# STRUCTURAL VOLATILITY

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# AUSTRALIAN ELECTRICITY MARKET

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***To my parents***

***For unconditionally providing their love, support, guidance and encouragement.***

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# SUMMARY

Australian electricity market has accepted deregulation since the early 1990's. The aims of deregulation of electricity supply included promoting market competition and ensuring reliable supply of electricity at stable prices to consumers. However, it has been observed that spot price for electricity can be volatile and occasionally spikes to extremely high levels. This thesis examines the latter phenomenon with the help of quantitative techniques of operations research and statistics. Closer examination shows that bidding behaviour of generators is affecting the price volatility in Australian electricity market especially in high demand periods. In particular, our analyses suggest that some of the observed volatility may be due to the underlying structure of the currently used optimisation model's design that does not exclude the possibility of generators being able to exercise market power. We also propose a novel pricing mechanism designed to discourage strategic bidding.

In the preliminary analysis we discuss the history of price volatility and possible exercise of market power in Australia as mentioned in the literature. According to Australian Energy Regulator the significant increase in the number of price spikes occurred in South Australia during the years 2008-11 where "disorderly bidding strategies" by generators were addressed as one of the underlying reasons for this high electricity price fluctuations.

Exploratory analysis of data from South Australian electricity market identified and exhibited a number of phenomena which contribute to the high cost of electricity supply to consumers and volatility in spot prices. It identified certain characteristic bidding behaviours of generators during the periods when spot price spikes occurred.

For this reason, the bidding behaviour by generators was investigated in detail. Our analysis showed that, observed bid structures exhibit bimodal form in higher demand trading intervals.

In particular, we considered the potential consequences of the fact that generators can influence some parameters of the dispatch linear program that is used to determine shadow prices of demands which, in turn, determine the spot price. Indirectly, this influence opens the possibility of them being able to impact the marginal prices of electricity in each state and hence also the spot prices. Indeed, due to the non-uniqueness of solutions to linear programs, a phenomenon that we call “instability gap” may arise whereby some optimal shadow prices favour the generators and some favour consumers.

We also considered changes to the electricity pricing mechanism aimed at creating disincentives to strategic bidding. We proposed a Mean-Value approach to determine the spot-price that is inspired by the famous concept of Aumann-Shapley Prices. We demonstrated that this approach has the potential for discouraging strategic bidding and for reducing the ultimate spot price for electricity. Furthermore, we showed how generators would benefit – under a mean value pricing scheme - by offering a uniformly distributed bid stack.

Finally, we showed that the mean value pricing mechanism proposed above can be easily generalised to the whole network in NEM which consists of 5 interconnected regions.

# DECLARATION

I certify that this thesis does not incorporate without acknowledgment any material previously submitted for a degree or diploma in any university; and that to the best of my knowledge and belief it does not contain any material previously published or written by another person except where due reference is made in the text.

Signed

Date 20/04/2016

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# CHAPTER 1. INTRODUCTION

Electricity is a secondary form of energy which is converted from other sources of energy such as coal, natural gas and oil[1]. It is produced from the flow of electrons in the electrical wiring, called "Conductors", which are generally produced from copper and aluminium.

Electricity has two notable characteristics. First, it is not easily storable so demand and supply for electricity need to be matched instantaneously. Second, as each unit of electricity is not distinguishable from the other, it is not possible to determine the generator that produced each unit. These special characteristics of this product make it well suited to be traded through a pool.

The consumption of electricity includes heating, lighting, air conditioning and their uses in in power machines. The rate at which electricity converts to other forms of energy such as heat or light is measured through a unit called wattage or "watt". One megawatt $(MW)$ equals to one million watts $(W)$ and one gigawatt $(GW)$ equals to one thousand megawatts $(MW)$. For instance, a kettle uses 2400 watts to produce boiling hot water. One watt $(W)$ is equal to one joule $(J)$ of work per second $(S)$; $W = {}^{J}/_{S}$.One megawatt hour $(MWh)$ is the energy required to power ten thousand 100 $W$ light globes for one hour. A 100 megawatt will thus power one million 100 $W$ light globes simultaneously.

[1] Solar energy and wind power are other sources of renewable energy which are becoming increasingly more important.

In Australian electricity market, more than the 90% of the electricity is produced from the chemical energy released from burning fossil fuels such as coal, gas and oil. In this process, the chemical energy is used to heat water and produce steam which is conducted through turbines that power a generator (AEMO, 2010).

Although the transmission of electricity occurs instantaneously, a specific sequence of events takes place to ensure the delivery of the required electricity. As Figure 1.1 shows, initially a transformer increases the voltage of electricity produced at power plants and efficiently transforms electricity through the transmission lines. Before electricity reaches consumers' end, a substation transformer converts the high voltage electricity to the low one and now it is ready for distribution to the power outlets through distribution lines.

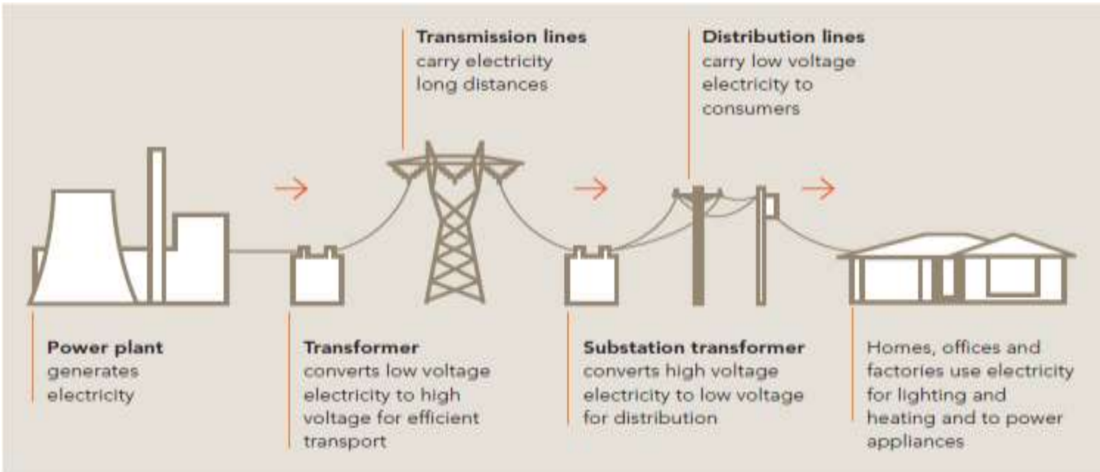


Figure 1.1. Transport of electricity (Source: AEMO, 2010)

## 1.1 NATIONAL ELECTRICITY MARKET

National Electricity Market (NEM) in Australia began to operate in December 1998. With the new restructuring, eastern states of Australia planned to form National Electricity Market (NEM). These states included New South Wales, Australian Capital Territory, Victoria, Queensland and South Australia. When the Basslink interconnector was completed, Tasmania also joined NEM on the 2 April 2006. Joining NEM is still not possible for the state of Western Australia and also the Northern Territory due to large geographic distances in these regions, rendering connecting with these states not economically efficient. Hence NEM works as a wholesale electricity market which consists of five interconnectors regions (Australia Bureau of Statistics: Year Book Australia, 2000).

It should be noted that, NEM spans distances of about 4500 kilometres which is one of the longest alternating current systems in the world: from Queensland to Tasmania, and west to Adelaide and Port Augusta. NEM's turnover was about $12.2 billion in 2012-13 for the total energy generated of 199TWh which was about 2.5 percent lower than the previous year (AER, 2013).

NEM involves both wholesale generation that is transported via high voltage transmission lines to electricity distributors, and also delivery of electricity to the end users (i.e. businesses and households). NEM's infrastructure is partly owned by the government and partly owned by the private sector. In each state, the electricity supply industry had to be privatised. The generators also needed to be linked to generating system in other states via interconnectors (Outhred, 2004).

In principle, NEM has six participants, in terms of the role they play, in the wholesale electricity market. These are generators, Distribution Network Service Providers (DNSP), market consumers, Transmission Network Service Providers (TNSP), Market Network Service Providers (MNSP), and traders. It should be noted that by market consumers we mean both electricity retailers and end user consumers. Figure1.2 shows the electricity consumption by main industry sectors.

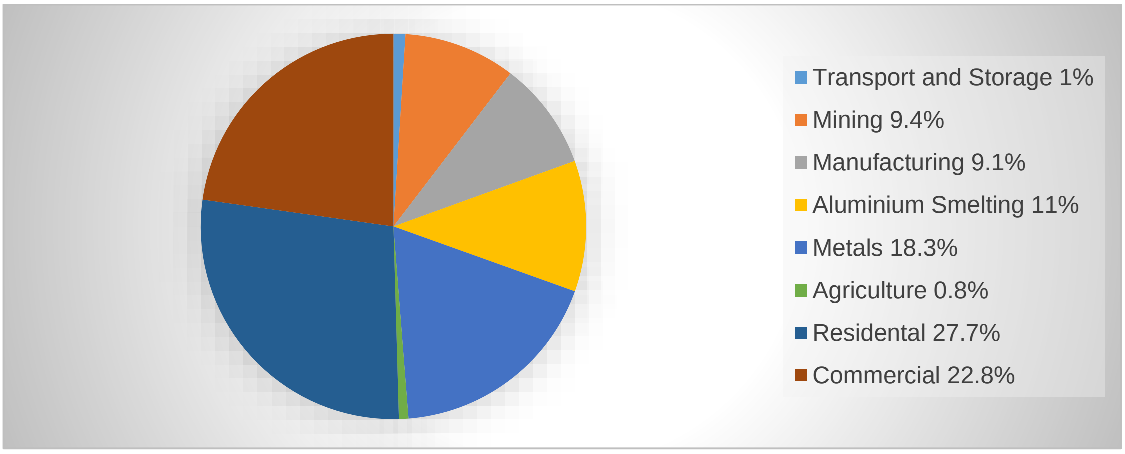


Figure1.2 Electricity consumption by sector, (Source: AEMO, 2010)

Electricity supply industry includes three divisions of generation transmission and distribution of electricity to end users. As electricity is not easily storable, the electricity supply industry needs to operate dynamically. On the other hand, it is the electricity supply obligation to match the electricity supply and consumption in an instantaneous manner to prevent outages and also to ensure that electricity supply is operating at a reliable and safe frequency and voltage for end users such as industries and house hold appliance.

### 1.1.1 Main responsibilities of NEM

The reforms in the electricity market in Australia are believed to be successful especially in the state of Victoria where they saved the government from a high level of debt (Quiggin, 2004). One of the primary goals of the reforms was to establish a wholesale electricity market where generators were able to bid and sell their productions to end users and retailers. In this market, all the electricity sold by generators in NEM is cleared through a spot market settled half hourly.

The spot market includes a pool where the bids from all generators are aggregated and then scheduled to meet demand. Here, by pool we mean a financial settlement system where sellers, generators, are paid for the portion of electricity they sell and buyers, retailers will pay for the amount of electricity they buy from the pool. In other words, by pool we do not mean a physical location but a set of procedures based on a sophisticated information technology system.

The wholesale electricity market is managed by the Australian Energy Market Operator (AEMO, 2010) based on the provisions of National Electricity Law and Statutory Rules (the Rules). The market uses this system to inform generators on how much energy to produce at each five minutes to match the production level to consumer requirements. One of the intended advantages of this mechanism is that generators were to be encouraged to be more competitive and minimise the price they bid in order to win higher share from the total electricity load. This keeps an extra capacity ready for the emergencies (AEMO, 2010).

It should be noted that in order to minimise the risk of significant fluctuations in the electricity price, hedge contracts are designed to cover majority of the transactions among generators, retailers and large consumers. These contracts can be both, one way or two way contracts to minimise the risk for both buyers and sellers in the market. These contracts are mentioned again in Section1.8.

## 1.2 ELECTRICITY GENERATION IN NEM

A generator converts sources of energy to electricity mainly by burning fuel to make steam which turn a turbine. Generators are grouped into four categories based on their duties in NEM (NEMMCO, 2005).

(i) Market generators: the whole production of these generators is sold in spot market by NEMMCO.

(ii) Non market generators: they sell their production directly to a retailer or a customer outside the spot market.


Figure1.3. Large generators in NEM, Source AER, 2013.

(iii) Scheduled generators: generators with the capacity of more than 30 megawatts (MW).

(iv) Non-scheduled generators: generators with the capacity of less than 30 megawatts (MW).

In Australia, the main fuels used in the electricity generation process are fossil fuels such as coal and gas. Other technologies used to produce electricity in Australia are relying on hydro and renewable energies such as water, sun and wind technologies. Figure1.3 shows the large generators in NEM and the source of energy they use (AER, 2013).

### 1.2.1 Generation technologies in NEM

The demand for electricity can be reasonably volatile throughout the year. Depending on the time of the day and the season, the demand can significantly fluctuate. As a result, different type of generators, based on their fuel type, would be appropriate for different trading interval. Table 1.1 show all type of generators, based on the fuel they use, with their special characteristics in NEM.

Table 1.1. Type of generators in NEM (Source: AEMO, 2010)

| **Characteristic** | **Type** | | | |
|---|---|---|---|---|
| | **Gas and Coal - fired Boilers** | **Gas Turbine** | **Water (Hydro)** | **Renewable (Wind/Solar)** |
| **Time to fire-up generator from cold** | 8-48 hours | 20 minutes | 1 minute | Dependant on prevailing weather |
| **Degree of operator control over energy source** | High | High | medium | low |
| **Use of non-renewable sources** | High | High | nil | nil |
| **Production of greenhouse gasses** | High | Medium-high | nil | nil |
| **Other characteristics** | Medium-low operating cost | Medium-high operating cost | Low fuel cost with plentiful water supply; production severely affected by drought | Suitable for remote and stand-alone applications; Batteries may be used to store power |

In 2010, shares of electricity generation by fuel type in Australia were as shown in Figure1.4. In the following the use of these generators are described in more details.

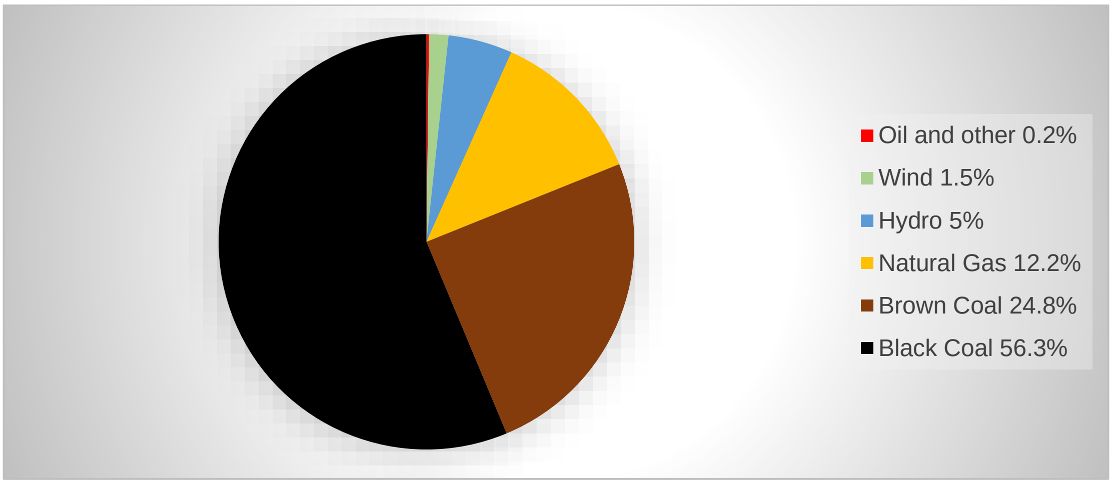


Figure 1.4. Generation by fuel type in NEM, 2010, (Source: AEMO, 2010).

### *1.2.2.1 Coal generators*

In general, the main sources of energy used in NEM are fossil fuels. Specifically, in New South Wales, Queensland and Victoria, coal is used to produce electricity. Whereas in South Australia the electricity production stations mainly use gas and wind power. Although coal generators have high start-up and shut down costs, they are very suitable for the base load as they can work continuously with relatively lower operating cost (AER, 2013).

### *1.2.1.2 Gas generators*

For some peak periods, generators which can start up quicker are needed. Gas generators are suitable in these situations although they have relatively high operating costs. In South Australia, electricity generation is mainly relying on gas powered generators (AER, 2013).

### *1.2.1.3 Hydroelectric generators*

These generators are becoming more popular especially with the introduction of a carbon pricing scheme and also the increase in rainfall in certain areas in 2012-13. Tasmania is the region which uses hydroelectric generators more than other regions in NEM. However, Queensland, Victoria and New South Wales also use this type of generation technology (AER, 2013).

### 1.2.1.4 *Renewable energy based generators*

Other energy sources for electricity production are the so-called renewable energies that have been developing in the Australian electricity market especially in the last decade. Wind generators are registered as semi-scheduled and connected to the network for the electricity production. Generators which use wind and solar energy to produce electricity can only be reliable when the weather conditions are appropriate. One limitation of this source of energy's production is that it cannot increase with the demand as wind is intermittent. Therefore wind generators are semi-scheduled to the network as they cannot be scheduled in the usual way. Nevertheless, the market has been designed in a way that allows the wind generators to participate in the market as the other base-load generators (AER, 2013).

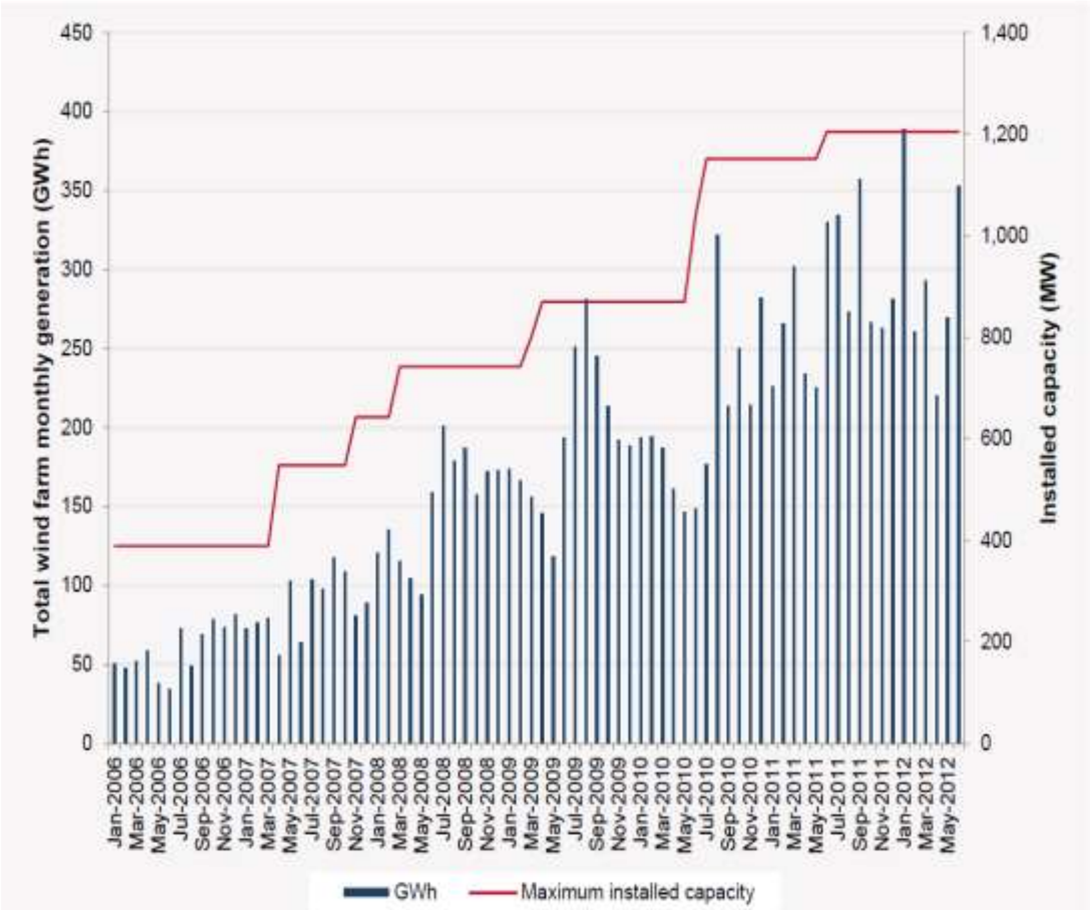


Figure 1.5. Total monthly South Australian wind generation. Source: AEMO, 2012a.

