be above $200/MWh the decision to curtail is made, otherwise the site continues to operate). In many situations, the use of *Boomer-Consumer* would increase profitability as compared to the continuous operation strategy.

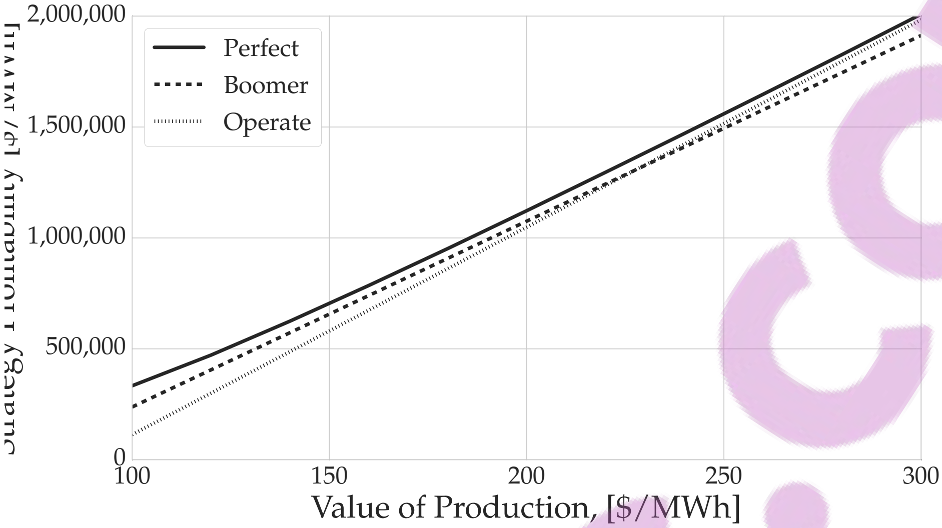

Figure 5.11: Profitability of using Boomer-Consumer as a basis for decision making, as opposed to the perfect response strategy and the continuous operation strategy in the NZEM, on a per MWh basis. The optimal response is susceptible to different valuations of production.

5.5 Model Extensions

IL Offers

In this section, an extension to incorporate the interruptible load offers is detailed. The integration of IL adds an additional layer of complexity. Instead of optimisation over a single variable, the site consumption, each consumption level has an associated optimal reserve stack. Reserve influences the optimal site decision both directly and indirectly. The site earns revenue from reserve dispatched which can be sufficient to offset high energy prices. Hence, curtailment of load may be inappropriate in these situations. Indirectly, the site contributes a portion of the reserve supply stack and in doing so, alleviates the requirement for generation plants to provide reserve. The reserve provided may be lower cost, directly reducing prices, or alternatively, can alleviate any reserve constraints which may be acting.

The problem of offering IL in quantities great enough to move market prices is similar to that of a generator offering spot energy. In this case, it is desirable to create a multiple tranche offer which will maximise our expected benefit. The energy only case is considered in Neame et al. (2003) which we adapt for the reserve situation.

The quantity, price plane of possible offers is subdivided into a finite grid consisting of rectangular cells. This simplifies our problem as admissible offer stacks are those which follow the edges of the cells. The expected value of any particular set of tranches decomposes to the sum of terms corresponding to the horizontal or vertical line segments on the edges of the cells. The optimal offer stack optimisation may be efficiently solved using a dynamic programming method which gives the optimal stack subject to the assumed grid, a prize collecting process.

This process is repeated to develop an optimal reserve stack for each level of demand, subject to the initial assumed grid. The consumption optimisation procedure is then repeated for each demand level, subject to uncertainty, with the developed optimal reserve offer intact. Hence, the complete process is to solve the consumption element of *Boomer-Consumer*, utilising a placeholder reserve offer stack in order to develop the required grid. A dynamic programming procedure is applied to this grid in order to calculate the optimal reserve offer for each level of demand. The stochastic sampling procedure for demand is repeated at different levels, with the optimal IL offers in place.

Base Scenario Optimisation

Boomer-Consumer requires a representation of the underlying market participants offers in order to formulate prices. In the NZEM, generation companies represent energy offers in a five tranche stack to the SO. For a single trading period, this represents more than eighty separate generation facilities across twelve different companies and five primary technology types. To theoretically determine the energy offer stacks that each company will submit is an exercise in both hubris and futility. Not only is each set of market offers related to the contractual position of the participants, but market spot traders are continuously iterating their offers. Offers are also a function of any outages in the system. For example, certain transmission outages may limit the ability of particular units to be offered to the grid.

The benefit of using vSPD is the level of granularity encapsulated within the model. However, this prevents representation of other offers through methods such as supply function equilibria (SFE), or as a market distribution function. Each set of offer stacks is specific to an individual trading period. Arbitrarily changing minor details in a participants offer can lead to unexpected results, such as infeasible solutions or penalty pricing.

There exists a published database of offer stacks which contains the full set of offers for both energy and reserve since 2004, consisting of over 150,000 trading periods. Fortuitously, each of these stacks is contained within a GDX file, released daily by the Electricity Authority. As an alternative to recreating the offer stacks we use a simpler approach and identify trading periods which are similar to the period of interest. Common periods we may wish to consider include the previous days, or the offer from the same trading period in the previous week. The assumption being that market participants will behave in similar ways.

In Chapter 4 a kNN based method of identifying similar trading periods was presented. As part of that method two approaches were considered, the full set of training information, and a subset based upon high prices. The kNN technique has two functionalities; regression of specific values or the identification of mathematically similar periods. It is the latter functionality which we utilise to act as a source of market offers. By determining the nearest set of trading periods relative to expectations of the current trading period, greater variety can be included in *Boomer-Consumer*. However, this occurs at the cost of increased solution requirements and under the caveat that some contextual information may change over time. A period identified as mathematically similar may in fact be entirely different when the unknown contextual information becomes fully known.

This approach is best implemented in parallel with many separate instances of *Boomer-Consumer* as there exists no relationship between solves and they may thus be solved independently. A parallel implementation dramatically increases the number of market situations which can be contained within the optimisation process and solved within a reasonable period of time.

5.6 Conclusions

The integration of consumers into the electricity market dispatch process has large potential for economic benefits. In some markets, consumers have tools to submit consumption profiles to the SO. Aggregation companies have arisen to combine disparate loads and reduce the threat of non-compliance with market dispatch situations. These initiatives both support short run operational efficiency and reduce long term capital investment requirements. By reducing the peak consumption, either gross or net after taking into account renewable generation, the level of investment in carbon intensive peaking generation is reduced. For consumers this should have long term benefits and reduce the rate of increase in electricity costs (noting that marginal costs of electricity are sticky downwards to a certain extent).