South Australia has the highest percentage contribution to peak demand in NEM. In South Australia this type of generation is used more frequently and in some periods it has accounted for up to 65 percent of the total generation in the state. The contribution of wind generation units has resulted in decreasing spot price in the periods of high wind. (AEMO, 2012a). Figure 1.5 shows total monthly South Australian wind generation.

### 1.2.2 Climate change policies

One of the main objectives of climate change policies driven by the government is to transfer the reliance of industries, especially electricity industry, on coal fired generation in favour of the ones with lower carbon energy sources. At the moment around 35 percent of the greenhouse gas emission in Australia is related to the electricity industry. For this purpose, Renewable Energy Target (RET) was introduced by Australian government in 2001 and revised in 2007 and 2011. The main objective in this scheme is to achieve a share of 20 percent for renewable energy in the electricity production by the year 2020. The RET scheme includes large scale scheme such as installation of wind farms with the target of generating 41000 GWH electricity by 2020.

Furthermore, RET includes small scale RET scheme such as rooftop solar PV installations. The use of rooftop solar generation especially in the last five years, created an opportunity for households to sell the electricity generated from their rooftop installations to the distributors or retailers. This is facilitated through a reduction in their electricity bill. Electricity generation from rooftops increased from 1500 MW in 2011-12 to 2300 MW in 2012-13. The government has committed to review the RET scheme in 2014.

The climate change policies have considerable effect on the electricity generation in Australia. The introduction of carbon pricing[2] in 2012 led to some coal generators retiring. This resulted in 2300 MW of electricity reduction in the grid. In general, the black and brown coal generation were most popular until the years 2008-2009 and then the usage of these types of fuels has declined and shifted to other type of electricity generation. Table 1.2 shows generation plants shut down since 2012 (AER, 2013).

The carbon pricing plan also stimulated the hydro generation so that in 2012-13, 9 percent of the total supply in NEM belonged to the hydro generation. Gas power plants started to develop, especially in the last decade. The investment in wind generation

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[2] The Australian labor government introduced the carbon pricing plan in 1 July 2012 as part of its Clean Energy Future Plan. It aims to reduce carbon and other greenhouse emission to at least 5 percent below 2000 level by 2020 (AER, 2013). In 2014, this tax has been repealed by the current liberal government.

has also increased since the introduction of RET scheme in 2007 (AER, 2013). The trend in falling demand and also the overall changes in the generation shifts, resulted in total fall of 7 percent in emissions from the electricity generation sector in 2012-2013 (AEMO, 2013a).

Table 1.2. Generation plants shut down since 2012 (Source: AER, 2013).

| Business | Power Station | Technology | Capacity (MW) | Period Affected |
|---|---|---|---|---|
| **Queensland** | | | | |
| Stanwell | Tarong (2 units) | Coal fired | 700 | October 2012 to at least October 2014 |
| RATCH Australia | Collinsville | Coal fired | 190 | From December 2012 until viable |
| **New South Wales** | | | | |
| Delta Electricity | Munmorah | Coal fired | 600 | Retired July 2012 |
| **Victoria** | | | | |
| Energy Brix | Morwell unit 3 | Coal fired | 70 | From July 2012 until viable |
| Energy Brix | Morwell unit 2 | Coal fired | 25 | Not run since July 2012; only operates when unit 1 is under maintenance |
| **South Australia** | | | | |
| Alinta Energy | Northern | Coal fired | 540 | April to September each year from 2012 |
| Alinta Energy | Playford | Coal fired | 200 | From March 2012 until viable |

### 1.2.3 Ownership arrangement in electricity generation

The ownership arrangements in electricity market, either private or government owned, varies in different regions. Most of the generation capacity in Victoria and South Australia belongs to the private sector. For Queensland and New South Wales and also Tasmania, government still controls most of the capacity generation in these states (AER, 2013).

Figure1.6 shows the generators and entities which control the dispatch. The main private businesses are AGL Energy, Origin energy, EnergyAustralia (formerly Truenergy), International Power and InterGen. On the other hand, government owns Macquarie Generation, Delta generation, Stanwell, CS Energy and Snowy Hydro. The Hydro Tasmania is also a state owned entity.

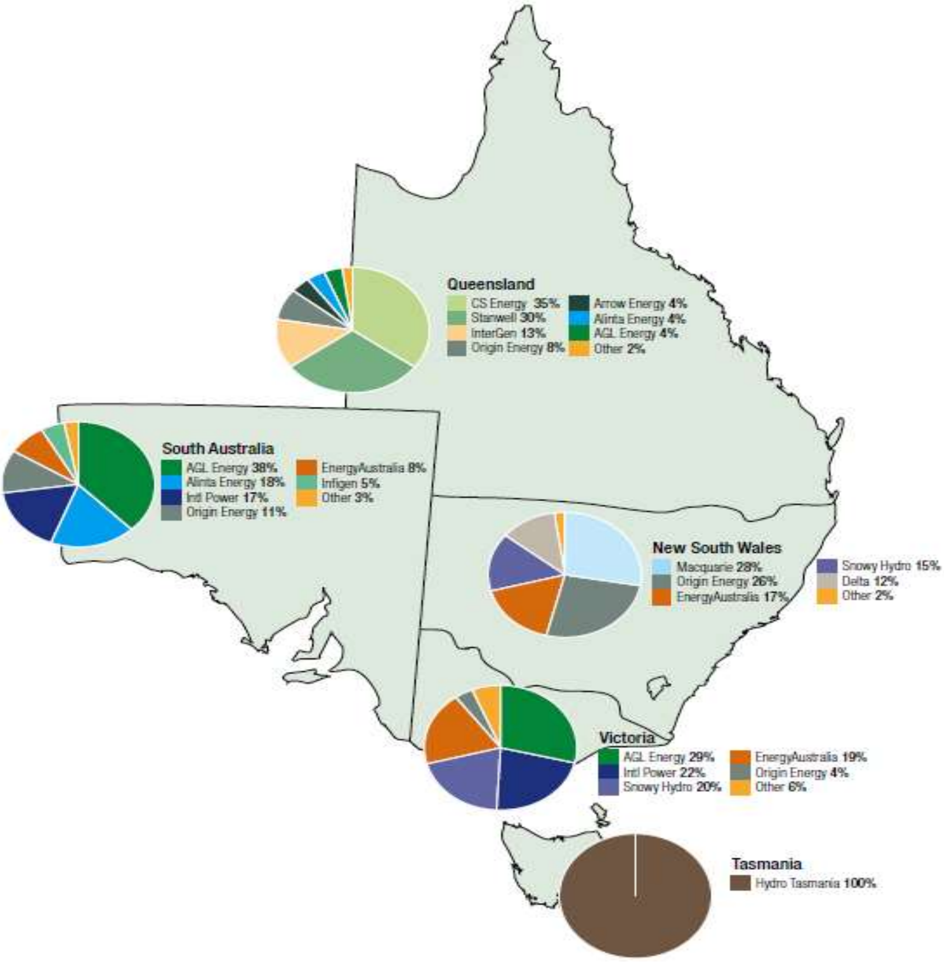


Figure1.6. Market shares in electricity generation capacity by region, 2013 (AER, 2013).

### 1.2.4 Regulation and deregulation

In this section, we continue to introduce Australian electricity supply industry and briefly examine how it was restructured from a regulated monopoly to the deregulated market. As mentioned earlier, the National Electricity Market (NEM) began to operate as a wholesale electricity market in early 1990s. One of the main objectives of forming this market was to prevent generators from exercising any market power by promoting competition among generators. Establishing this market would also benefit the consumers through more choices of suppliers and higher efficiency and reliability in the network. In the following we highlight some main changes which happened before and after deregulation in the electricity supply in Australia (NEMMCO, 2005).

#### *1.2.4.1 Before deregulation*

The electricity supply industry was mainly managed by the state governments before the deregulation. They had to supply electricity to the costumers and were obliged to provide electricity in a safe and technical reliable manner and to ensure that the end user could consume electricity at the minimum of possible price. As the electricity suppliers were publically owned monopolies, the authorities did not have to compete with the private suppliers in the states but they were trying to minimise their costs in order to compete with other providers of energy supply such as gas and oil.

In order to minimise their cost, they also needed to encourage the efficient energy use in the production, such as reusing the heat in the production process and preventing it from being wasted. This would also result in reducing any damage to the environment.

Power stations of various types, before and after deregulation, were also used in different situations. Hydroelectric power stations were used more frequently before the deregulation as they have low operating cost and the starting up process is relatively quick. Therefore, the use of these stations increased during the peak load periods and were mostly used in New South Wales and Victoria. Gas turbine stations were mainly used in the state of Queensland and South Australia in the peak load hours as there were no hydroelectric power station in these states and they operate with natural gas. Finally, coal power stations are mostly used for the base load as they are able to operate at a very low cost. More information about the electricity industry restructuring is provided in Saddler (1981), Joskow (2000), Quiggin, (2001) and Borenstein (2000).

#### *1.2.4.2 After deregulation*

Electricity market in Australia used to be regulated as a "Natural Monopoly"[3] before the deregulation in 1990s. The presence of natural monopoly situation in the market gives a large supplier in an industry a cost advantage over other suppliers in the market. Australian electricity market was one of such examples before the deregulation where state government used to control the supply of electricity to the market. In this regulation, the state government's main concern was to manage the market in favour of community and to keep the electricity industry as a reliable and a sustainable source of energy. As the capital cost of the electricity production was quite substantial, it was more economically efficient for the state governments to manage

[3] Joskow (2000) defines the natural monopoly as an industry where it is more economical in terms of costs to supply the output within a single firm rather than multiple firms. This tends to be the case in industries where economies of scale are large in relation to the size of the market. As the capital costs is high in these industries, it creates barriers for others to enter the market.

the market entirely (Saddler, 1981). However, these state owned electricity markets resulted in significant employment and investment costs. This provided the main motivation for the economic reform in the electricity market.

Generally, regulatory reforms in the electricity market were started by separating the three functions of generation, transmission and distribution in the market. The reform in the electricity market was mainly implemented in the generation sector in which, with the new restructuring, promoted competition in electricity. Later, more advanced concepts to stimulate competition among generators were introduced. In particular, setting electricity price through spot market was brought in (NEMMCO, 2005).

With the aid of deregulation, the pricing mechanism was supposed to become transparent of the underlying costs of electricity production which intended to result in reducing the cost to end users. There is a broad literature available in this area including Steiner (2000), Saddler (1981), Joskow (2008).

## 1.3 REGULATORY ARRANGEMENTS

In this section we provide information about the influential regulatory committees and rules which monitor the wholesale electricity market in Australia. We also briefly introduce the Australian energy market operator (AEMO, 2010) which is the primal manager of the wholesale electricity market in Australia.

### 1.3.1 National electricity law and rules

Previously, National Electricity Code (NEC) used to prepare the rules to manage NEM and it was driven by the deregulation plans of the government for the electricity supply industry. National Electricity Code was the regulation appointed by government with the aid of electricity supply industry and electricity users. It aimed to monitor the market rules, network connections, access and pricing for the network, market operations and the power system's security in NEM. NEC was related to all the regulations which are needed to ensure there is a fair access for all the stakeholders in the electricity network. It also monitored that all the technical requirements in the electricity supply needed to meet the required standards.

In June 2005 NEC was replaced by the National Electricity Laws and Rules. One of the important actions of the National Electricity Laws and Rules was to replace NEMMCO by AEMO in 2009. The fundamental responsibilities of the National Electricity Laws and Rules is to set the actions for the market operation, network connection and access, power system security and national transmission (AEMO, 2010).

### 1.3.2 Australian Energy Market Commission (AEMC)

The primary role of Australian energy market commission is to ensure the power system remains secure and reliable by setting certain standards and guidelines. AEMC provides advice on the safety, security and reliability of the national electricity system monitors. It also reviews the reliability standards and mentions reliability settings which are needed to reach this standard for the National Electricity Market, every four years. The settings are included the market price cap, the cumulative price threshold, and the market floor price (AEMC website, Accessed 2/7/2014).

### 1.3.3 Australian energy Regulator (AER)

Established to regulate electricity and gas transmission and distribution in the future. Basically, since 2005 the responsibility for market regulation for NEM rests with the Australian Energy Market Commission (AEMC) and the Australian Energy Regulator (AER). AEMC manages the process of any possible changes in the existing rules and provides reviews on the operation of the Rules for the Ministerial Council on Energy. AER is responsible for the monitoring the implementation of the Rules and is also responsible for economic regulation of electricity transmission (AEMO, 2010).

### 1.3.4 Australian Competition and Consumer Commission (ACCC)

If any changes are to be made in NEC, ACCC needs to control them. The other responsibility of the ACCC is to manage the regulation regarding the transmission network in the Australian electricity supply (AEMO, 2010).

### 1.3.5 National Electricity Market Management Company (NEMMCO)

NEMMCOs main objectives were to control and manage NEM, monitor any changes to market operations and constantly, check the market efficiency. It began to operate in 1996 and was responsible to manage the spot market and instantaneously balance the demand and price through the pool. In 2009, NEMMCO was replaced by Australian Energy Market Operator (AEMO, 2010).

### 1.3.6 Australian Energy Market Operator (AEMO)

As mentioned above, the Australian Energy Market Operator (AEMO) was created by the Council of Australian Government (COAG) to manage NEM and gas markets from 1 July 2009. The National electricity law and rules were modified to replace NEMMCO with AEMO as the operator of national electricity market (AEMO, 2010).

The main roles of AEMO are in the areas of Electricity Market (power system and market operator), gas market operator, national transmission planner, transmission services and energy market development. Members of AEMO are from both government, 60%, and industry, 40%. The government members are from Queensland, New South Wales, Victorian, South Australian and Tasmanian state governments, the Commonwealth and the Australian Capital Territory (AEMO, 2010).

Primary functions of the AEMO are to operate the power system and to manage the market. Some of the key responsibilities of AEMO are as follows:

(i) Manage an effective structure for the operation of NEM.
(ii) Develop market and improve market efficiency.
(iii) Monitor security and reliability of NEM.
(iv) Coordinate planning of the interconnected power system.
(v) Monitoring the demand and supply and balance the generation level to meet the demand.
(vi) Encourage generators to increase the generation capacity during shortfalls.
(vii) Cover the operating cost by the bills paid by the consumers. Ensure supply reserve for the unexpected circumstances.
(viii) National transmission planning for the electricity transmission network.
(ix) Electricity emergency management.
(x) Provide the electricity statement of opportunity.
(xi) Prepare the facilities to encourage the Full Retail Competition.

AEMO manages the system from two centres located in different. Both centres have the same operating system and any part of NEM is manageable from either centre. The benefit of having these parallel systems is that in case of emergencies, such as natural disasters, AEMO has the opportunity to control the system from either centre. This increases the flexibility to respond rapidly to critical events (AEMO, 2010).

## 1.4 ELECTRICITY NETWORK

As mentioned earlier, NSW, Queensland, Victoria, South Australia and Tasmania are the five interconnected electrical regions in NEM. High voltage electricity is transmitted between these regions by the interconnectors. When the demand is so high in one region that the local generation cannot satisfy it, or in the situations when the spot price in one region is low enough to be economical for electricity to be transferred to other regions, interconnectors are used to import the needed electricity. However, the interconnectors have some technical constraints that limit the amount of electricity transferred each time.

In general, the interconnectors can be divided into two categories of regulated and unregulated interconnectors.

### *1.4.1.1 Regulated interconnectors:*

There is a regulatory test designed by ACCC and interconnectors which pass this test become regulated interconnectors. The benefit here is that these interconnectors receive a fixed annual income which is determined by ACCC and is collected as part of the network charges. For instance, Murraylink is a regulated interconnector between Victoria and South Australia. In general, regulated interconnectors are transferring electricity supply between all the regions in NEM except Tasmania (AEMO, 2010).

### *1.4.1.2 Unregulated interconnectors:*

As these interconnectors have not passed the ACCC exam, they do not receive the annual revenue. Instead, these interconnectors make money by buying electricity in a lower price region and selling it to higher price regions. At the moment, the Basslink is an unregulated interconnector which operates between Victoria and Tasmania. Figure1.7 shows the interconnectors in NEM.

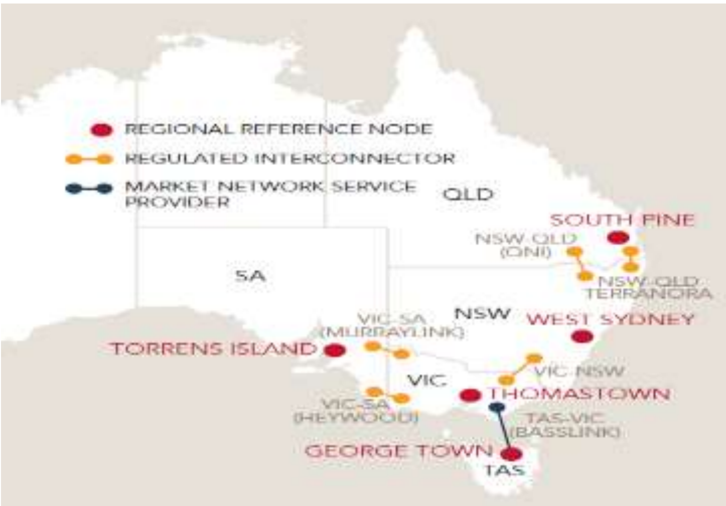


Figure1.7 Interconnectors in NEM, (Source: AEMO, 2010).

#### *1.4.1.3 Import and export via Victoria – South Australia interconnectors*

As Figure 1.7 above shows, South Australia and Victoria are connected using two interconnectors, Murraylink and Heywood interconnectors with nominal rating of 200 MW and 460 MW[4] . Murraylink interconnector allows electricity to flow between South Australia and north-west Victoria. Heywood interconnector connects south-west of Victoria to South Australia (South Australian electricity report, 2014).

Figure 1.8 shows the yearly import and export of electricity between South Australia and Victoria in the years 2004 to 2014. Prior to 2006-07 imports from Victoria dominated export. However, due to factors such as increased wind generation in South Australia, drought condition and expensive interstate supply this trend reversed from 2006-07.

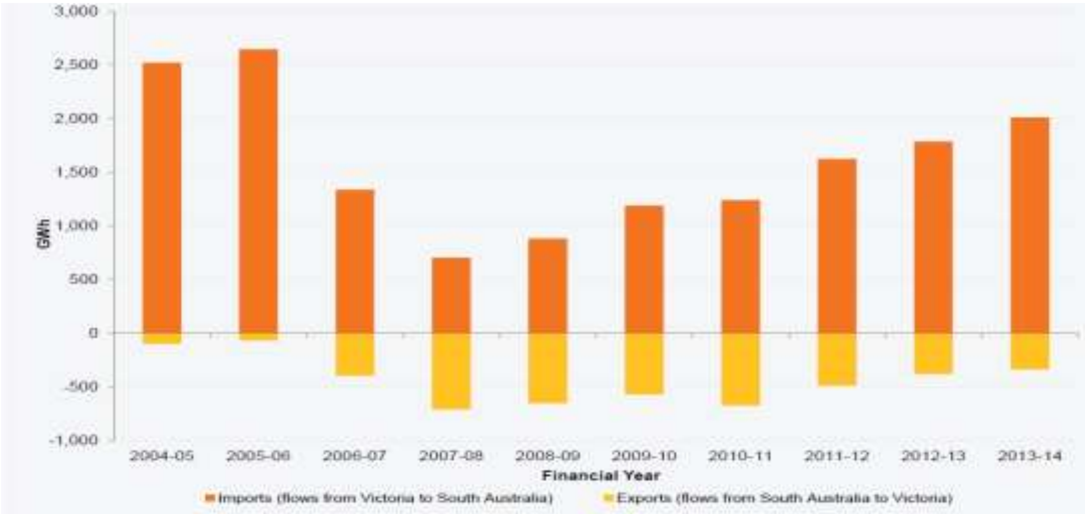


Figure 1.8. Victoria – South Australia electricity imports and exports via interconnectors. (Source: South Australian electricity report, 2014).

### 1.4.2 Ancillary services

Ancillary services are the services that keep the power system, safe, secure and reliable. They consist of standards for voltage, frequency, system re-start processes and network loading. For this purpose, Frequency Control Ancillary Services (FCAS) market was designed in September 2001, where providers compete and bid their services in the market. These services mainly control the frequency by raising or lowering it in the normal range of 49.9 to 50.1 Hertz.

Network Control Ancillary services (NCAS) are also designed to control the voltage at

[4] Many factors can limit the interconnector flow to less than the nominal rating such as thermal limitations and voltage limitations. More information about the constraint affecting the flow though interconnector between South Australia and Victoria is available in (AEMO, 2013e).

different points of the network as well as to monitor the power flow of network elements to remain according to standards. In the occurrence of critical events such as a major supply disruption, System Restart Ancillary Services (SRAS) are required to restart the electrical system safely (AEMO, 2010).

## 1.5 ELECTRICITY SUPPLY AND DEMAND IN NEM

As mentioned earlier, one of the primary roles of AEMO is to manage NEM and ensure that electricity demand and supply are instantaneously matched at five minute intervals. In this section, more details of the demand and supply characteristics in Australia are provided and, at the end, the procedures in which supply and demand are balanced are discussed.

### 1.5.1 Demand

One of the main responsibilities of AEMO is to operate NEM so as to forecast the demand for different regions. In a typical business day in Australia the level of load can reach some 25,000 megawatts. Many factors affect the level of demand through the year including temperature, population and industrial and commercial needs in a region. Demand for electricity, the so-called “load” is highly correlated with the temperature. It is on a low level during the night, from midnight to 7 am, and gradually increases until it reaches to the peak generally from 7am to 9am and also from 4pm to 7pm (AEMO, 2010).

The wholesale electricity market has been designed so that there is enough electricity generated even in the extreme conditions to ensure that the demand can be satisfied. The fluctuation in the electricity load varies due to a variety of reasons such as economic activities, type of the consumers (e.g., residential consumer, industrial consumer, etc.), and more importantly the temperature which results in increasing air conditioning usage in hot summer days or cold winter days (NEMMCO, 2005).

Nevertheless, satisfying the demand is facilitated by the fact that most of the peak demand periods due to temperature extremes do not occur simultaneously in all regions. Therefore, the power system can manage these critical conditions by sharing the supply through interconnectors between the regions.

For some states such as Victoria and South Australia extreme temperatures occur mostly in summer time which is manageable mainly with two specific actions. First, some generators have been assigned to specifically aid the network for the peak periods (also called peak generators). Second, when the spot price reaches a certain level, part of the consumers voluntarily disconnect from the network temporarily. This may help prevent the spot price from increasing too much (AEMO, 2010).

#### *1.5.1.1 Forecasting demand*

Forecasting electricity demand is one of the most critical tasks that AEMO needs to do every day. AEMO uses many forecast processes to ensure that electricity supply and demand are balanced all the time. With the aid of forecast procedures, in case of any emergencies such as shortfalls, the generators will be informed quickly and will try to increase their capacity in order to satisfy the demand entirely. This enables AEMO to schedule a reliable timetable of generation and balance the demand and supply with the minimum possible cost.

(i) Pre-dispatch forecasting:

Pre-dispatch forecasting includes the estimation of the upcoming day demand and also the amount of available capacity of generation from generators. This will help the system to monitor whether the demand and supply will be satisfied in the next day. Basically, on a day before the supply is needed, all generators are required to submit their maximum available capacity to the market. This will help AEMO to determine and publish any potential of shortfall against demand.

(ii) Project Assessment and System Adequacy (PASA)

AEMO also uses more long term viewing forecast processes to ensure whether the available generation capacity of generators is adequate to satisfy demand in the long term. These processes include, seven-day forecast and also a two-year forecast which are called, short-term and medium-term forecasts of Projected Assessment of System Adequacy (PASA), respectively. These forecasts are updated on a 2-hourly basis from 4:00am for the short-term PASA and on 2:00pm every Tuesday for the medium term PASA.

(iii) Electricity Statement of Opportunity (SOO)

Electricity Statement of Opportunities (SOO) is a 10-year forecast published by AEMO each year. It considers the future generation and demand side capacity and also the distribution of electricity in the future. It also contains information regarding ancillary service needs and minimum reserve level.

NEM covers about 9.3 million residential and business customers. The maximum historical winter demand occurred in 2008 with 34,422 MW and the maximum historical summer demand occurred in 2009 with 35,551 MW of electricity consumption (AEMO, 2013c). During the years 2008-2009 the demand rose at a higher rate than the average as a result of very hot summer days and increase in the usage of air-conditioning by consumers. The usage of air conditioning in households increased from 58 percent in 2005 to 73 percent in 2011 (AER, 2013a).

These significant increases in maximum demand led to the investment in energy network over the past decade. However, the maximum demand exhibited a flattening trend since 2009. For instance, January 2013 was the hottest summer month on record but the corresponding maximum demand was below the historical level (AEMO, 2013c).

Since 2009, market demand has had a decreasing trend by an annual average of 1.1 per cent. The reduction in electricity demand has number of causes including;

(i) As electricity price was high for a period around the years 2008-2009, consumers started a decreasing trend in their usage to respond to the high electricity cost (AEMO, 2013b).
(ii) Part of this reduction is related to the decrease in energy demand in the large industrial sectors which occurred since 2007-2008 (AEMO, 2013b). This decreasing trend has continued in the years 2013-14. Some industries as Kurri Kurri aluminium smelter have closed and also there has been a reduction in the level of demand in the Wonthaggi desalination plant in Victoria in 2013-14.
(iii) Part of the demand reduction through the grid is related to the rise in the usage of solar generation by consumers. In 2013-14 the photovoltaic generation increase by 58 percent to 2700 GWh which was about 1.3 percent of the total electricity consumption (AEMO, 2013c).

However, AEMO has estimated in the National forecasting report (2013f) that the electricity demand will grow annually by around 1.3 percent over the next decade. Moderation in electricity price growth, increasing trend in the population and development in the liquefied natural gas in projects in Queensland are number of the reasons outlined for this forecasted trend (AEMO, 2013c).

### 1.5.2 Submitting bid stacks to supply

Generators who are willing to participate in the electricity production need to submit the amount of electricity and the price offers to the pool. There are three types of bids which they need to submit:

(i) Daily bids: to be submitted before 12:30 PM on the day before supply is needed. These are an indication of the pre dispatch forecasts.
(ii) Re-bids: Generators have the flexibility to submit these bids up to 5 minute before the dispatch commences. They can change them by increasing or decreasing the volume offered at the same prices they have offered before. In other words they have the flexibility to change the volume of electricity they offered but not the prices.
(iii) Default bids: these bids are the base operating levels for generators and are used when no daily bids have been submitted (AEMO, 2010).

### 1.5.3 Supply and demand balance

AEMO manages the following procedures to ensure reliable supply to the consumers and also protect the power system from any potential risk (AEMO, 2010).

#### *1.5.3.1 Security of supply*

The main responsibility of AEMO as NEM operator is to ensure that the power system is secure. In other words, AEMO needs to monitor the electricity supply and prevent damage and overload in the power system. AEMO has the authority to direct generators into production to protect the security and reliability of the power system.

#### *1.5.3.2 Power system reliability*

Reliability standards are determined by AEMC Reliability Plan which set the expected amount of energy not being delivered to the consumers. Based on this, AEMO determines the extra amount of generation capacity needed for each trading interval. Currently, the reliability standard is set at maximum of 0.002 percent of unserved consumers per financial year. This percentage is equivalent to a maximum of a seven minute outage of electricity in a given year. To ensure this percentage is not breached in the market a number of strategies have been put in place by AEMO and AEMC Reliability Panel (AER, 2013a):

(i) AEMO publishes demand forecast to inform generators to manage the extra capacity needed.

(ii) AEMO has the power to direct generators to provide additional capacity in order to supply the whole demand across the grid.
(iii) AEMO can also enter into contracts with generators to make sure that the extra capacity is sufficient to meet the demand.
(iv) AEMC Reliability Panel set market price cap which has increased from \$12,900/MWh to \$13,100/MWh on 1 July 2013 to promote further investment in generation capacity. Market price floor is also set at -\$1000/MWh.
(v) AEMC Reliability Panel also determines a price threshold to protect consumer from very high prices. Based on the threshold set on 1 July 2013, if the cumulative spot price over seven days exceeds \$197,100/MWh then an administered price cap of \$300/MWh will be substituted (AER, 2013a).

Let us figure out how this threshold work in terms of the average of spot price at each trading interval. Recall that 48 trading interval exist within each day and consequently $7 \times 48 = 336$ trading intervals in 7 days. Therefore the \$197,100/MWh as a threshold for the maximum cumulative spot price is equivalent to the average of

$$\$197100 \div 336 = \$586.6,$$

for each trading interval in a week. In other words, even if the spot price reaches to \$586/MWh for all of the trading intervals within a week, then the maximum threshold has not breached yet. This means that generators have the opportunity to offer the cap price of \$13100/MWh for up to 15 out of 336 trading intervals

$$\$197{,}100 \div \$13{,}100 = 15.04,$$

in each week (and offer a very low price at the rest of trading intervals) to avoid breaching the maximum threshold which is set by AEMC.

Historically the reliability standard has only been breached twice in 2009 in the states of Victoria and South Australia and reached to 0.004 percent and 0.0032 percent respectively (AER, 2013a).

#### *1.5.3.3 Supply reserve*

The supply reserve is the minimum reserve level which is required to ensure that the reliability standards across NEM are satisfied. There is a list provided in the Electricity Statement of Opportunities by AEMO which specifies the minimum reserve level required for different NEM regions.

### 1.5.3.4 Demand side participation

Demand side participation is a deliberate action taken by customers to prevent significant increases in the spot price. For instance, for some peak periods, market customers reduce or withdraw their consumption from the market. They return to the normal consumption levels when the peak passes and the spot price falls under the desired threshold. Another strategy is called load shifting and arranges a settlement to shift the load partly to the off-peak periods. For example, some hot water arrangement can be deliberately shifted to the periods of time when the demand is relatively low. In general, large consumers have higher flexibility to manage their demand in the spot market (AEMO, 2010).

### 1.5.3.5 Generation investment

As mentioned earlier, the Australian electricity market has experienced high volatility in the spot price since deregulation. To overcome this problem one of the mitigating strategies was to invest more in the generation sector. Basically, the peak electricity prices and also the price signals in the derivative markets encourage new investment in NEM.

Since 1999 when NEM started to operate, new investments in the generation capacity added about 13850 MW of registered generation capacity, until 2013. New investments also have been made in the out of the grid generation such as rooftop PV installation. Moreover, out of 2000 MW of capacity added to the generation capacity over the three years to 2013, 50 percent was in wing generation as a result of RET scheme (AER, 2013a).

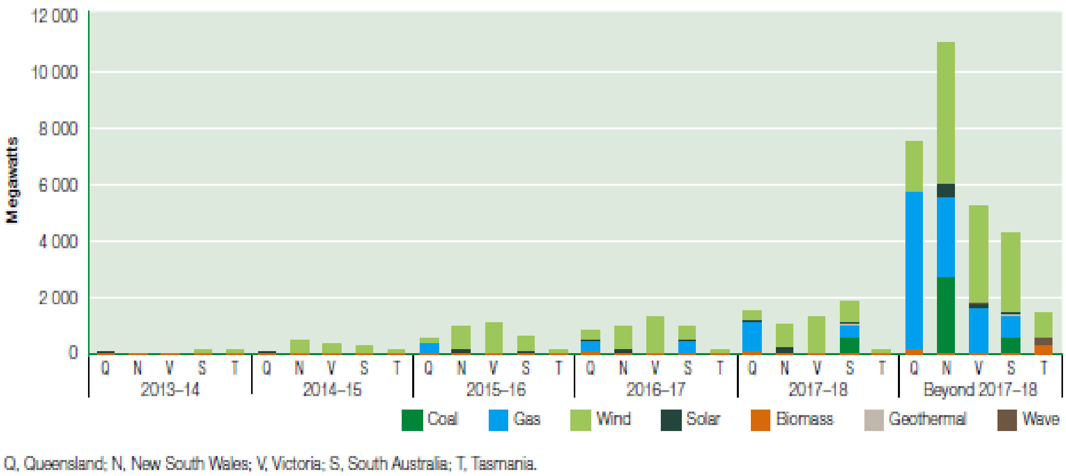


Figure 1.9. Major proposed generation investment by June 2012 (Source: AER, 2013a).

Although few new generation projects have been developed so far, AEMO has listed about 30,000 MW of proposed capacity in NEM where 6000 MW of new generation capacity is planned to be done before 2018-19. Figure 1.9 shows the cumulative proposed generation investment by June 2012. It includes 740 MW of solar generation investment in the three regions of NEM (New South Wales, Victoria and South Australia), 350 MW generation investment by wave technology in Victoria and Tasmania, and also 550 MW of Geothermal generation investment in South Australia (AER, 2013a).

#### *1.5.3.6 Load shedding*

The last action that would AEMO take to protect system security and reliability is to shed the load for some regions in order to balance the demand with the level of production. In this action, AEMO disconnects the supply of electricity to consumers of some specific regions in NEM to ensure that there is no risk to the security of the entire power system.

## 1.6 SPOT MARKET

National electricity market works through a pool where all generators submit their offers of volume and price for producing electricity. Generators submit these bids as pairs of price and quantity elements stating the amount of electricity they are willing to produce at the specific price to contribute the pool. A generator can bid at 10 different price levels and this bid stack should be submitted a day ahead. Generators have the opportunity to rebid and change the volume offered at each price band but they cannot change the prices offered.

The prices that generators offer depend on many factors including the type of fuel they use. Coal generators have a very high start-up cost therefore they need to ensure that they run constantly to be able to afford the high start-up costs. For this purpose they may be even willing to offer a certain volume of electricity at negative price bands[5]. Conversely, gas generators have high operating costs and are willing to be dispatched to only when the prices are high enough (AER, 2013a).

Based on generators bids, by considering the objective of minimising the cost to consumers and other transmission constraints in each region, the dispatch will be scheduled. AEMO dispatches as many generator as needed to satisfy the demand at

[5] The market price floor is -$1000/MWh.

every five minute interval.

The National Electricity Law and Rules has set a maximum and minimum prices that generator can offer to the market. These prices are reviewed every two years by the Reliability Panel[6]. The prices can vary between the market price floor and market price cap of set by AEMC[7] .

(i) Market Price Cap: The maximum price that generators can offer is called "Market Price Cap" and is set to $13,100/MWh by the Rules.
(ii) Market Floor Price: The minimum price that generators can offer is called "Market Floor Price" and is set to -$1,000/MWh by the Rules (AEMO, 2010).

Figure 1.10 shows a generic bid stack structure by a typical South Australian generator in a five minute interval. Basically, the structure of bids in Australian electricity market has been designed in a way that allows generators to offer volume and price of electricity production in a stack of 10 bands. As an example, the figure below shows a bid offered by a generator in South Australia at a five minute interval of 17:30 to 17:35pm on 31st March 2008.

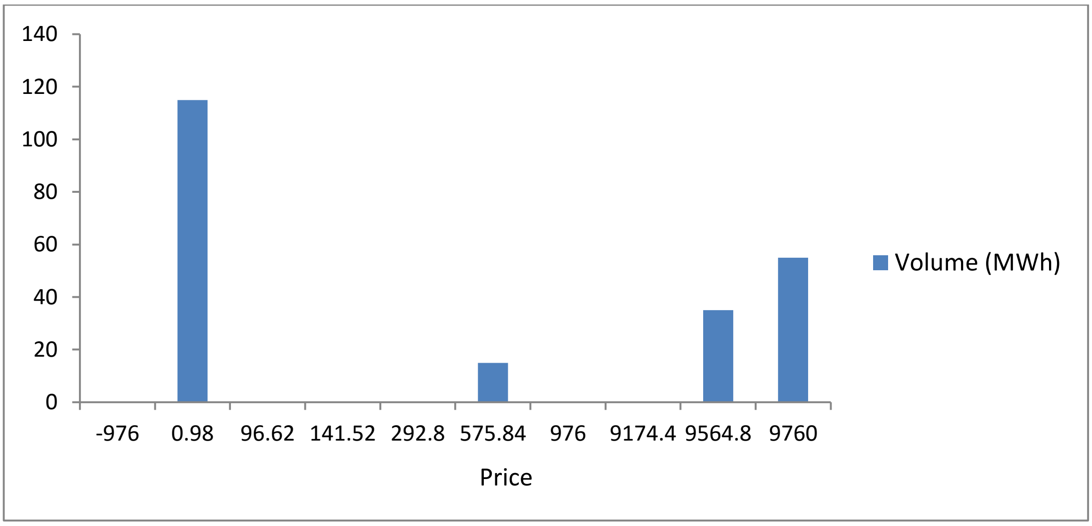


Figure 1.10. Bid offered, March 31th 2008 at 17:30 (AEMO Website, accessed 2/8/2012).

[6] The Reliability Panel was established by the AEMC under the National Electricity Law and Rules. This panel regulates standards to ensure the power system remains secure and reliable. (Source, AEMC website, Accessed 2/7/2014)

[7] Australian Energy Market Commission.

As displayed in Figure 1.10, this bid includes a stack of 10 bands and in each of these bands the generator offered the price and the volume of electricity that the generator is willing to produce, at that price. Prices at each band can vary in the interval from $-1000/MWh to $13,100/MWh and as shown in the figure they are sorted in an ascending order. The negative sign for the lowest price shows that a generator may even be willing to pay $1000 for generating some electricity for some specific reasons such as increasing the probability of winning a volume of production among other generators, or they may wish to avoid start up - cool down costs.

Figure 1.10 illustrates that this generator offered to produce approximately 110 MW, 10 MW, 25 MW and 55 MW at the prices of $0.98, $575.84, $9564.8 and $9760 per MWh respectively, in this five minute interval. Other six bands with zero volume of electricity purposely discarded by this generator at this five minute interval.

### 1.6.1 Setting the spot price

Basically generation offers are gather from all generators in the pool and AEMO dispatches generators to production at every five minute interval. In this manner, there are 288 dispatch prices every day. The dispatch price reflects the cost of last megawatt of electricity which is produced to satisfy the total demand. The latter is determined by dual variables of certain linear program called "the National Electricity Market dispatch engine (NEMDE)" that is solved every five minutes. Every half an hour period is called a "Trading Interval" in the market. There are 48 trading intervals and consequently 48 spot prices every day. Each of the five regions in NEM have their own spot price for every half an hour trading interval (AEMO, 2013d).

#### *1.6.1.1 Dispatch problem*

Dispatch problem is one of the main parts of the price setting mechanism in which a linear programming problem is solved to determine which generators require to produce electricity to meet the demand in a most cost efficient way. In this problem, the dispatch prices, for the five states, which represent the costs to supply the last megawatt of electricity, are determined by the optimal dual variable values ("shadow prices") corresponding to the demand constraint for these states. Thus, mathematically, at each five minute time interval, denoted by $t$, AEMO solves a linear programming problem of the generic form:

$$\min c(t)^T x$$
$$Ax \geq b(t) \qquad (LP(t))$$
$$x \geq 0.$$

The input data needed to construct $(LP(t))$ include generator's bid stacks, transmission network capacity and cost and many other parameters. The objective is to minimize the cost involving energy cost, ancillary service cost, transmission network cost and some security penalties to avoid overflow on the lines (Conticini, 2010).

Figure 1.11 shows NEM electricity grid which includes 5 interconnected regions. In $(LP(t))$, $b(t)$ includes demands in period t and there is a separate demand constraint for each region and the dispatch prices are the optimal dual variables $y_j(t)$, $j = 1,2,\ldots,5$ corresponding to the five demand constraints.