Demand response from large scale consumers can be thought of as a transitory step towards the full integration of retail and small commercial consumers. Large consumers have time of use pricing, continuously manned control rooms, and strong incentives to maximise profitability through appropriate curtailment mechanisms, which coincidentally support the grid. Many of these consumers are already participating in the IL market, where consumers support the grid from frequency collapse in the event of unexpected generator de-synchronisation. To improve these consumers' participation in electricity markets requires individual offer optimisation models. These models should take into account what effect, if any, the large consumer has on the full system. These consumers are price makers. They influence the marginal energy price and therefore their actions are not independent of their environment.

Boomer-Consumer has been assessed using a number of metrics, both quantitative and qualitative. From this assessment, we conclude that the best use of the model in its current state is as a spot price prediction tool. A large consumer using *Boomer-Consumer* to optimise their response to price *ex ante* would have been more profitable over the trading periods assessed than one who continued to operate regardless of the available information. Overall, accuracy and consistency metrics are reasonable for the identification of an extended number of high spot prices.

As a model, *Boomer-Consumer* has many possible improvement pathways. Large production sites cannot begin operation or curtail at a moments notice, nor may they curtail for extended periods of time. For each consumer there exists an individualised production and consumption model which takes these into account. The incorporation of such a model, as well as a temporally based optimisation process, would lead to more sophisticated outcomes.

Chapter Summary and Contribution to the Literature

This chapter has contributed to the literature by presenting a model to co-optimise energy consumption and reserve offers for an IL consumer. This represents the first known attempt within the literature to determine the optimal combined offer profile for such a consumer. *Boomer-Consumer* approaches this problem through a three stage approach. First, simulations to determine energy prices under uncertainty are performed. Second, a dynamic program is solved to determine the optimal reserve offer for each consumption level. Finally, the optimal reserve offer is substituted in place for each consumption level. Simulations are performed to determine energy prices for the consumer, with this optimal reserve offer in place.

Previously the literature the consideration of optimal offers has only been considered for generators. Furthermore, the case of large consumers with demand side offers has not been considered, let alone the case of an IL consumer with an associated reserve offer. This chapter (and the associated papers) thus represents some of the earliest work in this field.

Chapter 6

Conclusions

In this chapter we summarise the contribution of the preceding chapters to the wider literature. Within this thesis, the effect of co-optimised reserve markets on pricing mechanisms, generators, and IL consumers has been explored. Linear programming, equilibrium models, k nearest neighbours models and stochastic optimisation have all been applied to develop a number of theoretical and practical models. The insights of these theoretical models have been applied to the New Zealand Electricity Market where significant corroboration with real world events was observed.

This chapter does not present new information but instead summarises the contributions of this thesis to the wider literature.

6.1 Research Motivations

The design, operation, and sustainability of the electric power sector continues to draw attention from both politicians, researchers and the general public. Fossil fuel prices, resource availability, and climate change have all contributed to the search for greater efficiency. In this pursuit, both consumers and suppliers are beginning to alter their behaviour within the electricity grid. An increase in the use of complex, sophisticated tools has been enabled through communications technology and automated solutions. The operation of the grid is iterating towards the "Smart Grid" paradigm which should (theoretically) improve security and reduce costs.

The variety of models used to capture the full spectrum of phenomena within electricity markets continues to increase. In this thesis a number of these tools have been used to explore the relationship that co-optimised reserve markets have with their associated energy markets. In Chapter 2 the market dispatch model was considered analytically to explore pricing mechanisms. This approach illustrated the methods through which reserve prices become integrated with energy prices under *N-1* security, as well as extending the theoretical mechanisms to an empirical assessment. Whilst in Chapter 3 the simplified setting was extended through the addition of Supply Function Equilibria for both energy and reserve offers, in a two node, two player setting.

In Part II the theoretical underpinnings have been extended to optimise the decision making of IL providing industrial consumers. In Chapter 4 an *ex ante* trading period and price classification model was developed. The model uses the kNN technique to forecast which periods will be reserve constrained if a high price occurs. This was used to optimise a simplified demand side bidding process. The strategy applied in Chapter 4 cannot be used to optimise the internal consumption level of an IL consumer. Instead, it seeks to leverage the link between high energy prices and high reserve prices empirically shown in Chapter 2. In Chapter 5 a stochastic model was developed to optimise an IL consumer's consumption under uncertainty by explicitly modelling their effect on the marginal spot energy and reserve prices. The full grid dispatch model (as developed in vSPD by the Electricity Authority) has been embedded within a simulation process which models energy and reserve prices under different load conditions. These prices are used to optimise the combined, linked, energy and reserve offers for an IL consumer, under uncertainty in demand.

The investigation of co-optimised reserve markets have linked the different chapters in this work together. The presence of reserve influencing energy prices was identified theoretically and observed empirically in Chapter 2. The remaining chapters extended this insight. First in Chapter 3, where the effect of reserve constraints on competition was assessed and then in Chapter 4 and Chapter 5, where the results were extended to optimise IL consumer operation.

In this thesis, special attention has been made to apply each piece of theoretical analysis to a practical setting. The NZEM has been used for this purpose, as it is a reserve co-optimised in an island electricity market it is a particularly interesting model. The two islands of New Zealand have separate AC grids which are linked by a reserve constrained HVDC interconnection. The identification of transmission price separation, which could not be explained by losses or congestion, led to the investigation of reserve. New Zealand has a large installed capacity base of hydro units which also provide spinning reserve. The seasonal (and inflow dependent) behaviour of these units contributed to a number of natural experiments, as reserve market shortfalls occurred in both islands. These two characteristics, a two island market with large seasonal generation imbalance and a reserve constrained transmission line, mean the work in this thesis is crucial to understanding the dynamics at play in the NZEM.

6.2 Identifying Constraint Mechanisms

Chapter 2 makes two contributions to the wider literature on reserve constrained markets:

1. The enumeration of different mechanisms through which reserve constraints influence energy prices
2. Extension of these mechanisms to identify pricing phenomena in the NZEM where these influenced the final energy price

The models developed consist of a simplified electricity network with two nodes which reflects the market structure of the NZEM. These models consist of a simplified form of SPD which was stripped down to its core functionality of co-optimised energy and reserve dispatch. This work extends the theoretical literature of electricity and reserve pricing to assess the implications of a specific form of co-optimised market design. In reserve constrained markets, the dispatch of large generation units is limited by the availability of reserve. In markets with a deterministic (*N-1*) reserve risk, this places limits on the utility of large generation units. If reserve is scarce, high cost generation units are preferentially dispatched to reduce reserve requirements. If transmission is considered risk setting (as it is in the NZEM), the availability of reserve will influence the distribution of prices across the connected nodes. This implies that companies must account for the likely reserve price (at different risk levels) when pricing their offers into the energy market.