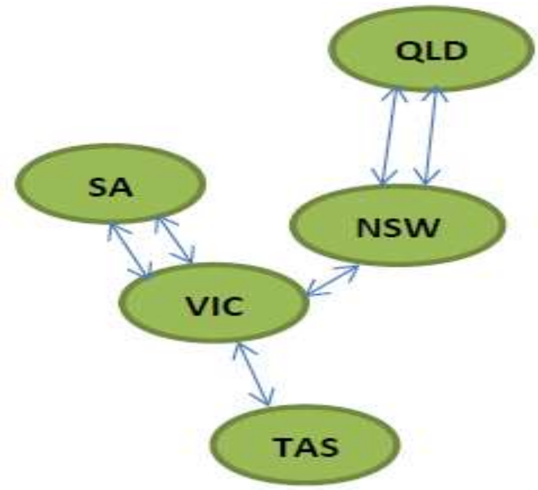


Figure 1.11. NEM electricity grid.

#### *1.6.1.2 Spot price*

Thus for each five minute interval t, an optimal solution of $(LP(t))$, determines five dispatch prices $y_j(t)$for the five states. In this way 288 dispatch prices are determined every day, for each state. Next, AEMO switches to the coarser, thirty minute, trading intervals denoted by $\hat{t}$. In each state, the spot price $y_j(\hat{t})$ for the trading interval $\hat{t}$ is the average of six (five minute) dispatch prices in a half an hour trading interval, namely

$$y_j(\hat{t}) = \frac{1}{6}\left[y_j(t_1) + y_j(t_2) + \cdots + y(t_6)\right]. \tag{1.1}$$

The above is the price according to which all generators in the state j are going to be paid equally no matter what price they have offered in their biding stacks.

**Remark 1.1** It essential to emphasize that all generators selected to produce electricity in the state $j$ during the trading interval $\hat{t}$ will be paid at the spot price $y(\hat{t})$ per MW for every megawatt they produce during that trading interval, irrespective of the prices comprising their original bid stacks.

### 1.6.2 Trends in the electricity spot price

As mentioned by AER (2012), during the years 2006-2010, most of the regions experienced peak electricity price. Many factors contributed to the high volatility in electricity price. For instance, drought was one of the reasons that limited the production of hydro plants due to shortage of water which resulted in problems in electricity production. Also as mentioned in AER (2013c) report evidence of exercising market power by generators has been observed, specifically by AGL in South Australia, which had a considerable effect on the price volatility between the years 2008-2010.

Since then, electricity demand has had a decreasing trend and with the aid of renewable energy generation in the grid, the spot price had also a decreasing trend until 2012. During the years 2012-13, the decreasing trend in the spot price changed its direction again and the market experienced high spot prices. The average spot prices increased to $70/MWh, $61/MWh, $74/MWh, $56/MWh, $49/MWh for the for the regions of Queensland, Victoria, South Australia, New South Wales and Tasmania in 2012-13. In general, the electricity price across NEM, by around $31/MWh (AER, 2013a).

One of the main reasons for the increasing spot price during 2012-13 was thought to be the impact of carbon pricing scheme introduced on 1 July 2012 which sets $23 per tonne of emission. However, the carbon price was not the only reason contributing to raising the prices. As mentioned by AER (2013c), in the two states of Queensland (August-October 2012) and South Australia (April-May 2013) which had the largest increase in electricity prices, some opportunistic bidding behaviour by generators has been noticed.

Indeed, the dependence of the spot price on the generators’ bids in the pool may be one of the main reasons for electricity price fluctuations. Although this mechanism was created to balance the demand and supply with the minimum possible cost, research shows that there has been times of the year when some generators were able to exercise their market power. There is a broad literature in this area ((Brennan and Melanie (1998), Wolfram (1999) and etc.). This has contributed to the high electricity price volatility in the Australian electricity market particularly in the recent decade. The spot price could be highly volatile and in some trading intervals it even has reached to the previous maximum cap price of $10000/MWh[8]. In Chapter 2 more literature in this area will be mentioned.

## 1.7 FINANCIAL RISK MANAGEMENT IN NEM

The fact that electricity price in the wholesale electricity market in Australia is dependent on the generators bids contributes to the price volatility in some trading intervals of the year. In addition, the limitation in the expansion of interconnectors in Australia also made the transmission of electricity a difficult task. Therefore, transmitting electricity can depend mostly on the local generations. Furthermore, other factors such as seasonal effects on rising demand is also contributing to fluctuation in the electricity price at specific times of the year. All these factors can lead to variation in the financial risk in the wholesale electricity market. This led to designing the appropriate financial contracts to hedge the risk of the electricity price volatilities for the stakeholder.

The hedge contracts are generally set between generators and consumers. These contracts reduce the risk of price volatility by locking the price in the financial contracts and are independent of the rules in the market and do not mean to balance the supply and demand. In hedge contracts, a strike price is set in these contracts for the electricity traded on the spot market. This enables parties to exchange money based on the agreed strike price for the specific amount of electricity.

Figure 1.12 shows an example of a hedge contract on the electricity in the financial market. This contract is between seller of the contract and the buyer, and the strike price is set to $40/MWh. As illustrated in the figure, when the spot price is lower than $40/MWh, the buyers of the contract pays the seller, the difference between the agreed strike price and spot price. In reverse, sellers are required to pay the difference

[8] After July 2013 the price cap increased to $13,100/MWh

to buyers when the spot price goes beyond the strike price. Many appropriate hedge contracts are designed in the financial market to deal with this volatility in the electricity price. For instance, in Sydney Future Exchange, future and option electricity contracts has been traded for the New South Wales electricity market (AEMO, 2010).

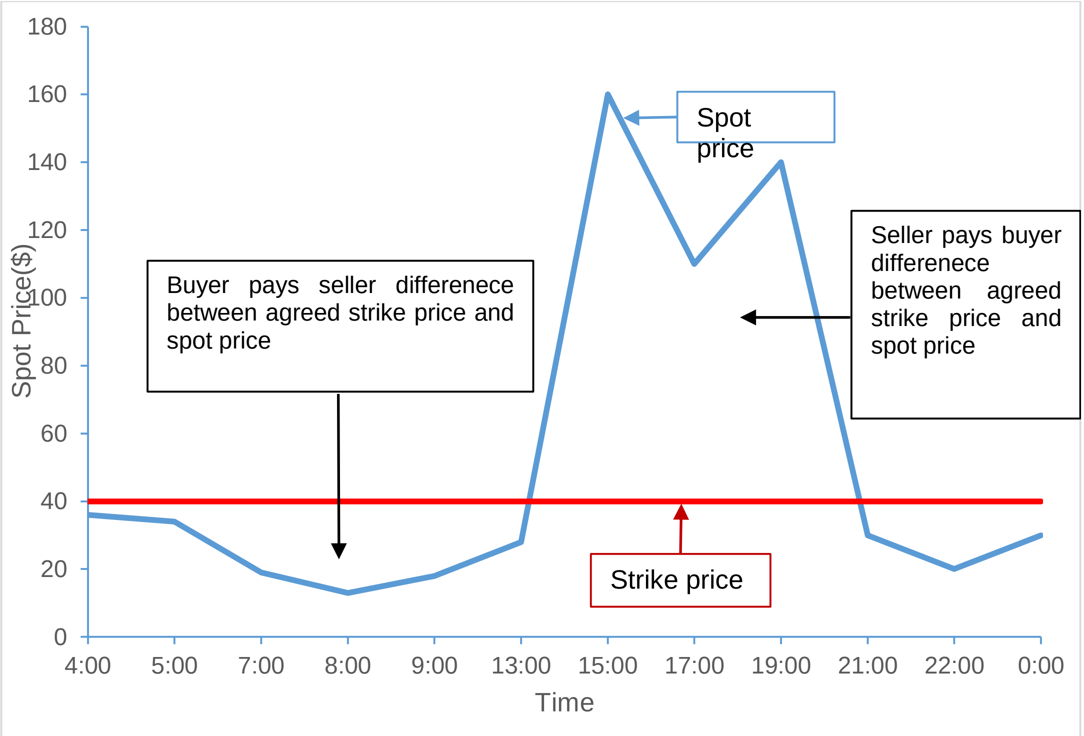


Figure 1.12. An electricity hedge contract (Source: AEMO July 2010).

## 1.8 THE RETAIL ELECTRICITY MARKET

The retailers in the electricity market are the parties which buy electricity from the pool (wholesale electricity market) and sell to the customers[9]. The main role of retailer in the wholesale electricity market is to buy electricity from the pool and with providing the transportation services, sell it to the consumers. Table 1.3 shows a number of retailers in Australia which supply electricity to the consumers in October 2013.

As Table 1.3 shows retails are not necessarily active in all the regions. Three privately owned retailers of AGL, Origin Energy and Energy Australia are the major suppliers in south and eastern parts of NEM. They cover about 77 percent of electricity supply to the consumers in their regions at 30 June 2013 (AER, 2013a).

[9] It should be mentioned that there are some consumers who directly buy electricity from the pool without the aid of retailers.

Table 1.3. Energy retailers- small customer market, October 2013 (AER, 2013a).

| Retailer | Ownership | QLD | NSW | VIC | SA | TAS | ACT |
|---|---|---|---|---|---|---|---|
| ActewAGL Retail | ACT government and AGL Energy | | | | | | |
| AGL Energy | AGL Energy | | | | | | |
| Alinta Energy | Alinta Energy | | | | | | |
| Aurora Energy | Tasmanian Government | | | | | | |
| Australian Power and Gas | AGL Energy | | | | | | |
| BlueNRG | Blue Energy | | | | | | |
| Click Energy | Click energy | | | | | | |
| Diamond Energy | Diamond Energy | | | | | | |
| Dodo Power and Gas | M2 Telecommunication Group | | | | | | |
| EnergyAustralia | CLP Group | | | | | | |
| Ergon Energy | Queensland Government | | | | | | |
| Lumo energy | Infratil | | | | | | |
| Momentum Energy | Hydro Tasmania (Tasmanian government) | | | | | | |
| Neighbourhood Energy | Alinta Energy | | | | | | |
| Origin Energy | Origin Energy | | | | | | |
| People Energy | People Energy | | | | | | |
| Powerdirect | AGL Energy | | | | | | |
| Powershop | Meridian Energy | | | | | | |
| Qenergy | Qenergy | | | | | | |
| Red Energy | Snowy Hydro | | | | | | |
| Sanctuary Energy | Living Choice Australia/Sanctuary Life | | | | | | |
| Simply Energy | International Power | | | | | | |

### 1.8.1 Retail price

In general, the energy bills that consumers pay consist of various costs such as cost of whole sale energy, transmission and distribution network costs and also retail cost. Table 1.4 shows the share of these costs in each region in a typical electricity retail bill for a residential consumer.

As shown in Table 1.4, the highest portion of electricity cost is related to the transmission and distribution of electricity through network. Carbon costs are introduced in July 2012. South Australia and Tasmania had the lowest percentage in carbon price as they have significant renewable generation. Green costs are related to schemes supporting renewable generation development, low emission generation and also supporting energy efficiency (AER, 2013b).

Table 1.4. Composition of residential electricity bills in the regions of NEM (AER, 2013b).

| Jurisdiction | Network Costs | Wholesale Energy Costs | Retail Costs | Carbon Costs | Green Costs |
|---|---|---|---|---|---|
| **Percent of Typical Small Customer Bill** | | | | | |
| Queensland | 52 | 21 | 15 | 9 | 3 |
| New South Wales | 51 | 23 | 10 | 7 | 8 |
| Victoria | 36 | na | na | 8 | 4 |
| South Australia | 55 | 21 | 13 | 4 | 8 |
| Tasmania | 57 | 27 | 9 | 3 | 4 |
| ACT | 43 | 26 | 11 | 12 | 8 |

## 1.9 COMPETITION IN NEM

In Australia, competition in the electricity industry became a hot topic since 1990's. Previously, the electricity supply was owned and operated by government organisations. Then electricity companies began to be privatised as the economic reforms and globalisation started to be implemented throughout the country. These aimed to result in more competitive outcomes for the consumers. However, research shows that the reforms also provided opportunities for the generators to exercise market power in some peak trading intervals (Higgs, 2006).

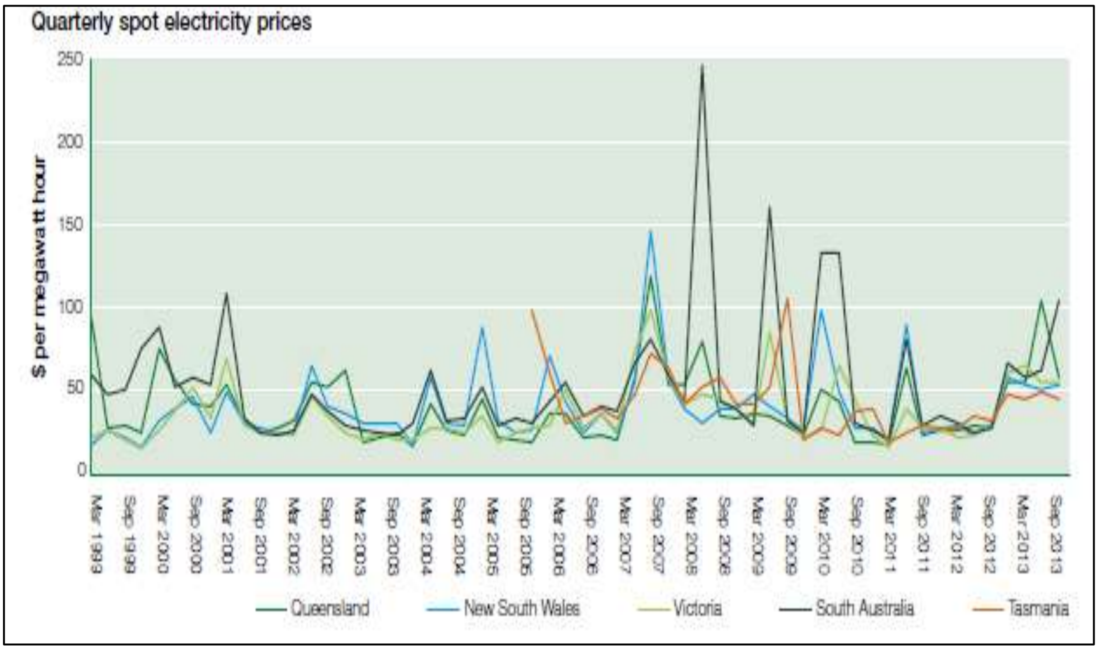


Figure 1.13. Quarterly spot electricity prices, (AER 2013a).

Figure 1.13 shows the quarterly base spot electricity price since deregulation. As shown in Figure1.14, electricity spot price has experienced high fluctuations since the deregulation in 1990s.

The volatility in the spot price was very high in the state of South Australia during the years 2008-2010. AER (2013a) has directly mentioned that there exists evidence of exercising market power in the recent years:

"In April 2013 the AEMC found potential for substantial market power to exist or be exercised in future in NEM, particularly in South Australia. It recommended the Standing Council on Energy and Resources (SCER) consider conferring on the AER powers to monitor the market for that possibility. In May 2013 the SCER agreed to task officials with further work around the need for changes to the National Electricity Law before the SCER considers its policy position" (AER, 2013a, p33).

It should be mentioned that, Australia is not the only country that has experienced exercising market power in the restructured electricity market. There is some evidence that such phenomena have also occurred in other countries such as USA and UK. This issue will be discussed further in Chapter 2.

# CHAPTER 2. PRICE VOLATILITY AND MARKET POWER IN ELECTRICITY MARKET

To encourage the competitiveness among producers the reforms in the electricity market designed in many countries around the world such as Australia. Although, the primary aim of the deregulation was to encourage market competition and to eliminate monopolistic market power, there is evidence that market power has been exercised within generation business in the electricity markets. There are various published papers that address price volatility and possible market power abuses all around the world.

Borenstein et al. (2000) addressed the potential for market power in California's wholesale electricity market after deregulation. Joskow and Kahn (2002) also provided evidence of generators exercising market power which was a result of withholding capacity offered to the market in California during 2000 and 2001.

David and Wen (2001) brought evidence of the market power in the electricity supply markets during the late 1990s. They highlight the fact that, despite accepting the deregulation in electricity markets, some generators are still able to exercise market power in peak period of demand. Mount (1999) also focuses on high price rises in UK electricity market as a result of two leading generators exercising market power in the 1990s.

Brennan and Melanie (1998) examined the potential market power by strategic pricing behaviour by generators in Australian electricity market. They provided evidence of non-competitive bidding behaviour by some large generators mainly in the high demand periods. Hu et al (2005) believe that large generators had the ability to push the price higher by withholding their generation capacity in the Australian National Electricity Market. There also have been other shifts in electricity prices in the restructured electricity markets examined by Wolak (2000) and Mount (1999).

Most definitions of market power emphasise the fact that the exercise of market power needs to be profitable. However, further investigations need to be carried out to analyse whether this profitability occurred intentionally or by accident. In other words, high prices are not necessarily an indication of generators exercising market power, rather they can be a result of a shortage of supply in a competitive market. Therefore, further investigation needs to be done to examine the actual exercise of market power in the electricity markets.

Besides it should be mentioned that, exercising market power may not be the only reason for the price volatility in the electricity markets. Recall that, electricity has a specific characteristics which need to be considered while assessing the competitiveness among generators in the market. These characteristics include, high volatility in the electricity demand during the day, the lack of flexibility to response to the sudden increase in the electricity demand, difficulty in electricity storage and the essential need to balance the electricity demand and supply instantaneously through time. These features contributed to the cost of electricity production being highly volatile even within a short period of time such as a day (ABARE 2002).

As understanding of the volatility process is critically important to distributors, generators and market regulators allowing them to better manage their financial risk, in this chapter we aim to examine some mechanisms by which generators could exercise market power[10]. Section 2.1 describes techniques which were used by economists to identify the possibility of exercising market power by generators. Moreover, the history of price volatility in Australia and also discussion of exercising of market power by generators in the literature are provided in Section 2.1 and 2.2. We focus on the state of South Australia which had the highest spot price fluctuations since the deregulation was introduced.

[10] It is important to note that it is not within the scope of this thesis to determine whether or not Australian generators have exercised market power but only to demonstrate that such possibilities exist in the market.

## 2.1 INDICES AND MODELS OF DETECTING MARKET POWER

Market power is defined as the ability to change the price from the competitive levels. There have been number of measures and tools identified by economist to detect the exercise of market power in different industries. Apparently, some of these measures would be suitable for specific industries and some may not be suitable to be used in the electricity market (Stoft, 2002).

Generally, the detection of market power includes two forms of “Potential” for market power or actual “Exercise” of market power. Monitoring the potential for exercising market power is as important as detecting the actual exercise of market power for market monitors as it is considered as a useful procedure for prevention of any exercise of market power (Twomey, P. et al, 2005).

Detecting market power in electricity markets is not easy (Baker, J., 1992, Twomey, P. et al, 2005 and Blumsack, 2003). On the other hand, electricity market has some characteristics which facilitate the detection of the market power. For instance, it is possible to estimate the cost of production more precisely in electricity market than in many other industries.

Various measures are available to detect potential for market power and actual exercise of market power by generators. Here we briefly provide an introduction to some of these measure which have been used to monitor the market power in industries such as electricity market.

### 2.1.1 Market power indices

Traditional industrial organisation theory defines some industrial indices which have been also applied in the electricity markets to measure the potential for exercising market power. In this section some of these measures and their application are outlined.

#### *2.1.1.1 Market share*

The motivation behind this index is that the more concentrated a market, the more likely is the ability of its participants to exercise market power. The market share concentration ratio is the percentage of market share of $n$ largest companies in the industry.

In order to calculate this index many features need to me be measured first such as identifying the product in the market and the competitors in the market. Also a “significant market share” threshold needs to be defined in a way that any market share above this threshold would be considered as a sign of potential for market power (Twomey, P. et al, 2005).

Basically, market share provides information about the ratio of the capacity which is controlled by one or number of generators. In the electricity market with this specification, the exercising of market power by generators is more likely. As an example, Australian Energy Regulator indicates the relatively strong market positions held by AGL Energy in South Australia, Macquarie Generation in New South Wales, and the state-owned generators CS Energy and Stanwell in Queensland in the recent years (AER, 2013a).