The optimal dispatch of individual stations may also influence the energy market. A set of three constraints, known colloquially as the "inverse bathtub" limit the combined dispatch of energy and reserve offers to a feasible region. If the marginal provider of reserve is a unit operating at the edge of this feasible region, the procurement of reserve can involve compromises in the associated energy dispatch for the unit. When this occurs both final energy and reserve prices cannot be directly linked to participant offers on the supply stack. In this case the marginal unit of energy (and reserve) is often served by a combination of units. This effect is consistent over both generator and transmission risk setters, although the transmission case is easier to identify empirically.

The identified mechanisms were formulated as tests for a set of more than 100,000 trading periods taken from the NZEM. The mechanisms were formulated as combinations of boolean constraints and used to identify the trading periods where a constraint was binding on the basis of interlinked prices. The transmission example can be identified once transformations, to compare the combined FIR and SIR reserve prices with the difference in island energy prices, have been made. Over 10,000 trading periods from the start of 2008 to mid 2014 were identified in Figure 2.4 and Figure 2.5 as exhibiting pricing phenomena consistent with the effects of reserve constraints. Reserve constraints are associated with high electricity prices, in particular, those where prices exceed \$500/MWh as shown in Figure 2.6. The occurrence of these periods has a strong seasonal component, which has been linked to extremes in hydro storage conditions.

In high reservoir storage periods, hydro generators are used extensively while maintenance is performed on thermal units. This leads to a large dependence upon the SI hydro lakes and consequentially, high northward HVDC flows and NI reserve requirements. At the alternative extreme, low storage levels lead to southward HVDC flows and increased reserve requirements in the substantially less competitive SI reserve market.

For a South Island generator such as Meridian Energy, the reserve constrained transmission line leads to price separation between the islands. The implication for Meridian Energy is that any MW of energy they contractually supply (to their retail customers) in the NI must be purchased from the spot market. On occasion, due to reserve, this purchase will be at a significant premium to the price received for their SI generation. To minimise this risk, generation units at the "sending" island may choose to self withhold their capacity from the market, to avoid binding the constraint. This strategy sacrifices potential generation volume in order to minimise price separation. Other strategies could include limiting contractual obligation (be a net seller in the marketplace (permanently long)), or negotiating for long term supply contracts. The net effect in this case is a geographical imbalance in power structures within the NZEM due to the presence of reserve constraints. In Chapter 3, theoretical equilibrium models have been designed to test this effect in a simplified setting.

6.3 Application of Equilibrium Models

The models used to identify the reserve constraint mechanisms in Chapter 2 were extended through the application of supply function equilibria in Chapter 3. SFE models were first developed by Klemperer and Meyer (1989), applied to electricity markets by Green (1996), and were extended to reserve constrained electricity markets by Bautista et al. (2007b). The application of equilibrium models to co-optimised markets is still relatively new and is inherently linked to specific reserve procurement mechanisms in the dispatch model. This chapter (and the associated paper) are the first detailed attempt to apply SFE to markets with reserve constrained transmission lines under *N-1* security.

A variant of the model developed in Chapter 2 was embedded as a sub problem within a profit maximisation problem. To ensure that equilibrium was reached, the primal and dual linear program (Panne, 1975), complementarity conditions (Cottle et al., 2009), and strong duality theorem (Bazaraa et al., 2013) were included as a set of constraints. Two generators competed (with one another), where each attempted to maximise profits subject to an assumed state of their opponent which was determined using the relaxation approach proposed in Contreras et al. (2004). In a market with reserve constrained transmission, the optimal offer strategy for participants was to price reserve highly in order to limit transmission flow (which required provision of reserve due to the risk requirement). This result was illustrated in a two person game without unit capacity constraints or the "inverse bathtub" constraints present. As transmission flows are limited, the participant who can no longer capture further volume responds by increasing their energy offer prices in order to minimise any nodal price separation. In this case, marginal transmission flow is eliminated and each participant once again becomes a local monopoly. In practical terms, the decision to defer a capacity upgrade at the Benmore hydro station upgrade was driven by cost concerns relating to HVDC transfers (Barker, 2014), of which reserve costs can be a significant contributor.

In Borenstein et al. (2000) the effect of transmission lines on competitive behaviour was assessed in an energy only setting. The authors illustrated that transmission lines of sufficient capacity to eliminate gaming, can lead to a decrease in prices without any utilisation of the line itself. In this situation, the benefit of a transmission line is as a competition enabler, which reduces participant market power. This result has been replicated and extended in this paper to include the effect of reserve on behaviour within a similar transmission based setting. The ability to constrain a transmission line with reserve, removes any competitive benefit associated with the construction of additional transmission capacity. In this case, reserves are used to recreate the congested transmission lines (which were at the heart of the problem) tackled by Borenstein et al. (2000).

In 2012/2013 the HVDC link connecting the North and South Island was extended in a $700 million (NZD) project. This chapter was largely motivated by the situations occurring within the NZEM at the time. Following this theoretical work the conclusion is that the benefit of the HVDC upgrade does not lie in capacity, nor directly in the competitive energy offers of participants. The transmission upgrade modified the risk profile and fewer reserves are required to secure the inter island flow now (due to self coverage between the poles). As transfers increase to high levels the twin parallel poles become unable to support one another to the same extent. As a result, reserve constrained prices become possible once again. This led to the conclusion that proposed upgrades to either the market or grid itself should not only consider the competitive benefits within the energy market but also the reserve market. Alternatively, it illustrates that operational alternatives may be lower cost. Encouraging additional IL participation would not only release units from combined generation and reserve provision, but would also decrease the market power of companies who own key spinning reserve assets.

6.4 Classifying Reserve Constrained Periods

In many situations an aware of the theoretical *potential* for a set of pricing mechanisms and competition behaviours to occur is insufficient. For a manager who must make decisions on a period by period basis, practical methods are required. In Chapter 4 a method to determine an *ex ante* classification of trading periods was developed. This method enabled a participant to answer the question “If a price spike were to occur, should I take corrective action in response?” For IL market participants interested in implementing demand response, a detailed understanding of their precise energy costs after taking into account reserve revenue, is needed in order to respond optimally.

Load curtailment as a form of demand response is particularly well suited to avoiding short duration spikes in the nodal electricity price. As such, it serves as a natural entry point to optimising the operation of a large (spot price exposed) consumer. An IL consumer cannot respond to energy prices alone as their true costs in a period are mitigated by reserve revenue. A simplified heuristic of *“curtail when prices exceed a price threshold”* will lead to non optimal behaviour.

A large consumer participating in a market with demand side offers must choose which offers to submit to both the energy and reserve markets. In a hypothetical situation, the consumer may submit an energy offer and be curtailed, whereas the net position for the site was positive due to reserve revenue. The integration of demand side offers guarantees a system level optimisation, rather than an individual profit maximisation for a specific consumer. As the site cannot indicate a net position to the SO for use in the optimisation, the energy and reserve tranches exist as the tools through which they must operate.

A k Nearest Neighbours (kNN) model has been developed to classify a trading period *ex ante*. Using this model, a consumer may assess the likelihood of reserve market compensation if energy prices spike and thus, the optimal choice of action (curtail or continue to operate). The model identifies a number of mathematically similar periods, based upon numerous factors including hydrology and demand along with temporal adjustments. Each factor in the model can be weighted to bias the selection of the trading periods to create a subset of the information. The consumer may also choose an energy price threshold to further winnow the database to those trading periods of greatest interest. The site then uses information from this subset, either directly to assess the probability of their optimal action at the specific price level, or indirectly to understand the likelihood of an energy price spike occurring in general[1]. This assessment leads to the optimal *ex ante* decision for that trading period, in the event of a price spike.

The kNN model was used to forecast the optimal choice of strategy for each trading period where the price exceeded $200/MWh over a six year period. Two alternative strategies, to curtail in every period, or to operate in every period, were presented as comparisons (along with the

[1]In this case, a very high distance metric between trading periods implies that the model has had to expand it's search to find enough trading periods. This can indicate that in similar situations high energy prices are unlikely and is thus a rough estimate of the likelihood of a spike in the current period. Likewise, if the distance metric is very low, for example the set of returned periods were all price spikes from the past 72 hours, then the site could reasonably conclude that a spike is more likely in the current period.

"perfect response" strategy). The kNN method was the best choice of strategy at the 70% prediction threshold. The model was capable of identifying up to 95% of trading periods, with 80% of the predicted reserve constrained periods being accurate.

The model presented in Chapter 4 assumes that a consumer has only two possible states; full operation or curtailment. For large IL consumers the choice of an *optimal* combined energy and reserve offer must be made. This offer should take into account the effect the consumer has upon the final clearing price at different consumption levels under uncertainty. To approach this problem, a model called *Boomer-Consumer* has been developed in Chapter 5.

6.5 Optimal Combined Offers

The choice of *optimal* consumption strategies for an IL consumer has two components:

1. The optimal energy offer
2. The associated reserve offer attached to this energy offer

Both 1. and 2. are interlinked with each other and cannot be considered separately. As such, consumers can not make use of a simple decision heuristic to construct an offer stack (namely at each price what is the optimal level of consumption). This problem is inherently linked to the problem faced by a generator who offers spot market energy.

In electricity markets uncertainty exists in the exact market offers of competitors, as well as the final demand level in a trading period. Consumer's cannot therefore perform a deterministic optimisation, they do not have the information necessary to make such a decision. Instead, stochastic optimisation under uncertainty must be performed to determine the consumer's optimal consumption decision, under a range of potential outcomes. Ideally, this problem would be approached analytically for the combined energy and reserve offers. However, no solution currently exists for such a problem, instead numerical simulations have been used.

The full market dispatch model (vSPD) has been embedded in the consumer decision making process. For a given set of market offers, a range of demand scenarios are sampled and for each consumption level, the expected energy and reserve prices are determined. In a second stage, these energy and reserve prices are used in a dynamic program to construct the optimal reserve offer using the approach outlined in Neame et al. (2003). Finally, the first stage of the process is repeated, but for each consumption level the associated optimal reserve offer has been included. The final result is the creation of the optimal consumption offer for which an optimal reserve offer exists.

The model has been assessed using a number of metrics, both quantitative and qualitative. At the heart of the model is the ability to simulate energy prices at different consumption levels for the site. Five separate metrics have been used to assess this. These results indicate that the best use of the model can be used to predict high spot prices on either a trading period by trading period basis or for an extended period of high prices in a day.

A strategy based upon using Boomer-Consumer to forecast when the site should curtail or operate as compared to a naive (price insensitive) strategy and "perfect response" strategy was undertaken. The Boomer-Consumer strategy led to improved outcomes as compared to the naive strategy and approached the perfect response when the marginal benefit of production was low.

6.6 Contributions to the Literature

Co-optimised reserve markets are promoted within the wider literature as improving market efficiency. However, the majority of the literature has focussed upon the development of these models in a theoretical setting. As they are relatively new in many jurisdictions, there does not yet exist a substantial quantity of data on the effect of reserve markets over the long term. The NZEM has had co-optimisation in place for more than a decade using the model proposed in Alvey et al. (1998). In this thesis, the NZEM has served as a model to understand the practical issues which can arise in this specific implementation.

In particular, Chapter 2 contains a clear enumeration of the mechanisms through which reserve offers may limit the optimal energy dispatch. Examples of this pricing behaviour in a number of situations including; marginal risk setting generation and transmission, multiple risk setters, along with the behaviour of price when unit level constraints are binding. The developed mechanisms were translated to a practical setting and over 10,000 trading periods were identified as having reserve constraints (over a five year period).

The assessment of competition in reserve markets within the literature has been limited to formulations of market models which include multiple products. Chapter 3 extends this work to assess the effect of deterministic *N-1* security (earlier models used fixed reserve requirements) and applied this to the NZEM. The model was used to illustrate that participants with a dominant reserve market position can use this to increase energy prices. This result was observed empirically in the NZEM by identifying a case in 2012, when a company in the NZEM used reserve to limit Southward HVDC transfer.

The optimal decision in response to high electricity spot prices for an IL consumer has been presented in Chapter 4. A model was developed to take advantage of the mechanisms through which energy and reserve prices become linked. The model allows a consumer to determine the optimal *ex ante* decision to a high energy spot price. The model was superior to two naive decision strategies and enables an IL consumer to optimise their response to high prices. High electricity spot prices have traditionally been approached from the viewpoint of forecasting in the literature, with few papers exhibiting positive results[2]. This chapter contributed to the literature by approaching the problem differently. Forecasting the optimal response to a spike and not the spike itself, has many of the same benefits for an IL consumer who is concerned with optimising their profits.

The problem of optimal IL consumer participation (not just the optimal response to prices presented in Chapter 4) was presented in Chapter 5. A model called *Boomer-Consumer* was developed to determine through simulations the optimal combined consumption and reserve offers. This determination of combined optimal offers is a challenging problem in the literature in co-optimised electricity markets. This chapter used numerical methods in a series of stages to approximate the optimal combined solution.

[2]The few cases in the literature was limited to small selections of data, in one case just three months from more than a decade ago. To determine a robust method of assessing price spikes a significantly greater time horizon is required due to their relative rarity.

The full contribution of this thesis has been to explore co-optimised reserve markets in both a theoretical and practical setting. Each theoretical development has been applied to a market situation in the NZEM to tie together the theoretical and empirical developments in a cohesive assessment. As such it represents the first body of work to focus solely on this problem (in the literature).

Bibliography

AESO (2013). 2013 Annual Market Statistics.

Aggarwal, S. K., Saini, L. M., and Kumar, A. (2009). Electricity price forecasting in deregulated markets: A review and evaluation. *International Journal of Electrical Power & Energy Systems*, 31(1):13–22.