#### *2.1.1.2 Herfindahl-Hirschman Index (HHI)*

The Herfindahl-Hirschman Index (HHI) determines the size of the firm as the sum of squared of percentages of market shares of all firms in the market.

$$HHI = S_1^2 + S_2^2 + \cdots + S_n^2,$$

where $S_i^2$ is the percentage market share of company $i$. The benefit of using $HHI$ is that it also considers the size of other participants in the market. Obviously, a company with market share of 20% where other competitors have small percentage of share has a different market power compared to the situation where that company is the second or third largest player in a highly concentrated market. (Calkins, 1983)

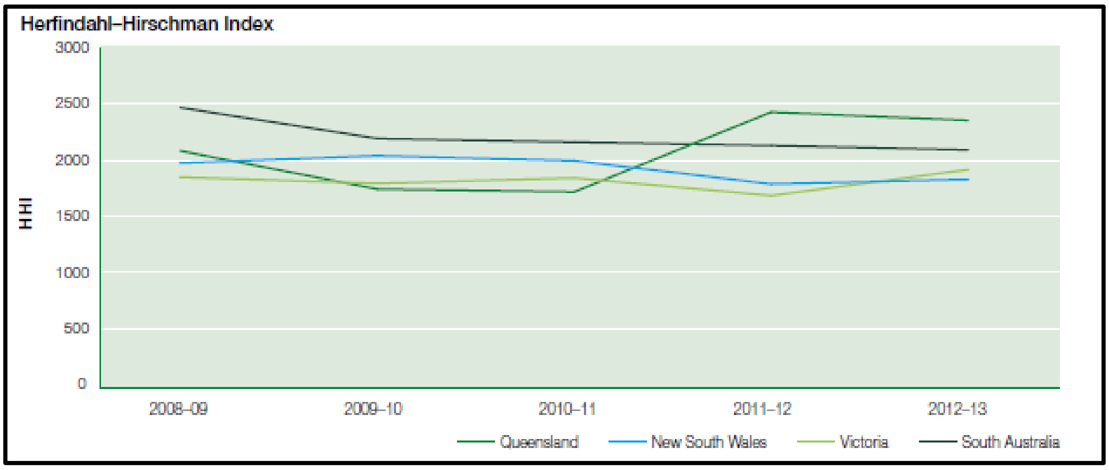


Figure 2.1 HHI in NEM during 2008-09 to 2012-13 (AER, 2013a).

When a market includes a large number of firms, $HHI$ can even approach zero but in a monopoly situation it reaches $(100\%)^2$ or 10,000. High value of $HHI$ shows a less competitive situation in the market. Figure 2.1 shows the $HHI$ in NEM regions from 2008 to 2013. As shown in Figure 2.1 the state of SA had the highest $HHI$ during 2008-2009.

#### 2.1.1.3 Pivotal Supplier Indicator (PSI)

Pivotal supplier index considers not only the supply but also the demand conditions in the market to measure the potential for market power. It measures whether a certain generator has a crucial (or pivotal) role in meeting demand.

Basically the generator is called pivotal if the capacity of that generator is greater than the "surplus supply"[11]. Pivotal supplier indicator is defined as a binary indicator which is set to one or zero where the generator (supplier) is pivotal or not pivotal at point in a time, respectively. It is called Pivotal supplier index which helps to determine the percentage of time when a supplier was pivotal. Bushnell et al (1999) found that the largest supplier in the region of Wisconsin/Upper Michigan was a pivotal supplier for 55% of the hours in a year.

AER (2013a, pp.51-57) lists the percentages of time when the largest generator in the market became pivotal in 2012-13 across NEM regions in Table 2.1. As shown in Table 2.1, state of South Australia has the highest potential to exercise market power during 2012-13.

Table 2.1. Percentage of trading intervals when large generators were pivotal in 2012-13

| QLD | NSW | VIC | SA |
|---|---|---|---|
| 17 | 18 | 20 | 29 |

#### 2.1.1.4 Residual Supply Index (RSI)

The Pivotal supplier Index mentioned above, has been criticised specially on the implementation of this index. These criticism include the application of this index to address exercise of market power just for peak hours, the lack of coordination among generators and etc (see Vassilopolous 2003). Therefore, the Residual Supply Index developed to address these criticism which is similar to PSI but it is not measured by the binary basis rather a continuous scale.

The Residual Supply Index (RSI) measures the extent to which one or more generator can be "Pivotal" in the market. A generator $g$ is called pivotal in a trading interval if demand in that trading interval exceeds the capacity of all other generators in the market. Note that this notion of "pivotal" need not be the same as that described in section 2.1.1.3. It measures the supply capacity remaining in the market after subtracting company $g$'s capacity of supply.

[11] The surplus supply is the difference between total supply and demand.

$$RSI_g = \frac{Total\ Capacity - Company\ g's\ Relevant\ Capacity}{Total\ Demand},$$

where, total capacity includes both regional supply and also supply imports. Relevant capacity for a company $g$ shows the company's capacity minus all the contract obligations of that company. Value of $RSI_g$ shows how company $g$ has influence on the market to meet the demand. An $RSI_g$ value less than a 100 percent shows that the company is a pivotal player in the market. Sheffrin (2002) believes that RSI must be more that 110 percent for 95 percent of the hours in a year.

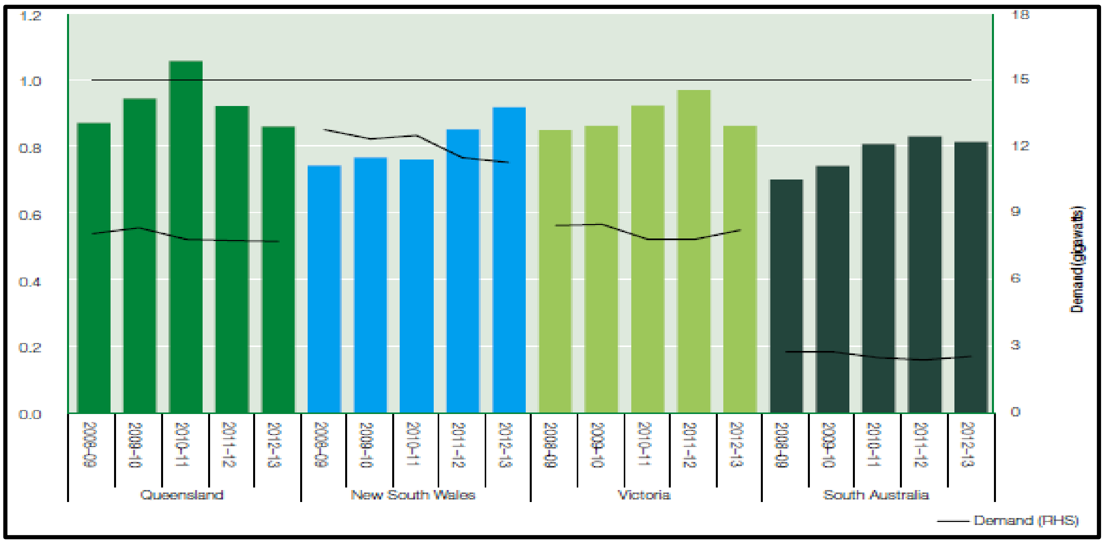


Figure 2.2. RSI-1 index at times of peak demand, AER (2013a).

AER provides evidence of potential market power by largest generator in the state of SA during 2008 using RSI-1. This index measures the ratio of demand that can be met by all but the largest generator in a region. If RSI-1 is less than 100 percent then the largest generator becomes pivotal and indicates a less competitive market.

Figure 2.2 shows the RSI-1 index at times of peak demand since 2008 in NEM. As shown in Figure 2.2 SA had the highest potential to exercise the market power by the largest generator. In South Australia, AGL is the largest generator and offers around 34 percent of the total capacity in the state[12].

According to AER (2013a), since 2012 some of thermal generators as Alinta has decided to withdraw capacity from market. As it is reflected in Figure 2.2, this

[12] International Power with 21 percent of the total capacity, Alinta with 12 percent and Origin Energy with 12 percent are other large firms is South Australia.

increased the pivotality of AGL, as the largest generators in South Australia, to meet demand during peak trading intervals.

#### 2.1.1.5 Residual demand analysis

To find the residual demand curve corresponding to a company $g$ , one should subtract all of supply offers by the other participants in the market from the demand curve. The elasticity[13] of this curve is an indicator of company $g$'s incentive to exercise the market power. In a competitive market, a company has no power to raise the price by capacity withholding and has a very high elastic residual demand curve. High elasticity shows that, this company has the power to not to be disadvantaged by charging high prices (Baker & Bresnahan, 1992). As an example, Wolak (2003) shows the incentive for five large electricity supplier to exercise the market power in California 1998-2000.

### 2.1.2 Behavioural indices

The other indicators to measure the competitiveness in the market are behavioural indicators. These indicators examine the relationship between generators bidding behaviour and the spot price outcomes. The following are some of the main behavioural indices defined by economists.

#### 2.1.2.1 Bid-Cost margins

Comparing company's bid prices and marginal cost would also be an indication of exercising market power. In a competitive market, it is expected that generators bid at a level close to their marginal cost. If a company frequently bids at much higher prices than the marginal cost, then this may be an indication of exercising market power by that company. The following indices, Lerner Index and Price-Cost Margin Index, measure whether the market power exists. In this sense:

$LI = (P - MC)/P,$

$PCMI = (P - MC)/MC,$

where $P$ and $MC$ show the price and marginal cost respectively. In a perfectly competitive market, the value of these indices would be zero. However, estimating the marginal cost of a company is not always an easy task which is one of the main difficulties in determining the accurate value of these indices. There is some evidence

[13] Elasticity is a measure used in economics to show the sensitivity of the change in quantity demanded of a good or service to a change in its price, ceteris paribus ( More information available at Samuelson, 2001).

of companies exercising market power in California 2000-2001, as well as in England and Wales in 1990-1991 (Twomey, P. et al, 2005).

### *2.1.2.2 Withholding analysis*

Withholding analysis is the basic measure to detect any withholding capacity in the electricity market. Two types of withholding are examined in this measure: economic withholding and physical withholding. Economic withholding refers to the situation where output is bid by generators at over the competitive bid price. In physical withholding the output is not bid to the market at all. Both of these capacity withholdings would reduce the supply in the market (Twomey, P. et al, 2005). Table 2.2 shows the average capacity withheld by large generators in NEM during 2008-2010 and 2011-2013 periods when the spot price rose above $300 per MWh[14].

Table 2.2. Average capacity not dispatched when spot price exceeds $\$300/MWh$, AER (2013a).

| Generator | Capacity Not Dispatched (MWh) | |
|---|---|---|
| | July 2008-December 2010 | January 2011- June 2013 |
| CS Energy (QLD) | 543 | 826 |
| Macquarie Generation (NSW) | 243 | 41 |
| International Power (VIC) | 260 | 177 |
| AGL Energy (SA) | 328 | 250 |

Figure 2.3 also shows the relationship between capacity withholding and price rise during 2008-2013 in South Australia. As shown in the Figure 2.3 AGL which is the largest generator in SA and offers around 34% of the total capacity, tends to withhold part of its capacity when the price is relatively low.

For example, as shown by the dark green line, the spot price was in the range of $0-$25 in years 2008-09. AGL offered only some 30% of its total capacity to the market. The fact that for three, out of five, of these curves the slope is negative for higher values of spot price should be noted, as it raises questions as to why capacity was withheld at times of increasing spot price.

[14] This price is sufficient to cover the marginal cost of majority of plants in NEM (AER 2013a).

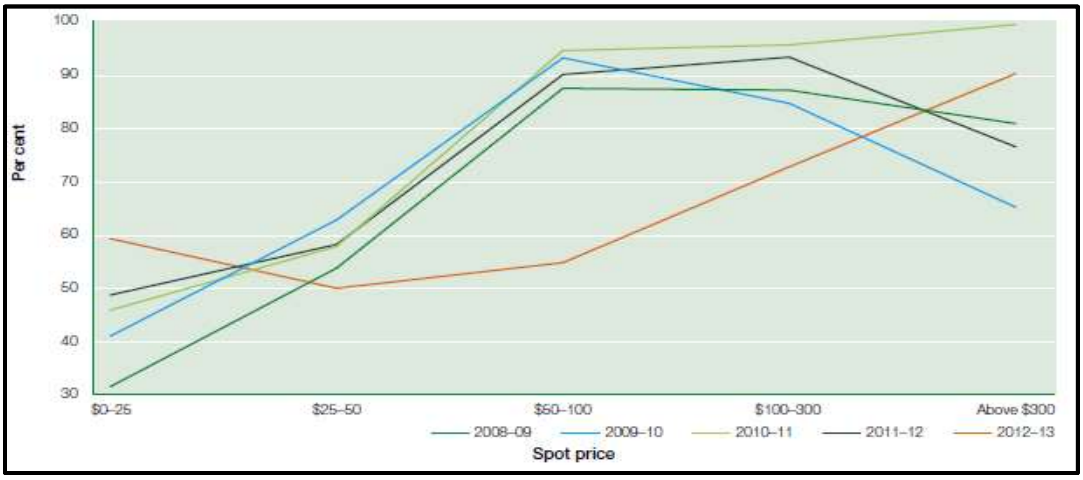


Figure 2.3. Average annual capacity utilisation, AGL Energy, South Australia, AER (2013a).

### 2.1.3 Other indices

#### *2.1.3.1 Simulation models*

In this form of market power analysis, some aspects of market are simulated with sophisticated modelling techniques to make a benchmark for the comparison of the market outcomes if the generators behaved differently. The two popular models in this area are as follows.

(i) Competitive benchmark analysis

In this form of analysis a hypothetical competitive market is simulated. This provides a benchmark to compare the actual price with a hypothetical price if all generators behaved differently. For this purpose, the generation technologies data are collected to estimate the supply curve which ultimately will result in estimating the marginal cost of production. However achieving this goal is not an easy task and determining a proper comparative benchmark has been always a controversial task (Twomey, P. et al, 2005).

(ii) Oligopoly simulation models

Oligopoly simulation models provide a game theoretic framework to estimate the market price within a specified market design and structure. These models are more powerful than any other indices as they consider many factors to examine the exercise of market power. These factors include, demand elasticity, supply curve, concentration, forward contracting and transmission constraints. One of the most powerful models in this area is Cournot competition model which identifies the market equilibrium based on the generators level of output (Twomey, P. et al, 2005).

#### *2.1.3.2 Net revenue benchmark analysis*

Net revenue benchmark is another measure to analyse the existence of market power. Although high net revenue is not necessarily an indication of market power, many researchers consider abnormal profits as a useful measure for monitoring market power in electricity markets (Twomey, P. et al, 2005).

## 2.2 PRICE VOLATILITY IN THE AUSTRALIAN ELECTRICITY MARKET

The current Australian Electricity Market was designed to operate in a competitive national market using private industry. However, evidence shows that the volatility in the electricity spot price has been one of the electricity market features since the deregulation (Quiggin 2001). The main reasons which can lead to price volatility recorded in the literature are:

(i) When a generation station falls over and its capacity will be removed from the pool.

(ii) Extreme temperature conditions which directly affects the demand. For instance, in the cold winter days or hot summer days the consumption of air-conditioning rises and increases the load significantly. In this situation generally generators bid at higher price levels as they claim they need to generate more to meet the demand.

(iii) Any fault in the network may increase the prices as sections of the grid may be unable to work properly (IEA, 2001).

Basically, considerable fluctuations in the electricity price in the Australian electricity market occurred during the years 2008-2010 when the electricity price reached to the maximum of $10,000/MWh for a number of trading intervals. During 2009-10, there were 95 trading intervals which had a corresponding spot price greater than $5000/MWh in the market. Thereafter, as a result of some changes in the market conditions, the number of extreme electricity spot price declined. The reduction in energy use by consumers was one of the main reasons as it caused surplus in the installed capacity in the most of the regions.

Although the number of price spikes has decreased since 2010, there has been more trading intervals with the corresponding spot price greater than $200/MWh. In 2012-13, there were 704 such trading intervals compared to only 99 in the year 2011-12. This has happened mainly in the states of Queensland and South Australia. Moreover, during summer 2013, Queensland experienced 116 instances of prices above $300/MWh and 16 spot prices above $1000/MWh. One of the main reasons was the

12 percent lower capacity offered by the generators during summer time comparing to the same quarter in 2012 (AER, 2013a).

Disorderly bidding by generators was thought to be one of the underlying reasons including the price spikes. Such disorderly bidding is not limited to the central Queensland. Other regions in NEM have experienced these forms of behaviour by generators. “Disorderly Bidding” has been defined by AER (2013b) as a bidding strategy which is in contrary to the underlying cost structure and/or technical limitations of generation plant.

*“ In particular, generators tried to maintain output levels and receive high spot prices by rebidding capacity from high to low (or negative) prices.” (AER, 2013b, p.40).*

Table 2.3 shows the average of spot prices since the deregulation in the 4 regions of NEM. As highlighted with the arrows in Table 2.3, the average of spot price seem to experience significant increase in specific years. For instance, the average of spot price increase from around $30/MWh to more than $50/Mwh from the year 2005-06 to 2006-07 in all of the 4 regions. This significant increase in the average of spot price also occurred from 2011-12 and lasted to 2013-14 in these regions of NEM.

Table 2.3. Average of spot prices per year, (AEMO accessed 23.09.2014).

| Year | NSW | QLD | SA | VIC |
|---|---|---|---|---|
| **1999-2000** | 28.27 | 44.11 | 59.27 | 26.35 |
| **2000-2001** | 37.69 | 41.33 | 56.39 | 44.57 |
| **2001-2002** | 34.76 | 35.34 | 31.61 | 30.97 |
| **2002-2003** | 32.91 | 37.79 | 30.11 | 27.56 |
| **2003-2004** | 32.37 | 28.18 | 34.86 | 25.38 |
| **2004-2005** | 39.33 | 28.96 | 36.07 | 27.62 |
| **2005-2006** | 37.24 | 28.12 | 37.76 | 32.47 |
| **2006-2007** | 58.72 | 52.14 | 51.61 | 54.8 |
| **2007-2008** | 41.66 | 52.34 | 73.5 | 46.79 |
| **2008-2009** | 38.85 | 34 | 50.98 | 41.82 |
| **2009-2010** | 44.19 | 33.3 | 55.31 | 36.28 |
| **2010-2011** | 36.74 | 30.97 | 32.58 | 27.09 |
| **2011-2012** | 29.67 | 29.07 | 30.28 | 27.28 |
| **2012-2013** | 55.1 | 67.02 | 69.75 | 57.44 |
| **2013-2014** | 52.26 | 58.42 | 61.71 | 51.49 |
| **2014-2015** | 39.88 | 31.63 | 46.42 | 37.39 |

The rise in the average of spot price is even more substantial in South Australia. As shown in Table 2.3, the increase in the average of spot price in South Australia started from 2005-06 where it increased from about $37/MWh to about $51/MWh in 2006-07. This increasing trend continued to the year 2009-10. Between these years the average of spot price per year even reached to a considerable high price of $73/MWh in 2007-08.

Furthermore, similar increasing trend occurred during the years 2011-12 to 2013-14 in South Australia. As mentioned by AER (2013b, P38), the significant increase in the average of spot prices was often unrelated to the demand. In South Australia, even minor increases in the demand led to spikes in the electricity price as a result of significant decrease in the capacity offered by generators. Section 2.2.1 provides more detail about the history of price volatility in South Australia.

### 2.2.1 Spot price volatility in South Australia

Since the deregulation in 1990's, exercising market power has been reported in some periods of time in various regions of NEM. As mentioned above, one of the states which had experienced high electricity price volatility particularly in the higher demand periods is South Australia. For this reason, in this thesis, our focus is mainly on the variation in the spot prices and its underlying causes, in South Australia.

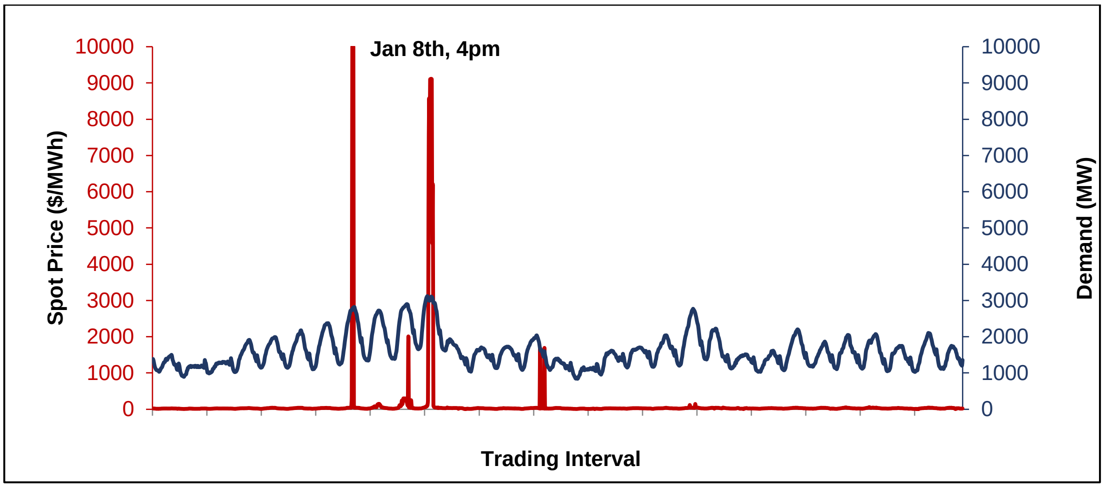


Figure 2.4. Electricity demand and spot price at January 2010.

During the years 2008-2010, South Australia has also experienced price spikes in high demand periods similar to the other regions of NEM. The supply-demand condition is often claimed to be the tightest in South Australia since the blackout in summer 2009. Figure 2.4 shows the spot price and demand at half hour intervals for all 1488 trading intervals within the month of January 2010 in the state of South Australia.

As Figure 2.4 illustrates, spot prices which are shown by the red curve exhibit higher fluctuations than demand which is depicted by the blue curve. As seen in the figure, most of the time spot price varies over a range of $100 per MWh but it also approaches the very high price of $10,000 in some trading intervals. For instance, the spot price for the interval of January 8th at 4:00pm reached to almost $10,000[15] for the state of SA. This happened even though the demand did not have an exceptionally high increase during that period.

Furthermore, South Australia experienced high price volatility especially in April-June 2013. The lack of generation capacity was the main reason resulting in these fluctuations. The reduction in the generation capacity offered was mainly done by three major generators, “Alinta”, “International Power” and “AGL Energy”. Alinta offlined both Northern power station units and International Power reduced the capacity offered by Pelican Point power station to the half of the maximum available. AGL energy offered around 225MW less capacity at Torrens Island and also offered higher prices for the remaining capacity (AER, 2013a).

In general, the generators in South Australia offered 700MW lower capacity during April-June 2013 compared to the same period in 2012. This led to 212 spot prices above $200/MWh, which included 19 spot prices above $1500/MWh. It should be mentioned that, during the corresponding period in 2012, there were no trading intervals with spot prices above $200/MWh. The average of spot price in April-June 2013 was about $106/MWh which was almost twice that of other regions in NEM. While high spot price in South Australia during April-June 2013 led to import electricity from Victoria, the lack of available capacity was the key factor which led to the tight condition to meet the demand (AER, 2013a).

Table 2.4 provides more information about the history of price volatility in South Australia. As Table 2.4 illustrates besides the significant increase in the electricity prices, disorderly bidding by generators led to negative prices in some trading intervals[16]. Table 2.4 also illustrates that during the years 2008-2010 there were 59, 77 and 44 trading intervals, respectively, which had the corresponding spot price reaching to above $1000/MWh[17]. Also the average of spot price reached its peak during these years. It should be mentioned that, during 2007 to 2011, the increase in

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[15] It should be mentioned that, $10,000 was the market price cap before 30 June 2010 and that it was increased to $12,500 per MWh thereafter.

[16] More information is available in AER (2013b), State of the energy market 2012, pp.16-17 and 46-47.

[17] In Chapter 3 the categories of spot price will be introduced. Based on the categories of spot prices we call these trading intervals as “High” spot price periods.

the average annual spot price in South Australia was more than 50% higher compared to the other regions of NEM (AEMO, 2010).

Table 2.4. History of price spikes in South Australia.

| Year | | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 |
|---|---|---|---|---|---|---|---|---|---|
| Number of trading interval with the corresponding spot price greater than $1000/MWh | | 33 | 21 | 59 | 77 | 44 | 22 | 13 | 75 |
| Price | Min | -160.37 | -888.78 | -1000.00 | -663.17 | -996.70 | -996.70 | -995.70 | -289.43 |
| | Max | 7758.08 | 7813.10 | 9999.72 | 9999.92 | 9999.92 | 12199.53 | 4140.15 | 10627.00 |
| | Mean | 38.68 | 57.50 | 66.38 | 60.47 | 40.28 | 37.41 | 44.21 | 71.68 |
| | Variance | 17046.96 | 15033.01 | 272637.96 | 253996.36 | 114977.87 | 76116.29 | 5393.01 | 27712.24 |
| | $C_v$ | 3.38 | 2.13 | 7.87 | 8.33 | 8.42 | 7.38 | 1.66 | 2.32 |
| Demand | Min | 767.54 | 784.15 | 847.36 | 834.21 | 814.70 | 853.99 | 868.62 | 728.59 |
| | Max | 2873.03 | 2854.13 | 3079.82 | 3331.12 | 3120.89 | 3385.42 | 2939.39 | 2991.27 |
| | Mean | 1494.98 | 1524.12 | 1527.40 | 1538.42 | 1547.25 | 1494.64 | 1477.40 | 1426.57 |
| | Variance | 85509.34 | 102893.12 | 101064.42 | 125910.03 | 106537.83 | 86109.79 | 83056.06 | 91027.32 |
| | $C_v$ | 0.20 | 0.21 | 0.21 | 0.23 | 0.21 | 0.20 | 0.20 | 0.21 |

Additionally, the variance of spot price demonstrates the high fluctuation in the electricity price that the market experienced in these years. To measure the dispersion of demand-price distribution in these years "Coefficient of Variation",$C_v$ of the spot price, is reported in the seventh row of Table 2.4.

$$C_v = \frac{\sigma}{\mu}$$

Comparing these measures in the spot price rows and the corresponding ones in the demand rows in Table 2.4 indicates that the variation in the spot price was significantly higher than the variation in the demand, specifically, during the years 2008-2010. We provide more information to support the latter in Chapter 3.

This highlights the fact that the increase in electricity demand did not seem to be the main underlying reason for the significant rise in the spot price during these years. Instead, it seems that the price spikes in the electricity price during this period are more related to the exercise of market power by generators than the shortage in the generation capacity.

Energy Users Association of Australia has published a report in November 2012 which directly addressed some concerns about possible exercise of market power by generators during the years 2008-2011.

The high spot prices mainly happened during January-February when the temperatures peaked. During that period, evidence of generators exercising market power has been observed in the high demand periods where generators tried to influence the spot price output by either strategic form of bidding behaviour or withholding the generation capacity in high demand periods in recent years (Mountain, 2012).

In a competitive market, if the prices are higher than the production costs, generators should have enough incentive to increase their capacity to benefit the market situation. However, there are indications that in some trading intervals in high demand periods, generators tried to either withhold their generation capacity available to the market or offer it in very high price bands. In 2008, a generation capacity of around 667 MW at Torrens Island Power Station was not available to the market in some trading intervals. Same behaviour was seen by other generators in 2009-11 which made the spot price reach the market price cap of $10,000/MWh at the time (CME, 2012).

It should be mentioned that, withholding capacity was not the only reason to shift the prices to the peak levels. It has been observed that, there has been sufficient generation capacity even during high demand periods. Further, in Chapter 3 we examine forms of strategic bidding by generators and the corresponding risk imposed on the end users by high spot prices.

#### 2.2.1.1 *Impact of exercise of market power on consumers*

Generally, the degree of impact of spot price spikes on consumers depends on the types of consumers in the market. For non-household consumers, these effects are depending on other hedge contracts in the financial market and for household consumers they depend on the standing contracts[18] with AGL which are determined by the Electricity Supply Commission of South Australia. Nonetheless, indirectly, increases in spot prices will, ultimately, be passed on to consumers.

The price of hedge contracts in the financial market is also showing the same trend as spot price over the period of 2007-11 in South Australia. Overall, higher spot prices have resulted in higher future contracts prices and in this way generators have

[18] The standing contract is the retail electricity contract that AGL SA must offer to all South Australian small customers which is set by Electricity Supply Commission of South Australia. (ESCOSA, http://www.escosa.sa.gov.au/projects/177/1-july-2012-electricity-standing-contract-price-adjustment.aspx Accessed 23.08.2014).

benefited over the period of 2008-11 even when the spot prices reached the market price cap of \$10,000/MWh (AER, 2013a).

For household consumers in South Australia, the Essential Services Commission of South Australia calculates the market price cap that AGL can charge residential or small consumers. However, AEMC report has shown that this price is higher in South Australia comparing to other regions of NEM (AEMC, 2011).

Overall, the significant increase in the number of price spikes in South Australia during the year 2008-11 did not happen in other regions of NEM. This raises the questions:

(i) Does the very high Market Price Cap in NEM, recently increased to \$13,100/MWh, provides an incentive for generators to exercise market power?

(ii) Is the flexibility of generators to shift the volume of generation offered to different price bands as quickly as in five minute intervals, providing them an opportunity to exercise the market power?

(iii) Does the market needs any change in the system design in Market Price Cap or mandatory minimum volume to be offered at each price bands to address the market power concerns?

## 2.3 STRUCTURAL VOLATILITY

As discussed above, volatility in the spot price for electricity is very high. Furthermore, there are many factors that may be contributing to this high volatility. These range from stochasticity of demands and weather conditions, through supply of renewable energy (e.g., wind, solar), to financial management strategies such as hedging.

However, in this thesis we examine in some detail the impact of generators' bidding strategies on the volatility of spot prices, in the context of the mechanism by which these prices are derived (see Section 1.6). We refer to this form of volatility as "structural volatility" because it stems from the design of NEM and its regulations.

We feel that structural volatility deserves close scrutiny because the latter design is, in principle, controllable and hence may be altered if changes were deemed to be desirable. By contrast, volatility due to natural phenomena such as heat waves, or cold spells cannot be significantly altered. Of course, the latter can still be understood and its impact mitigated typically with the help of accurate forecasts, but this is not an objective of the present study.

## 2.4 ALLEVIATING MARKET POWER

Some economists believe that as a result of special characteristics of electricity markets, these markets are susceptible to the exercise of market power (Baker, J., 1992, Twomey, P. et al, 2005 and Blumsack., 2003). First, as electricity is not easily storable, the production is needed to match the demand instantaneously and this makes the electricity supply to be relatively inelastic. Second, most of the electricity consumers are not exposed to real time prices. Therefore, only the demand from very large consumers is elastic to the real time prices. The inelasticity of electricity supply and demand provides an opportunity for generators to exercise their market power specifically in the high demand periods.

To alleviate the market power by generators, economists suggest a number of solutions. These solutions include, “Structural solutions”, “Regulatory solutions” and “Market rules solutions”. Structural solutions include encouraging the dominant generators to divest their assets. At the same time, new competitors need to be encouraged to enter the market by reducing or removing barriers to entry.

Regulatory solutions include imposing constraints to control the price such as market price cap. Another regulatory solution would be setting the rule by which the dominant generators are required to provide a certain amount of capacity to the network in the long term.

Market rules solutions are the regulations which might be considered harsher such as setting caps on unit specific bidding or asking for a specific information from generators which would be very difficult to acquire (Twomey, P. et al, 2005).

# CHAPTER 3. STATISTICAL APPROACH

As mentioned in Chapter 1, the wholesale electricity market is managed through a spot market which consists of a pool where electricity supply and demand are matched instantaneously. In this market, generators' offers for electricity production are designed to be submitted to the pool in a stack of 10 bands at every five minute interval. This bid stack includes the volume and price of electricity they are willing to generate and it needs to satisfy certain regulatory restrictions for floor and cap price at each band. As mentioned by AEMO (2010a), the price offered at each band should not be less than $-1000 and not more than $13,100 per MWh, respectively[19].

Combination of all these offers by generators determine, albeit indirectly, the marginal price of generation and consequently the electricity spot price at each half an hour interval. Recall that, AEMO collects all the bids offered by generators, then solves an LP problem (Chapter 1, Section 1.6), which determines the generators who are required to produce at each five minute interval, considering two main objectives of meeting prevailing demand and minimising cost of production. The result of this dispatch process is called a "Dispatch Price". Thereafter, the spot price is determined as the average of six dispatch prices in every half an hour trading interval (see equation (1.1.)). This is the price that generators receive for the amount of electricity they contributed and also the price that, ultimately, consumers need to cover.

[19] Recall that this upper bound was increased from $10,000/MWh in 2010.

In subsequent sections we investigate the effects of the different bidding behaviours on both generators and end users as the two main constituencies in this market. We aim to highlight the fact that the bid stacks offered by generators may increase the income to generators and eventually impose the risk of higher cost to the end users in the Australian electricity market[20].

In Section 3.1 we differentiate the trading intervals using a spot price frame with two different colours: high and low. Then we discuss the correlation of demands and spot prices during selected periods of time in South Australia.

Section 3.2 is dedicated to introducing forms of strategic bidding behaviour by generators. Further in Sections 3.3 - 3.4 we investigate how generators form specific groups/clusters in which they follow the same pattern in changing the bid stack offered to the pool, especially in the higher spot price trading intervals. In Section 3.5 we examine the strength of the competition among generators and investigate whether the electricity auction is running strong or weak in different trading intervals. Results show that in the high spot price trading intervals the competition among generators was weak and hence such auction underperformed.

In Section 3.6 we show that the competition among generators can be considered as a lottery model. Then the choice of offering price and volume of electricity production would be a tool for designing this lottery at each trading interval.

In Section 3.7 we examine the bid to cover ratio in the Australian electricity market. We compute this ratio by the value of money claimed from the electricity pool by generators divided by the value paid to the generators by AEMO.

Section 3.8 discusses the risk of loss to end users as an outcome of the lottery designed by generators using risk measures such as Value at Risk and Conditional Value at risk of loss.

## 3.1 CORRELATION OF ELECTRICITY DEMAND AND PRICE

This section discusses the correlation of demands and spot prices during selected periods of time in South Australia. For simplicity, a spot price frame has been designed using two different colours. Colours “Green” and “Red” are dedicated to the trading intervals of “low” and “high” spot price periods and they are recognized using

[20] Results of this chapter are published in a paper entitled ‘Australian Electricity Market and Price Volatility’ that appeared in the Annals of Operations Research (see Boland, J., et al (2011)).

the two chosen ranges of $-1,000/MWh to $1,000/MWh and $1000 to $13,100. From now on, we call these categories as Low, "L", and High, "H", spot price periods respectively. Table 3.1 shows these categories of trading intervals by range of spot price and the corresponding colour[21].

Table 3.1. Trading interval categories based on the level of sot price.

| | |
|---|---|
| **Low Spot Price Trading Interval** | **$-1000/MWh < Spot Price < $1000/MWh** |
| **High Spot Price Trading Interval** | **$1000/MWh < Spot Price < $12500/MWh** |

Based on the this trading interval categories, each point in Figure 3.1 shows the correlation of demand and price in the two mentioned categories of spot price periods. It should be mentioned that each point in this figure, corresponds to the correlation of electricity price and demand in a day, using 48 trading interval data points available in that certain day.

The colours are assigned based on the category of highest spot price occurring in that specific day. For instance, as there exist at least one trading interval in the day of Jan 8th when the spot price exceeded $1000 per MWh we show the whole day of Jan 8th by a red colour. By assigning a red or green colour we do not necessarily mean that the spot prices corresponding to all trading intervals of the day are in the categories of H and L (Table 3.1). These colours show that within the days with say red colour, there exists at least one trading interval in which spot price was in the interval (1000, 13100).

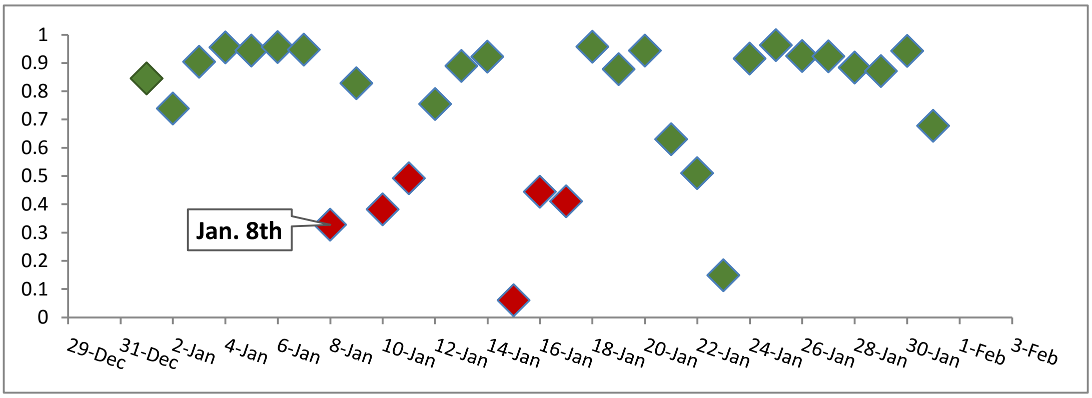


Figure 3.1. Correlation of electricity demand and spot price at each day.

[21] In this research project this category of trading interval is used to recognize the range of spot price in the different trading intervals.

From Figure 3.1 we observe that demand and electricity spot price seem to be highly correlated in the days with no spot price spikes. However, correlation of electricity demand and price falls significantly on days where we happen to have spike(s) in the day (e.g. see the red diamonds in Figure 3.1).

This highlights the fact that this significant rise in spot prices may be due to other important underlying reasons than merely demand fluctuation. In other words, the demand does not seem to be the main underlying cause of the sharp increases in the electricity price in these periods of time. Apparently, there exist other factors that affect these price spikes in relatively high demand periods. However, what we plan to highlight most is the behaviour of generators in different periods of time which we believe may increase consumers' risk of loss.

## 3.2 STRATEGIC BIDDING STRUCTURE IN THE AUSTRALIAN ELECTRICITY MARKET

In this section we examine a form of characteristic bidding structure by generators. Our study of generators' bid stacks within the two categories of trading intervals of L and H, indicates that there exist characteristic behaviours among generators in some specific trading intervals. Below we illustrate some of these characteristic bidding behaviours of generators in the two category of trading intervals mentioned in Table 3.1.

For simplicity, we chose one generator as a representative practitioner of this sort of behaviour among many generators in South Australia. Figures 3.2 - 3.4 show bidding strategy of a gas turbine generator in South Australia in low and high spot price trading intervals during the summer of 2010.

Figure 3.2 displays a bidding strategy of this generator in a low spot price period. As shown, a preferred choice of production for this generator is to offer the price and volume only in the very high price, $9760 per MW, band. This strategy by the generator may be based on the high cost of production in this trading interval or it may also show that this generator has low interest to participate in the competition against other generators in such a low demand period. As expected, competition among all generators during this trading interval resulted in a low spot price of about $100 per MW.

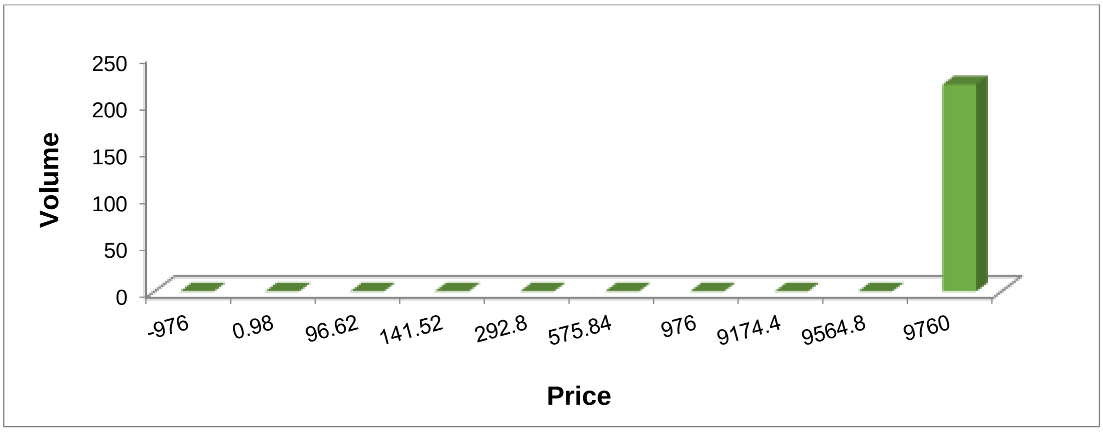


Figure 3.2. Volume and electricity price offered by a generator in a low spot price period.