Aghaei, J., Shayanfar, H., and Amjady, N. (2009). Joint market clearing in a stochastic framework considering power system security. *Applied Energy*, 86(9):1675–1682.

Albadi, M. and El-Saadany, E. (2007). Demand Response in Electricity Markets: An Overview. In *IEEE Power Engineering Society General Meeting, 2007*, pages 1–5.

Allaz, B. (1992). Oligopoly, uncertainty and strategic forward transactions. *International Journal of Industrial Organization*, 10(2):297–308.

Allaz, B. and Vila, J.-L. (1993). Cournot Competition, Forward Markets and Efficiency. *Journal of Economic Theory*, 59(1):1–16.

Alvey, T., Goodwin, D., Ma, X., Streiffert, D., and Sun, D. (1998). A security-constrained bid-clearing system for the New Zealand wholesale electricity market. *Power Systems, IEEE Transactions on*, 13(2):340–346.

Aminifar, F., Fotuhi-Firuzabad, M., and Shahidehpour, M. (2009). Unit Commitment With Probabilistic Spinning Reserve and Interruptible Load Considerations. *IEEE Transactions on Power Systems*, 24(1):388–397.

Amjady, N., Aghaei, J., and Shayanfar, H. A. (2009). Stochastic Multi-objective Market Clearing of Joint Energy and Reserves Auctions Ensuring Power System Security. *IEEE Transactions on Power Systems*, 24(4):1841–1854.

Amjady, N. and Keynia, F. (2010). Electricity market price spike analysis by a hybrid data model and feature selection technique. *Electric Power Systems Research*, 80(3):318–327.

Anderson, E. J. and Philpott, A. B. (2002a). Optimal offer construction in electricity markets. *Mathematics of operations research*, 27(1):82–100.

Anderson, E. J. and Philpott, A. B. (2002b). Using supply functions for offering generation into an electricity market. *Operations Research*, 50(3):477–489.

Anderson, G. (2012). Dynamics and Control of Electric Power Systems. Lecture notes, Swiss Federal Institute of Technology Zurich, ETH Zurich.

Arroyo, J. and Galiana, F. (2005). Energy and reserve pricing in security and network-constrained electricity markets. *IEEE Transactions on Power Systems*, 20(2):634–643.

Bai, J., Gooi, H., Xia, L., Strbac, G., and Venkatesh, B. (2006). A probabilistic reserve market incorporating interruptible load. *IEEE Transactions on Power Systems*, 21(3):1079–1087.

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(2):745–753.

Baldick, R., Grant, R., and Kahn, E. P. (2000). *Linear supply function equilibrium: generalizations, application, and limitations*. Citeseer.

Barbose, G., Goldman, C., and Neenan, B. (2004). A Survey of Utility Experience with Real Time Pricing. Technical Report LBNL–54238, Ernest Orlando Lawrence Berkeley National Laboratory, Berkeley, CA (US).

Barker, K. (2014). HVDC Charges Constrained Benmore Upgrade. *Energy News*.

Bartleet, M. and Gounder, R. (2010). Energy consumption and economic growth in New Zealand: Results of trivariate and multivariate models. *Energy Policy*, 38(7):3508–3517.

Bautista, G., Anjos, M., and Vannelli, A. (2007a). Formulation of Oligopolistic Competition in AC Power Networks: An NLP Approach. *IEEE Transactions on Power Systems*, 22(1):105–115.

Bautista, G., Anjos, M., and Vannelli, A. (2007b). Numerical Study of Affine Supply Function Equilibrium in AC Network-Constrained Markets. *IEEE Transactions on Power Systems*, 22(3):1174–1184.

Bautista, G., Anjos, M. F., and Vannelli, A. (2007c). Modeling Market Power in Electricity Markets: Is the Devil Only in the Details? *The Electricity Journal*, 20(1):82–92.

Bautista, G., Quintana, V., and Aguado, J. (2006). An oligopolistic model of an integrated market for energy and spinning reserve. *IEEE Transactions on Power Systems*, 21(1):132–142.

Bazaraa, M. S., Jarvis, J. J., and Sherali, H. D. (2011). *Linear Programming and Network Flows*. John Wiley & Sons.

Bazaraa, M. S., Sherali, H. D., and Shetty, C. M. (2013). *Nonlinear Programming: Theory and Algorithms*. John Wiley & Sons.

Benth, F. E., Kallsen, J., and MeyerâĂŘBrandis, T. (2007). A NonâĂŘGaussian OrnsteinâĂŞUhlenbeck Process for Electricity Spot Price Modeling and Derivatives Pricing. *Applied Mathematical Finance*, 14(2):153–169.

Borenstein, S. and Bushnell, J. (1999). An Empirical Analysis of the Potential for Market Power in California's Electricity Industry. *The Journal of Industrial Economics*, 47(3):285–323.

Borenstein, S., Bushnell, J., and Stoft, S. (2000). The Competitive Effects of Transmission Capacity in a Deregulated Electricity Industry. Staff General Research Paper 13145, Iowa State University, Department of Economics.

Borenstein, S., Bushnell, J. B., and Wolak, F. A. (2002a). Measuring Market Inefficiencies in California's Restructured Wholesale Electricity Market. *The American Economic Review*, 92(5):1376–1405. ArticleType: research-article / Full publication date: Dec., 2002 / Copyright Âl' 2002 American Economic Association.

Borenstein, S., Jaske, M., and Rosenfeld, A. (2002b). Dynamic Pricing, Advanced Metering, and Demand Response in Electricity Markets. *Center for the Study of Energy Markets*.

Bouffard, F. and Galiana, F. (2004). An electricity market with a probabilistic spinning reserve criterion. *IEEE Transactions on Power Systems*, 19(1):300–307.

Bouffard, F. and Galiana, F. (2008). Stochastic security for operations planning with significant wind power generation. In *2008 IEEE Power and Energy Society General Meeting - Conversion and Delivery of Electrical Energy in the 21st Century*, pages 1–11.

Bouffard, F., Galiana, F., and Conejo, A. (2005a). Market-clearing with stochastic security-part I: formulation. *IEEE Transactions on Power Systems*, 20(4):1818–1826.

Bouffard, F., Galiana, F., and Conejo, A. (2005b). Market-clearing with stochastic security-part II: case studies. *IEEE Transactions on Power Systems*, 20(4):1827–1835.

Boyle, G., Guthrie, G., and Meade, R. (2006). Real options and transmission investment: the New Zealand grid investment test.

Brausen, N. (2009). Alberta's Electricity Market.

Brownlee, G. (2010). Virtual asset swaps to benefit consumers.

Bunn, D. and Oliveira, F. (2001). Agent-based simulation-an application to the new electricity trading arrangements of England and Wales. *IEEE Transactions on Evolutionary Computation*, 5(5):493–503.