Figure 3.3 shows the bid offered by this generator in a trading interval in which the overall outcome of competition also resulted in low spot price. At this point, this generator seems to be somewhat more interested in competing with others and tries to offer a small part of total capacity in two lower price bands. This could increase the chance of winning a small part of the volume of production in this trading interval which results in a moderately higher income as a result of a higher spot price of about $340 per MWh.

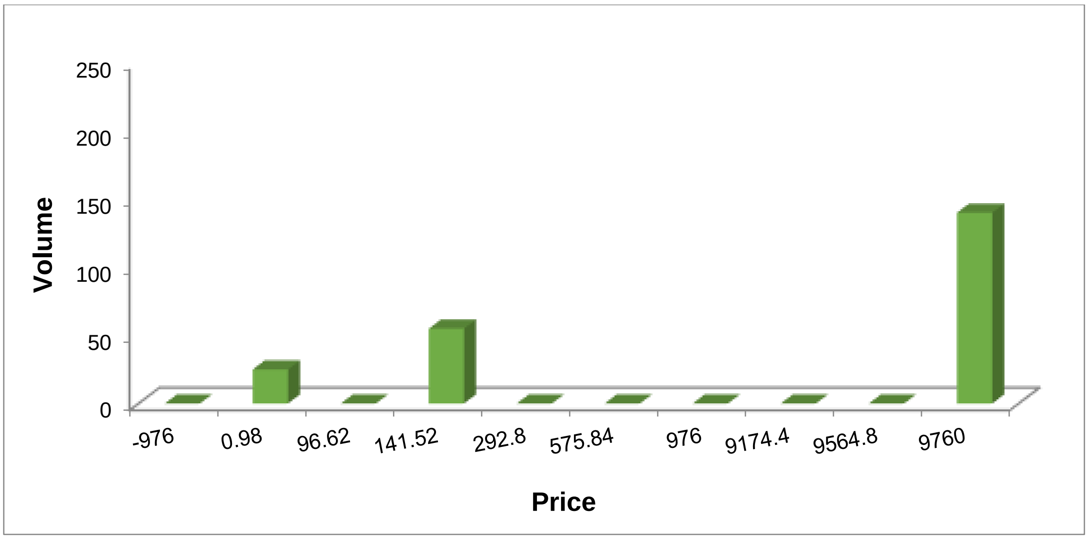


Figure 3.3. Volume and electricity price offered by a generator in a low spot price period.

As we approach the very high spot price periods, illustrated in Figure 3.4, the interest of generators in participating in the electricity production seems to increase. This can be observed by considering three aspects of behaviour by the generator. Figure 3.4 illustrates that, this generator assigns significant ratio of total capacity of its production, to a very low price, $-976 per MW, band and keeps a small fraction of total capacity at a very high price, $9760, band.

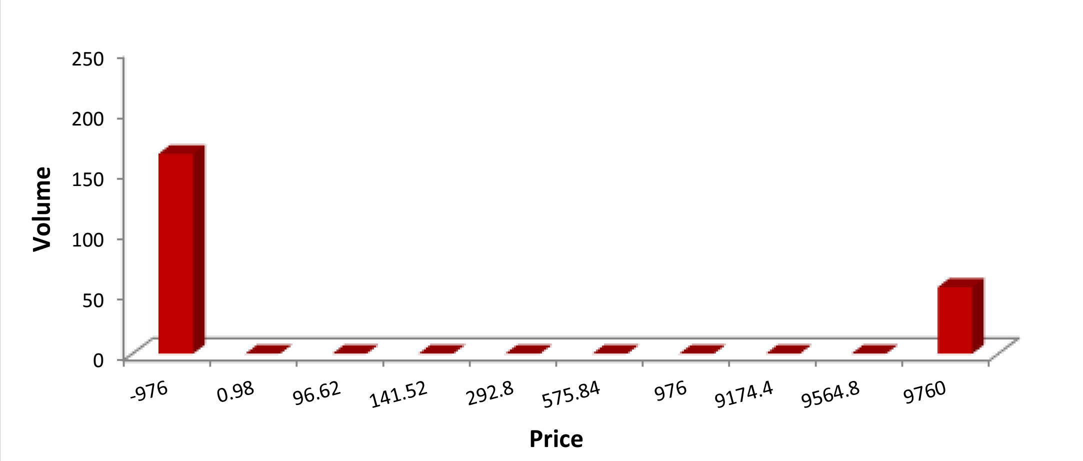


Figure 3.4. Volume and electricity price offered by a generator in a high spot price period.

This bimodal distribution in the volume of production in 10 bands may reflect the fact that, during some specific trading intervals (e.g. when demand is likely to be high because of hot conditions), this generator may be anticipating almost a guaranteed high spot price that will result, almost certainly, if sufficient number of other generators submit similarly structured bids.

This raises the following interesting question. Why does this generator feel confident enough to offer the kind of bid that is shown in Figure 3.4 despite the fact that it could be easily undercut by other generators offering enough electricity at prices lower than $9,760 per MWh? Is it because, for whatever reason, the generator feels that sufficiently many competitors will submit similar bimodal bids structured so that the sum total of the low price bars will not be sufficient to cover the demand? If so, all these generators could be rather safely betting on the spot price being set, at least, at their high price bars.

However, this form of shifting volume to other price bands by this generator is just one form of the bidding behaviour by generators in the high spot price periods. In the following sections, we investigate whether groups of generators behave in similar patterns of strategic bidding as we approach high spot price periods.

## 3.3 DISTANCE MEASURES

In this section we aim to investigate the fluctuations in the volume offered in various price bands. Mathematically, a typical bidding strategy, $\boldsymbol{v}^g$, of the generator g is a set of pairs $\boldsymbol{v}^g = \{(v_i^g, c_i^g) | i = 1,2, \dots, 10\}$, where $v_i^g$ is the MW volume of production at price $\$c_i^g$ in the $i^{th}$ band, for $i = 1,2, \dots, 10$.

In accordance with regulation $c_i^g \in [-1000{,}13100]$ and $v_i^g \in [0, \bar{v}^g]$ for $i = 1,2, \dots, 10$, where $\bar{v}^g$ is the maximum capacity the generator $g$ can produce. In practice, it has been observed that, for a generator $g$, $c_i^g$'s are the same for all trading intervals. Hence we simplify the notation for a bidding strategy to $\boldsymbol{v}^g = \{v_i^g | i = 1,2, \dots, 10\}$, as $c_i^g$'s are assumed to be known.

Based on the bid stack offered by generator $g$ at each band, the proportion of volume that is offered at the price band $i$ by generator $g$ is

$$q_i{}^g = \frac{v_i^g}{\sum_{i=1}^{10} v_i^g}; \quad for \;\; i = 1,2, \dots, 10. \tag{3.1}$$

In other words, $q_i{}^g$ shows the proportion of MW of electricity at the band price $i$ of their bid stack.

Table 3.2. Bid stack offered by generator $G18$ on January 8th at 15:30.

| Band | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| $v_i^g$ | 40 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 15 |

Table 3.2 shows the bid stack offered by generator $G18$ on January 8th at 15:30. Then the distribution of proportions of the volume offered at each price band is as shown in Table 3.3.

Table 3.3. Distribution of proportion of volume offered by $G18$ on January 8th at 15:30 .

| Band | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| $q_i{}^g$ | 0.73 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.27 |

As Table 3.3 shows the proportion of MW of electricity that generator $G18$ offers at the price band 1 in this trading interval, is approximately 73%. In other words, for this trading interval, generator $G18$ is interested to offer 73% of the total capacity at the price band 1. Generator $G18$ is not interested to offer any portion of volume at the price bands 2 to 9 but he offers the remaining 27% of the total capacity at the band price 10.

It should be noted that, the behaviour of generators in offering bid stacks change through time and so does the distribution of portions of volume offered at each price band. Hence, we use distance measure techniques to compare observed behaviour of a generator with a hypothetical situation where the generator offers equal portions of volume at each price band uniformly. We call this hypothetical generator an 'indifferent' generator.

Table 3.4. Distribution of proportion of volume offered by an indifferent generator.

| Band | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| $\acute{q}_i{}^g$ | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |

Table 3.4 shows the distribution of proportions of a MW of electricity expected to be offered at each price band by an indifferent generator. In this situation the distribution of proportions of volume offered at each price band is uniform.

Considering Table 3.4, we examine how generators' interest in offering production at different price bands may change in different trading intervals. For this purpose $D(q^g, \acute{q}^g)$, measures the distance between the distributions of proportions, $q^g$ and $\acute{q}^g$, at each trading interval. Here $\acute{q}^g$ refers to the uniform distribution.

The distance, $D(q^g, \acute{q}^g)$, between the two distributions, at each trading interval is calculated by[22]

$$D(q^g, \acute{q}^g) = 2\sum_{i=1}^{10} \frac{(q_i{}^g - \acute{q}_i{}^g)^2}{q_i{}^g + \acute{q}_i{}^g}\,. \tag{3.2}$$

For the example shown in Table 3.3 above, the distance between the distribution of proportions shown in Table 3.3 and the uniform distribution, shown in Table 3.4 is

$D(q^g, \acute{q}^g) = 2.71.$

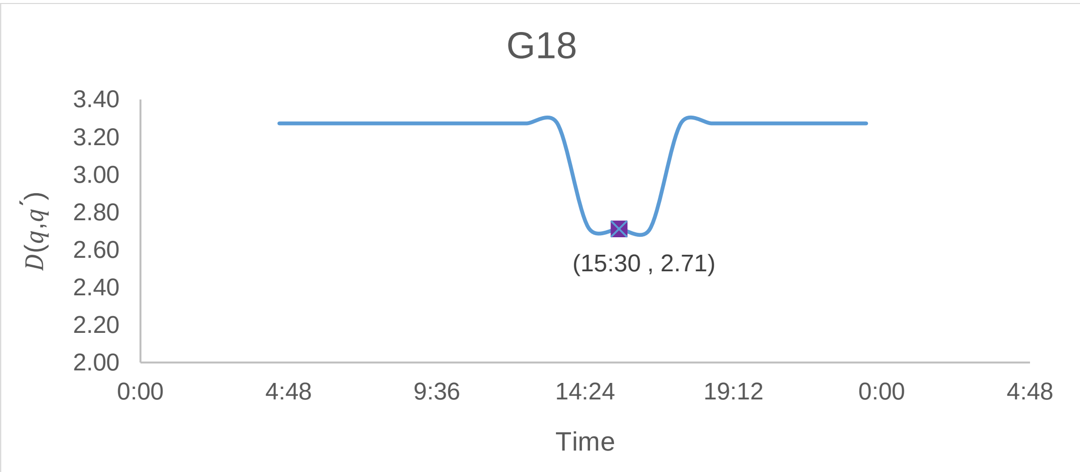


Figure 3.5. Distance values, $D(q, \acute{q})$, for generator $G18$ in January 8th 2010.

Similarly, Figure 3.5 below shows these distance values for the 40 trading intervals on January 8th 2010 in the case of generator $G18$. It can be seen that, this generator changes the bid stack offered to the pool during the peak hours of the day between

[22] Here we have chosen the widely used probabilistic symmetric $\chi^2$ distance.

2:00PM to 7:00PM. As a result of the change in the bidding behaviour by this generator, the distance between the distribution of proportions of volume offered at each price band by the generator and the indifferent generator has also changed during these hours.

As shown in Figure 3.5, this generator's offered bid stack seems to be closer to the bidding stack offered by the indifferent generator in the peak hours in the afternoon. This is because $G18$ went from an essentially unimodal to a bimodal bid distribution during the peak hours.

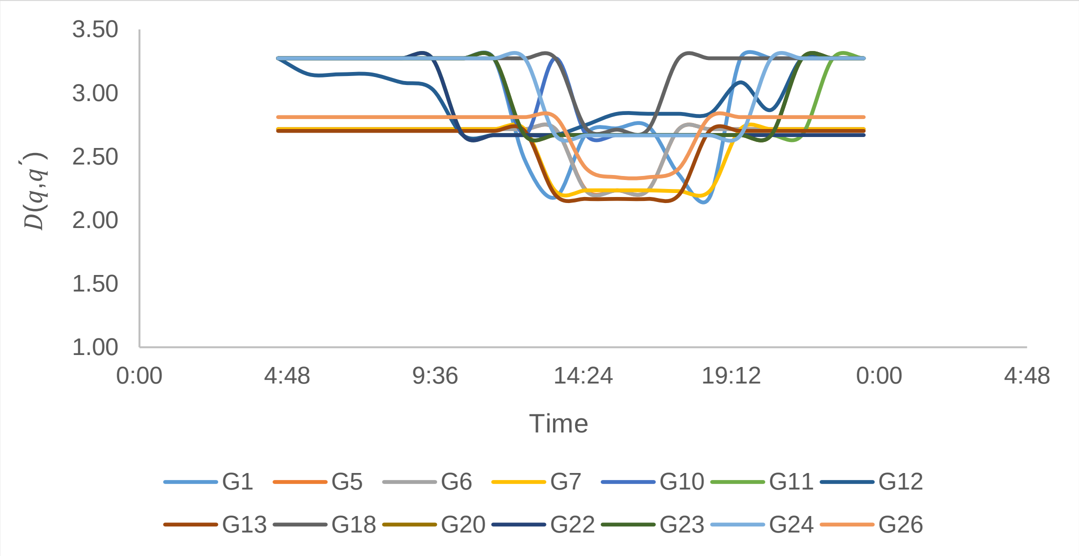


Figure 3.6. Distance values, $D(q,\acute{q})$, in January 8th 2010 for first class of generators.

Similarly, Figures 3.6 - 3.8 show the distance measure $D(q,\acute{q})$ is calculated for all the other generators who have participated in the electricity market pool in South Australia for the whole day of January 8th 2010. Based on the change in bidding behaviour, Figures 3.6 - 3.8 show these generators can be grouped into three classes. As shown in Figures 3.6 - 3.8, the generators in each class tend to change their bid stacks with similar pattern in terms of increasing or decreasing distance from the uniform distribution.

Figure 3.6 shows the first class who are, similar to generator $G18$ in Figure 3.5, namely, they tend to offer their bid stacks more uniformly distributed as we approach the high spot price period.

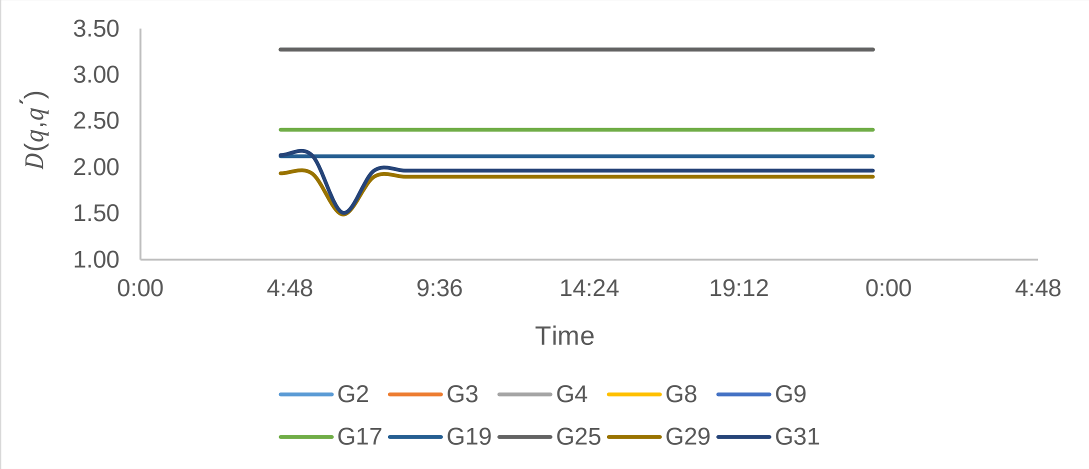


Figure 3.7. Distance values, $D(q, \acute{q})$, in January 8th 2010 for second class of generators.

Figure 3.7 shows the second class of generators whose behaviour exhibits no change in terms of our distance measure during peak hours. Finally, third class consists of generators who tend to increase the distance of their bid stack from the uniform distribution as we approach the high spot price period, see Figure 3.8.

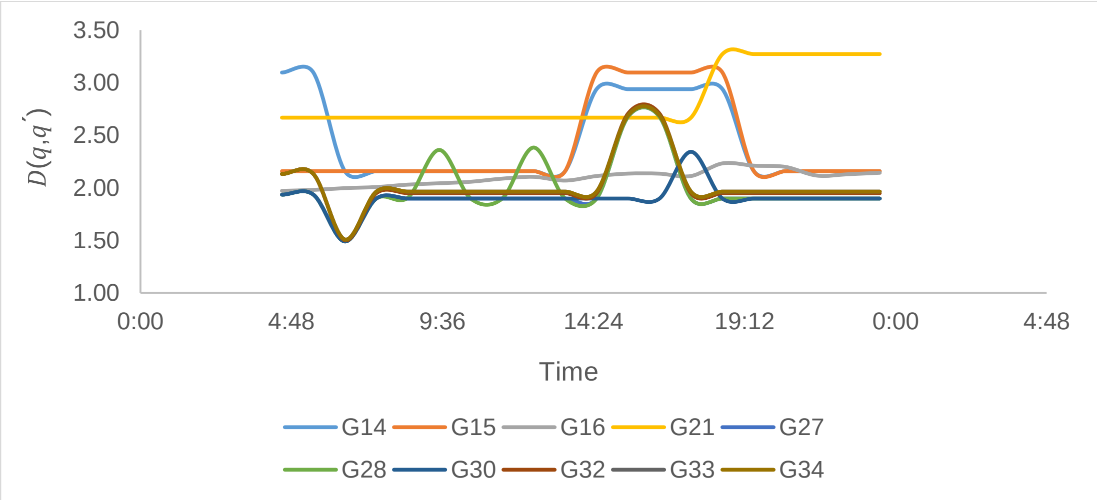


Figure 3.8. Distance values, $D(q, \acute{q})$, January 8th 2010 for the third class of generators.

As Figures 3.6 - 3.8 show, the change in bidding behaviour by generators does not seem to occur randomly. Rather, generators seem to gather in three specific classes in which they follow similar patterns in changing their bidding behaviour.

## 3.4 CLUSTERING ANALYSIS

Based on the changes in bidding strategy by generators in South Australia, in this section we aim to investigate the following questions.

(i) Do the shifts in volume offered by generators in higher spot price periods follow special pattern?

(ii) Are there groups/clusters of generators who tend to follow the same pattern in the high spot price trading intervals?

For this purpose, we investigate the "change" in generators bidding behaviour when we approach the higher spot price periods. We begin by setting a starting point, $t_o$ at a low spot price period such as 10:00AM in a day. Then for each trading interval, the bid stack of changes in the volume offered by a generator is calculated.

Recall that, a typical bidding strategy by generator $g$ simplified to $\boldsymbol{v}^g = \{v_i^g | i = 1,2,\dots,10\}$. We define the change in bid stack offered by generator $g$ in the trading interval $t$, by

$\Delta\, v^g(t) = \{\Delta v_i^g(t) | i = 1,2,\dots,10\}$, where $\Delta v_i^g(t) = v^g{}_i(t) - v^g{}_i(t_o)$.

As an example, suppose we aim to find the bid stack of changes in the volume offered for generator $g$ on 8/1/2010 at 4:30PM. Assume that we set the starting point, $t_o$ , at 10:00AM. Suppose that generator $g$ has offered the following bid stacks at 10:00AM and 4:30PM as shown in Table 3.5.