Bunn, D. W. and Oliveira, F. S. (2003). Evaluating Individual Market Power in Electricity Markets via Agent-Based Simulation. *Annals of Operations Research*, 121(1-4):57–77.

Bushnell, J. (1999). Transmission Rights and Market Power. *The Electricity Journal*, 12(8):77–85.

Callaway, D. and Hiskens, I. (2011). Achieving Controllability of Electric Loads. *Proceedings of the IEEE*, 99(1):184–199.

Catalao, J. P. S., Mariano, S. J. P. S., Mendes, V. M. F., and Ferreira, L. A. F. M. (2007). Short-term electricity prices forecasting in a competitive market: A neural network approach. *Electric Power Systems Research*, 77(10):1297–1304.

Catalao, J. P. S., Pousinho, H. M. I., and Mendes, V. M. F. (2011). Short-term electricity prices forecasting in a competitive market by a hybrid intelligent approach. *Energy Conversion and Management*, 52(2):1061–1065.

Chakrabarti, B. (2007). Multiple Security Constrained Energy Dispatch Model.

Chang, Y. (2007). The New Electricity Market of Singapore: Regulatory framework, market power and competition. *Energy Policy*, 35(1):403–412.

Chitkara, P., Zhong, J., and Bhattacharya, K. (2009). Oligopolistic Competition of Gencos in Reactive Power Ancillary Service Provisions. *IEEE Transactions on Power Systems*, 24(3):1256–1265.

Cleland, N., Young, B. R., and Zakeri, G. (2014a). Reserve constraints in electricity markets; Effects on large scale integrated consumers. In *2014 IEEE Innovative Smart Grid Technologies - Asia (ISGT Asia)*, pages 296–301.

Cleland, N., Zakeri, G., Pritchard, G., and Young, B. (2014b). Integrating Consumption and Reserve Strategies for Large Consumers in Electricity Markets. In *11th International Conference on Computational Management Science - Lisbon 2014*, Lisbon.

Contreras, J., Klusch, M., and Krawczyk, J. (2004). Numerical solutions to Nash-Cournot equilibria in coupled constraint electricity markets. *IEEE Transactions on Power Systems*, 19(1):195–206.

Cottle, R. W., Pang, J.-S., and Stone, R. E. (2009). *The Linear Complementarity Problem*. SIAM.

Cramton, P. (2003). Electricity Market Design: The Good, the Bad, and the Ugly.

Cramton, P. and Stoft, S. (2006). The convergence of market designs for adequate generating capacity.

Diaz, C. A., Campos, F. A., Villar, J., and RodrÃ■guez, M. Ã. (2012). Endogenous computation of conjectured supply functions with network constraints. *Electric Power Systems Research*, 90:117–125.

Doherty, R. and O'Malley, M. (2005). A new approach to quantify reserve demand in systems with significant installed wind capacity. *IEEE Transactions on Power Systems*, 20(2):587–595.

Drayton-Bright, G. R. (1997). *Coordinating energy and reserves in a wholesale electricity market.* PhD thesis, University of Canterbury, Christchurch, New Zealand.

EA (2014). [Online] Electricity Authority Reporting Portal.

Ela, E., Milligan, M., and Kirby, B. (2011). Operating Reserves and Variable Generation: A comprehensive review of current strategies, studies, and fundamental research on the impact that increased penetration of variable renewable generation has on power system operating reserves. Technical Report NREL/TP-5500-51978, NREL, NREL.

Ellison, J. F., Tesfatsion, L. S., Loose, V. W., and Byrne, R. H. (2012). Project Report: A Survey of Operating Reserve Markets in US ISO/RTO-managed Electric Energy Regions. *Sandia NatâĂŹl Labs Publications. Available Online: http://www. sandia. gov/ess/publications/SAND2012_1000. pdf.*

Galiana, F., Bouffard, F., Arroyo, J., and Restrepo, J. (2005). Scheduling and Pricing of Coupled Energy and Primary, Secondary, and Tertiary Reserves. *Proceedings of the IEEE*, 93(11):1970–1983.

Gao, C., Bompard, E., Napoli, R., and Cheng, H. (2007). Price forecast in the competitive electricity market by support vector machine. *Physica A: Statistical Mechanics and its Applications*, 382(1):98–113.

Gillingham, K. (2009). Economic efficiency of solar hot water policy in New Zealand. *Energy Policy*, 37(9):3336–3347.

Gonzalez, P., Villar, J., Diaz, C. A., and Campos, F. A. (2014). Joint energy and reserve markets: Current implementations and modeling trends. *Electric Power Systems Research*, 109:101–111.

Goodwin, D. (2006). The Wholesale Electricity Market a 10 year retrospective.

Gooi, H., Mendes, D., Bell, K. R. W., and Kirschen, D. (1999). Optimal scheduling of spinning reserve. *IEEE Transactions on Power Systems*, 14(4):1485–1492.

Green, R. (1996). Increasing Competition in the British Electricity Spot Market. *The Journal of Industrial Economics*, 44(2):205–216.

Gunn, C. (1997). Energy efficiency vs economic efficiency?: New Zealand electricity sector reform in the context of the national energy policy objective. *Energy Policy*, 25(4):445–458.

Guthrie, G. and Videbeck, S. (2002). High Frequency Electricity Spot Price Dynamics: An Intra-Day Markets Approach. SSRN Scholarly Paper ID 367760, Social Science Research Network, Rochester, NY.

Guthrie, G. and Videbeck, S. (2007). Electricity spot price dynamics: Beyond financial models. *Energy Policy*, 35(11):5614–5621.

Haghighat, H., Seifi, H., and Kian, A. (2007). Gaming Analysis in Joint Energy and Spinning Reserve Markets. *IEEE Transactions on Power Systems*, 22(4):2074–2085.

Haghighat, H., Seifi, H., and Kian, A. (2008a). Joint energy and spinning reserve dispatch under imperfect competition. In *Power Symposium, 2008. NAPS '08. 40th North American*, pages 1–7.

Haghighat, H., Seifi, H., and Rahimi Kian, A. (2008b). The role of market pricing mechanism under imperfect competition. *Decision Support Systems*, 45(2):267–277.

Hall, M. (2012). Increased South Island reserve offer prices May 2012. Technical report, Electricity Authority - Market Performance Group, Wellington, N.Z.

Halliburton, T. S. (2004). An optimal hydrothermal planning model for the New Zealand power system. *Australian Journal of Electrical and Electronics Engineering*, 1:193–198.

Hobbs, B., Metzler, C., and Pang, J.-S. (2000). Strategic gaming analysis for electric power systems: an MPEC approach. *IEEE Transactions on Power Systems*, 15(2):638–645.

Hogan, W. (2002). Financial transmission right formulations. *Report, Center for Business and Government, John F. Kennedy School of Government, Harvard University, Cambridge, MA*.

Hogan, W. W. (1996). Markets in Real Electric Networks Require Reactive Prices. In Einhorn, M. and Siddiqi, R., editors, *Electricity Transmission Pricing and Technology*, pages 143–182. Springer Netherlands.

Huang, K.-Y. and Huang, Y.-C. (2004). Integrating Direct Load Control With Interruptible Load Management to Provide Instantaneous Reserves for Ancillary Services. *IEEE Transactions on Power Systems*, 19(3):1626–1634.

Hurlbut, D., Rogas, K., and Oren, S. (2004). Protecting the Market from âĂIJHockey StickâĂİ Pricing: How the Public Utility Commission of Texas is Dealing with Potential Price Gouging. *The Electricity Journal*, 17(3):26–33.

Joskow, P. L. and Tirole, J. (2000). Transmission Rights and Market Power on Electric Power Networks. *The RAND Journal of Economics*, 31(3):450–487.

Karangelos, E. and Bouffard, F. (2012). Towards Full Integration of Demand-Side Resources in Joint Forward Energy/Reserve Electricity Markets. *IEEE Transactions on Power Systems*, 27(1):280–289.

Kelly, G. (2007). Renewable energy strategies in England, Australia and New Zealand. *Geoforum*, 38(2):326–338.

Kirby, B. J. (2003). *Spinning reserve from responsive loads*. United States. Department of Energy.

Kirschen, D. (2003). Demand-side view of electricity markets. *IEEE Transactions on Power Systems*, 18(2):520–527.

Klemperer, P. D. and Meyer, M. A. (1989). Supply Function Equilibria in Oligopoly under Uncertainty. *Econometrica*, 57(6):1243–1277.

Krichtal, V. (2006). National Instantaneous Reserve Market in NZEM.

Krichtal, V. and Edwards, C. (2012). HVDC Roles in the Economic Operation of the New Zealand Electricity Market. In *Proceedings of the 46th Annual Conference of the Operations Research Society of New Zealand*, page 9, Wellington, N.Z. Victoria University Press.

Krichtal, V. and Edwards, C. (2013). National Instantaneous Reserve Prices and Revenue in New Zealand Electricity Market. In *Proceedings of the 47th Annual Conference of the ORSNZ*, Hamilton New Zealand. ORSNZ.

Krumdieck, S. (2009). New Zealand energy strategyâĂŤIntroduction to the energy policy special issue. *Energy Policy*, 37(9):3297–3300.

Lee, T.-Y. (2007). Optimal Spinning Reserve for a Wind-Thermal Power System Using EIPSO. *IEEE Transactions on Power Systems*, 22(4):1612–1621.

Li, Y. and Flynn, P. C. (2006). Electricity deregulation, spot price patterns and demand-side management. *Energy*, 31(6âĂŞ7):908–922.

Lobato Miguelez, E., Egido Cortes, I., Rouco RodrÃ■guez, L., and Lopez Camino, G. (2008). An overview of ancillary services in Spain. *Electric Power Systems Research*, 78(3):515–523.

Lora, A., Santos, J., Exposito, A., Ramos, J., and Santos, J. (2007). Electricity Market Price Forecasting Based on Weighted Nearest Neighbors Techniques. *IEEE Transactions on Power Systems*, 22(3):1294–1301.

Lora, A. T., Santos, J. M. R., Riquelme, J. C., ExpÃşsito, A. G., and Ramos, J. L. M. (2004). Time-Series Prediction: Application to the Short-Term Electric Energy Demand. In Conejo, R., Urretavizcaya, M., and PÃľrez-de-la Cruz, J.-L., editors, *Current Topics in Artificial Intelligence*, number 3040 in Lecture Notes in Computer Science, pages 577–586. Springer Berlin Heidelberg.

Lora, A. T., Santos, J. R., Santos, J. R., Ramos, J. L. M., and Exposito, A. G. (2002). Electricity Market Price Forecasting: Neural Networks versus Weighted-Distance k Nearest Neighbours. In Hameurlain, A., Cicchetti, R., and TraunmÃijller, R., editors, *Database and Expert Systems Applications*, number 2453 in Lecture Notes in Computer Science, pages 321–330. Springer Berlin Heidelberg.

Lu, F. and Gan, H. (2005). National Electricity Market of Singapore. In *Power Engineering Conference, 2005. IPEC 2005. The 7th International*, pages 1007–1012 Vol. 2.

Luh, P., Blankson, W., Chen, Y., Yan, J., Stern, G., Chang, S.-C., and Zhao, F. (2006). Payment Cost Minimization Auction for Deregulated Electricity Markets Using Surrogate Optimization. *IEEE Transactions on Power Systems*, 21(2):568–578.

Ma, X. and Sun, D. (1998). Energy and ancillary service dispatch in a competitive pool. *IEEE Power Engineering Review*, 18(1):54–56.

Mangasarian, O. L. (1993). *Nonlinear Programming*. SIAM.

Martinez-Alvarez, F., Troncoso, A., Riquelme, J., and Aguilar-Ruiz, J. (2008). LBF: A Labeled-Based Forecasting Algorithm and Its Application to Electricity Price Time Series. In *Eighth IEEE International Conference on Data Mining, 2008. ICDM '08*, pages 453–461.

Miller, R. (2009). SDDP, SPECTRA and Reality.

Molina-Garcia, A., Bouffard, F., and Kirschen, D. (2011). Decentralized Demand-Side Contribution to Primary Frequency Control. *IEEE Transactions on Power Systems*, 26(1):411–419.

Naidoo, R. (2013). vSPD - vectorised Scheduling Pricing and Dispatch Model.

Nash, J. (1950). Equilibrium Points in N-Person Games. *Proceedings of the National Academy of Sciences of the United States of America*, 36(1):48.

Neame, P. J., Philpott, A. B., and Pritchard, G. (2003). Offer stack optimization in electricity pool markets. *Operations Research*, 51(3):397–408.

NERC, R. S. (2011). NERC Balancing and Frequency Control. Technical report, NERC, Princeton, NJ.

Neuhoff, K., Barquin, J., Boots, M. G., Ehrenmann, A., Hobbs, B. F., Rijkers, F. A. M., and Vazquez, M. (2005). Network-constrained Cournot models of liberalized electricity markets: the devil is in the details. *Energy Economics*, 27(3):495–525.

Nigel Cleland (2014). Tessen: Citation Release.

Ortega-Vazquez, M. and Kirschen, D. (2009). Estimating the Spinning Reserve Requirements in Systems With Significant Wind Power Generation Penetration. *IEEE Transactions on Power Systems*, 24(1):114–124.

Panne, C. V. D. (1975). *Methods for linear and quadratic programming*. American Elsevier.

Parsons-Brinckerhoff (2007). [Online] Transmission to Enable Renewables. Technical report, Parsons Brinckerhoff Associates Ltd., Wellington, N.Z.

Pereira, M. V. F. and Pinto, L. M. V. G. (1991). Multi-stage stochastic optimization applied to energy planning. *Mathematical Programming*, 52(1-3):359–375.

Philpott, A., Guan, Z., Khazaei, J., and Zakeri, G. (2010). Production inefficiency of electricity markets with hydro generation. *Utilities Policy*, 18(4):174–185.

Pina, A., Silva, C., and FerrÃčo, P. (2012). The impact of demand side management strategies in the penetration of renewable electricity. *Energy*, 41(1):128–137.

PJM (2014). Energy & Ancillary Services Market Operations. Manual M11, PJM.

Pritchard, G. and Zakeri, G. (2003). Market offering strategies for hydroelectric generators. *Operations Research*, 51(4):602–612.

Ramos, A., De Jonghe, C., Six, D., and Belmans, R. (2013). Asymmetry of information and demand response incentives in energy markets. In *European Energy Market (EEM), 2013 10th International Conference on the*, pages 1–8.

Read, E. G. (1997). Transmission pricing in New Zealand. *Utilities Policy*, 6(3):227–235.

Rosellon, J. (2003). Different approaches towards electricity transmission expansion. *Review of network economics*, 2(3).

Ruiz, N., Cobelo, I., and Oyarzabal, J. (2009). A Direct Load Control Model for Virtual Power Plant Management. *IEEE Transactions on Power Systems*, 24(2):959–966.

Schrage, L. (2006). Optimization modeling with LINGO. LINDO Systems. *Inc., Chicago*.

Schweppe, F. C., Tabors, R. D., Caraminis, M. C., and Bohn, R. E. (1988). *Spot Pricing of Electricity*. Kluwer Academic Publishers, Norwell, MA.

Shen, D. and Yang, Q. (2012). Electricity market regulatory reform and competition-case study of the New Zealand electricity market. *Energy Market Integration in East Asia: Theories, Electricity Sector and Subsidies, ERIA, Jakarta, Indonesia*, pages 103–139.

Soder, L. (1993). Reserve margin planning in a wind-hydro-thermal power system. *Power Systems, IEEE Transactions on*, 8(2):564–571.

Soleymani, S., Ranjbar, A. M., and Shirani, A. R. (2007). New approach for strategic bidding of Gencos in energy and spinning reserve markets. *Energy Conversion and Management*, 48(7):2044–2052.

Sorknaes, P., Andersen, A. N., Tang, J., and Strom, S. (2013). Market integration of wind power in electricity system balancing. *Energy Strategy Reviews*, 1(3):174–180.

Strbac, G. (2008). Demand side management: Benefits and challenges. *Energy Policy*, 36(12):4419–4426.

Strbac, G., Farmer, E., and Cory, B. (1996). Framework for the incorporation of demand-side in a competitive electricity market. *IEE Proceedings - Generation, Transmission and Distribution*, 143(3):232.

Szkuta, B. R., Sanabria, L. A., and Dillon, T. (1999). Electricity price short-term forecasting using artificial neural networks. *IEEE Transactions on Power Systems*, 14(3):851–857.

Tipping, J., Read, E. G., and McNickle, D. (2004). The incorporation of hydro storage into a spot price model for the New Zealand electricity market. In *Sixth European Energy Conference: Modeling in Energy Economics and Policy. Zurich. Available at http://www. mang. canterbury. ac. nz/research/emrg*.

Tirole, J. (1988). *The Theory of Industrial Organization*. Cambridge, Mass.

Tirole, J. (2014). [Online[Jean Tirole - Nobel Prize.

Transpower (2005). HVDC Inter-Island Link Upgrade Project. Investment Proposal Executive Summary.

Transpower (2008). SPD Model Formulation. Technical report, Transpower, Wellington, N.Z.

Transpower (2014a). 2013 Demand Response Programme Report. Technical report, Transpower, Wellington, N.Z.

Transpower (2014b). [Online] Maps and Diagrams.

Twigg, D. (2013). 12 November AUFLS Activation. Technical report, System Operator, Wellington, N.Z.

Vanderbei, R. J. (2014). *Linear programming*, volume 196 of *International Series in Operations Research and Mangement Science*. Springer, 4th edition.

Wang, D., Parkinson, S., Miao, W., Jia, H., Crawford, C., and Djilali, N. (2013). Hierarchical market integration of responsive loads as spinning reserve. *Applied Energy*, 104:229–238.

Wang, J., Redondo, N., and Galiana, F. (2003). Demand-side reserve offers in joint energy/reserve electricity markets. *IEEE Transactions on Power Systems*, 18(4):1300–1306.

Wang, J., Wang, X., and Wu, Y. (2005). Operating reserve model in the power market. *IEEE Transactions on Power Systems*, 20(1):223–229.

Wen, F., Wu, F. F., and Ni, Y. (2004). Generation capacity adequacy in the competitive electricity market environment. *International Journal of Electrical Power & Energy Systems*, 26(5):365–372.

Weron, R. (2007). *Modeling and forecasting electricity loads and prices: A statistical approach*, volume 403. John Wiley & Sons.

Wong, A., Lee, A., Chock, M. H., and Wong, A. (2012). Singapore Electricity Market. Technical report, Hogan Lovells Lee & Lee.

Wong, S. and Fuller, J. D. (2007). Pricing Energy and Reserves Using Stochastic Optimization in an Alternative Electricity Market. *IEEE Transactions on Power Systems*, 22(2):631–638.

Wright, S. J. (1997). *Primal-Dual Interior-Point Methods*. SIAM.

Yang, J. and Honavar, V. (1998). Feature Subset Selection Using a Genetic Algorithm. In Liu, H. and Motoda, H., editors, *Feature Extraction, Con-*

struction and Selection, number 453 in The Springer International Series in Engineering and Computer Science, pages 117–136. Springer US.

Young, D., Poletti, S., and Browne, O. (2012). Can Agent-Based Models Forecast Spot Prices in Electricity Markets? Evidence from the New Zealand Electricity Market. SSRN Scholarly Paper ID 2046853, Social Science Research Network, Rochester, NY.

Zareipour, H., Janjani, A., Leung, H., Motamedi, A., and Schellenberg, A. (2011). Classification of Future Electricity Market Prices. *IEEE Transactions on Power Systems*, 26(1):165–173.

Zhao, J., Dong, Z., Li, X., and Wong, K.-P. (2005). A general method for electricity market price spike analysis. In *IEEE Power Engineering Society General Meeting, 2005*, pages 286–293 Vol. 1.

Zhou, Z., Chan, W. K. V., and Chow, J. H. (2009). Agent-based simulation of electricity markets: a survey of tools. *Artificial Intelligence Review*, 28(4):305–342.