Table 3.5. Bid stack offered by generator$g$ on 8 /1/2010 at 10:00AM and 4:30PM.

| Band ($i$) | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| $v^g{}_i(t_o)$ | 80 | 0 | 0 | 40 | 0 | 0 | 0 | 0 | 0 | 10 |
| $v^g{}_i(t)$ | 50 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 80 |

Then, the change in bidding behaviour by generator $g$ between 10:00AM and 4:30PM is as shown in Table 3.6. As Table 3.6 shows this generator tends to shift the generation capacity offered in this day to the right where the higher price bands exist. In other words, generator $G$ was interested to decrease the capacity offered at the bands one and two, by 30MW and 40MW respectively, and increase the generation capacity offered at the last price band by 70MW.

Table 3.6. The change in the bid stack offered by generator$g$.

| Band ($i$) | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| $\Delta\, v^g{}_i(t)$ | -30 | 0 | 0 | -40 | 0 | 0 | 0 | 0 | 0 | 70 |

Similarly, Table 3.7 shows the corresponding changes in bid stacks offered by all other generators in South Australia in a high spot price period on 8/1/2010 4:30PM.

Table 3.7. Changes in the bid stacks offered by generators. 8/1/2010 4:30PM.

| Generator No. | Difference of volume offered at each band | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 171 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | -171 |
| 2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 3 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 4 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 5 | 50 | 0 | 0 | 0 | 40 | 0 | 0 | 0 | 0 | -42 |
| 6 | 50 | 0 | 0 | 0 | 40 | 0 | 0 | 0 | 0 | -42 |
| 7 | 50 | 0 | 0 | 0 | 40 | 0 | 0 | 0 | 0 | -42 |
| 8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 9 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 10 | 38 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 11 | 38 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 12 | 0 | 78 | 0 | 0 | 0 | 0 | 0 | -78 | 0 | 0 |
| 13 | 80 | 0 | 0 | 0 | 50 | 0 | 0 | 0 | 0 | -31 |
| 14 | 85 | -60 | -32 | 0 | 0 | 0 | 0 | 8 | 0 | -1 |
| 15 | 92 | -60 | -32 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 16 | 0 | 0 | -7 | 10 | 0 | 0 | 0 | 0 | 7 | 0 |
| 17 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 18 | 40 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | -40 |
| 19 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 20 | 20 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 21 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 22 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 23 | 20 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 24 | 120 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 25 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 26 | 60 | 0 | 0 | 60 | 0 | 0 | 0 | 0 | 0 | -59 |
| 27 | 0 | 0 | 0 | -50 | -20 | 0 | 0 | 0 | 0 | 70 |
| 28 | -30 | 0 | 0 | -40 | 0 | 0 | 0 | 0 | 0 | 70 |
| 29 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 30 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 31 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 32 | 0 | 0 | 0 | -95 | 0 | 0 | 0 | -45 | 0 | 140 |
| 33 | 10 | 0 | 0 | -100 | -40 | 0 | 0 | 0 | 0 | 130 |
| 34 | 10 | 0 | 0 | -100 | -40 | 0 | 0 | 0 | 0 | 130 |
| **Sum** | **904** | **-42** | **-71** | **-315** | **70** | **0** | **0** | **-115** | **7** | **112** |

As Table 3.7 illustrates, generators are grouped into three different forms of behaviour in bidding based on the shifts of volume offered in their bid stacks comparing the high and low spot price periods. These shifts are categorised as follows.

(i) Generators who behave as indifferent generators and do not shift any volume of electricity offered during peak and off peak periods, shown as rows with no colour (populated by zero entries).

(ii) Generators who shift a ratio of total volume of electricity offered to more expensive bands during peak periods and we call this behaviour as “shift to the right” shown as orange rows (featuring positive values in the rightmost price bands).

(iii) Generators who shift a ratio of total volume of electricity offered to the less expensive bands during peak periods and we call this behaviour as “shift to the left" shown as blue rows (featuring positive values in the leftmost price bands). Note that, for some generators such as $G_{10}$ and $G_{11}$ instead of shifting the volume offered to other price bands, they simply increase the volume offered at the first price band.

The last row of Table 3.7 shows the summation of the changes in the volume offered at each band by all 34 generators in South Australia. Overall, the distribution of total generation capacity offered at each band seem to have a form of bimodal distribution. In other words, a significant portion of the total generation capacity offered by all generators in South Australia is shifted to the first band with a very low price and a small portion is shifted to the last band with the very high price of $10,000/MWh in this specific trading interval. However, ultimately these shits in the volumes offered at different price bands resulted in a very high spot price of $9,999/MWh in that trading interval.

### 3.4.1 Ward's minimum variance method

The above classification of generators into three distinct group is based only on visual examination of data in Table 3.7. Hence a natural question is whether a similar classification could be obtained by standard, statistical, clustering procedure.

Next, we apply the Ward's minimum variance method (Ward, 1963) to analyse the groups of generators who shift the volume offered in different trading intervals. In this method, Ward applies the 'squared Euclidean distance'

$$d_{ij} = d(\{X_i\},\{X_j\}) = \|X_i - X_j\|^2 \tag{3.3}$$

as the objective function which needs to be minimised. To add the pairs of vectors to the clusters, at each step the pair of vectors that results in minimum increase in total within-cluster variance will be added to the cluster.

Using the same trading intervals as before using R software we analyse the groups of generators who tend to change their behaviour with in similar pattern. Figure 3.9 is the output of R software given the bid stack of changes in volumes offered at each price band by generators on January 8th 2010 at 16:30. As Figure 3.9 shows, there are three main groups of generators whose behaviours follow similar pattern.

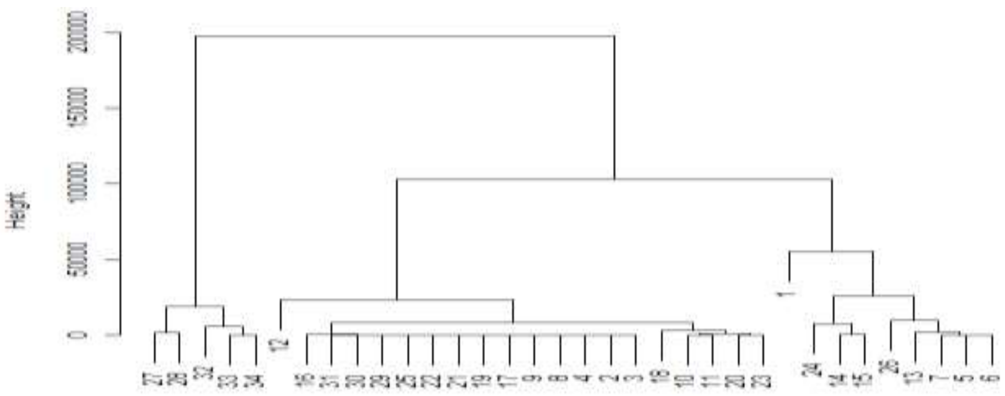


Figure 3.9. Ward's clusters for the change in bidding behaviour in a high spot price trading interval.

Table 3.8. The change in bidding behaviour on a high spot price trading interval.

| Generator No. | Difference of volume offered at each band | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 171 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | -171 |
| 2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 3 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 4 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 5 | 50 | 0 | 0 | 0 | 40 | 0 | 0 | 0 | 0 | -42 |
| 6 | 50 | 0 | 0 | 0 | 40 | 0 | 0 | 0 | 0 | -42 |
| 7 | 50 | 0 | 0 | 0 | 40 | 0 | 0 | 0 | 0 | -42 |
| 8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 9 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 10 | 38 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 11 | 38 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 12 | 0 | 78 | 0 | 0 | 0 | 0 | 0 | -78 | 0 | 0 |
| 13 | 80 | 0 | 0 | 0 | 50 | 0 | 0 | 0 | 0 | -31 |
| 14 | 85 | -60 | -32 | 0 | 0 | 0 | 0 | 8 | 0 | -1 |
| 15 | 92 | -60 | -32 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 16 | 0 | 0 | -7 | 10 | 0 | 0 | 0 | 0 | 7 | 0 |
| 17 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 18 | 40 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | -40 |
| 19 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 20 | 20 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 21 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 22 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 23 | 20 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 24 | 120 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 25 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 26 | 60 | 0 | 0 | 60 | 0 | 0 | 0 | 0 | 0 | -59 |
| 27 | 0 | 0 | 0 | -50 | -20 | 0 | 0 | 0 | 0 | 70 |
| 28 | -30 | 0 | 0 | -40 | 0 | 0 | 0 | 0 | 0 | 70 |
| 29 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 30 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 31 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 32 | 0 | 0 | 0 | -95 | 0 | 0 | 0 | -45 | 0 | 140 |
| 33 | 10 | 0 | 0 | -100 | -40 | 0 | 0 | 0 | 0 | 130 |
| 34 | 10 | 0 | 0 | -100 | -40 | 0 | 0 | 0 | 0 | 130 |

As Table 3.8 shows, generally, the orange cluster generators tend to shift their volume of electricity offered to the less expensive price bands in the peak periods. Generators in the cluster with no color, seem to almost have little change in their strategy in offering volume in different trading intervals. Finally, the blue cluster identifies generators who tend to shift their volume of electricity offered to the more expensive price bands in the peak periods.

It is interesting to check whether similar changes in generators bidding behaviour also arise during periods where the spot price has not peaked. This does not seem to be the case. Below we illustrate this claim with data from two low price trading intervals.

Table 3.9 and Figure 3.10 show the results of clustering analysis of the change in bidding behaviour in two low spot price periods, from 10 AM to 8 PM, with only two main clusters identified.

Table 3.9. The change in bidding behaviour on a high spot price trading interval.

| **Generator No.** | **Difference of volume offered at each band** | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 3 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 4 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 6 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 7 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 9 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 10 | 38 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 11 | 38 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 12 | 0 | -50 | 0 | 0 | 0 | 0 | 0 | 50 | 0 | 0 |
| 13 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 14 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 15 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 16 | 0 | 0 | -5 | -6 | 0 | 0 | 0 | 0 | 12 | 0 |
| 17 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 18 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | -0 |
| 19 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 20 | 20 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 21 | -22 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 22 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 23 | 20 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 24 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 25 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 26 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 27 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 28 | -30 | 0 | 50 | -40 | 0 | 20 | 0 | 0 | 0 | 0 |
| 29 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 30 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 31 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 32 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 33 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 34 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

Results show that, in a lower spot price period generators within the same cluster do not necessarily obey the same pattern. For instance, generators $G11$ and $G12$ are classified into the same main cluster, but $G12$'s bid stack includes a significant shift to the right. Similarly, generators $G12$ and $G28$ belong to same sub-cluster despite exhibiting some differences.

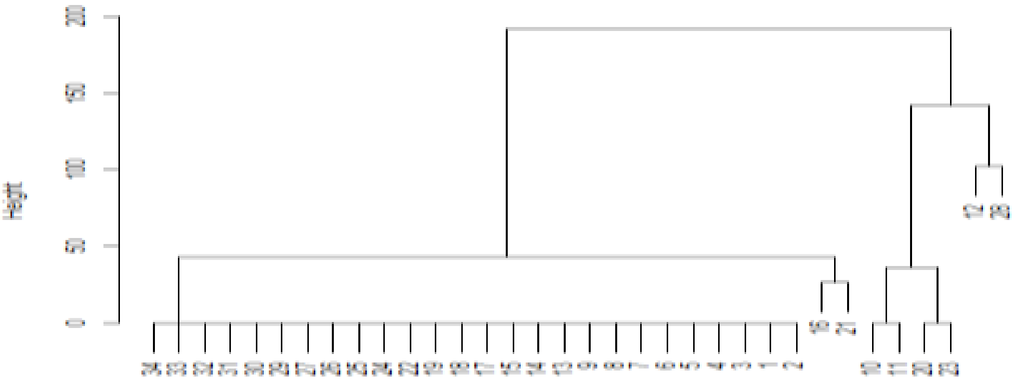

Figure 3.10. Ward's clusters for the change in bidding behaviour. A low spot price trading interval.

The behaviour of generators in this trading interval seem to have more irregular patterns comparing to the high spot price periods. This raises a question as to whether generators seem to learn from their experiences that specific forms of bidding behaviour would ultimately result in higher spot price for a trading interval.

## 3.5 BIMODAL BIDDING BEHAVIOUR BY GENERATORS

In Section 3.4, we observed that for some generators their stacks tended to exhibit "bimodal distribution patterns" during the high spot price periods. In this section we shall demonstrate this more formally with the help of the bimodality coefficient (Pfister, et al., 2013).

Toward this goal we create a pseudo probability distribution on a "random" variable $C^g$ that is the cost per MWh of electricity offered in any given bid stack. We shall assume that $C^g$ can only take values $c_1^g, c_2^g, \dots, c_{10}^g$ corresponding to the price of the ten bands in any bid stack. Furthermore, we assume that for generator $g$

$$\Pr\left(C^g = c_i^g\right) = q_i^g = \frac{v_i^g}{\sum_{i=1}^{10} v_i^g}; \quad i = 1,2,\dots,10. \tag{3.4}$$

That is, the expected price per MWh corresponding to a particular bid stack of generator $g$ is given by

$$\mu^g = E(C^g) = \sum_{i=1}^{10} c_i^g q_i^g. \tag{3.5}$$

The index $\mu^g$ captures the central tendency of the price band distribution corresponding to any given bid stack. For instance, suppose generator $G18$ has offered the following price, $c_i^g$, and volume, $v_i^g$, in a bid stack at a high spot price period (see Table 3.10).

Table 3.10. Price and volume offered by generator $G18$ at a high spot price period.

| Band | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| $c_i^g$ | -916.1 | 0 | 274.46 | 279.96 | 536.47 | 1374.7 | 4580.13 | 7786.48 | 8061.31 | 9160.63 |
| $v_i^g$ | 40 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 15 |

Using (3.4) the distribution of proportions of volumes offered by $G18$ in this trading interval is given in Table 3.11.

Table 3.11. Proportions of volume offered by generator $G18$ at a high spot price period.

| Band | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| ${q_i}^g$ | 0.73 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.27 |

Table 3.11 shows generator $g$'s interest at each price band in terms of proportions of volume offered at that band. In particular, Table 3.11 shows that generator $G18$ offers around 73% of total capacity at the first band with the cost of $c_1^g = \$-916.1$/MWh. This generator is not interested to offer any volume at bands two to nine and he offers the remaining 27% of the total capacity at the final band with the cost of $c_{10}^g =$ $\$9160.63$/MWh. Based on Table 3.10 and Table 3.11 above, the average of electricity price that generator $G18$ asked at this trading intervals is

$$\mu^g = \sum_{i=1}^{10} c_i^g {q_i}^g = \$1804.6/MWh.$$

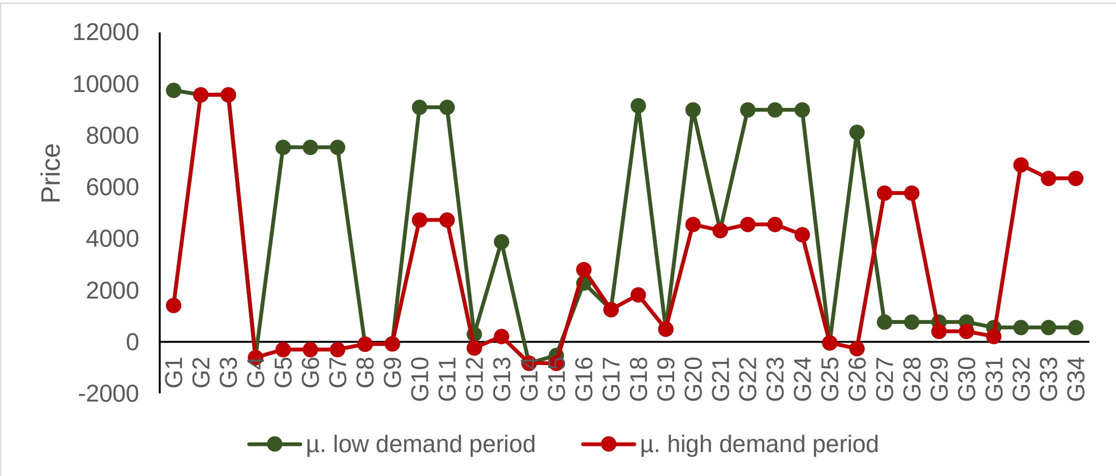


Figure 3.11. Average asked price by generators at low and high spot price period.

Figure 3.11 shows the average of price that 34 generators asked on 8th January 2010. The green line shows these values at 4:30 am and the red lines corresponding to the high trading interval at 16:30, which correspond to low and high spot price trading intervals respectively.

As shown in Figure 3.11, majority of generators tend to ask for lower prices as we approach the high demand periods. This is due to generators' shift of volume offered to the lower price bands in the higher demand trading intervals. There are few generators, such as G27, G28, G32, G33 and G34, who behave in an opposite direction and ask for higher average price per MWh. The standard deviation of the price asked by each generator, $\sigma(c^g)$, is shown in Figure 3.12.

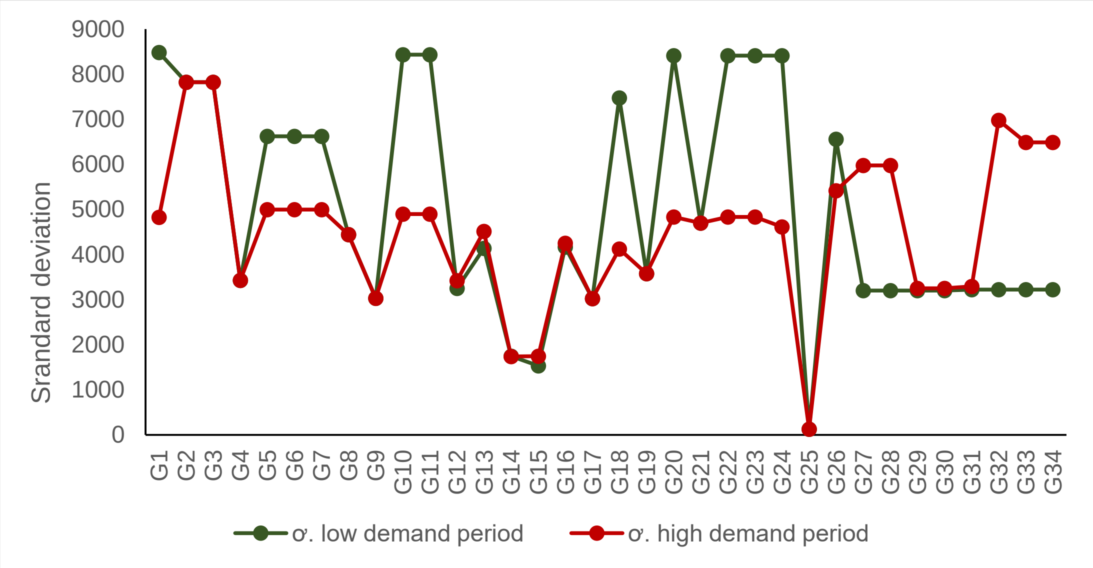


Figure 3.12. Standard deviation of asked price by generator. A low and high spot price period.

It should be noted that, the lower values of $\mu(c^g)$ and $\sigma(c^g)$ are mainly due to the strategic bidding behaviour by most of generators in the higher demand periods. By this form of bidding behaviour, majority of generators tend to offer higher portion of their total capacity in the low band price as we approach high spot price period (see Table 3.7).

Figure 3.13 shows skewness of the distribution, $\gamma^g$, of volume offered at price bands for all generators in SA at a low and high spot price period. As Figure 3.13 illustrates, this value has increased significantly for the majority of generators as we approach the high spot price period. For instance, $G7$'s bid stack distribution was negatively skewed in a low spot price trading interval, $\gamma^g = -0.97$. However, as we approach high spot price period, this generator changed the portion of volume offered at each price band significantly and as a result the distribution of volumes became positively skewed with $\gamma^g = 1.63$. This indicates that, $G7$ has shifted a high portion of the total capacity offered to the very low band prices.

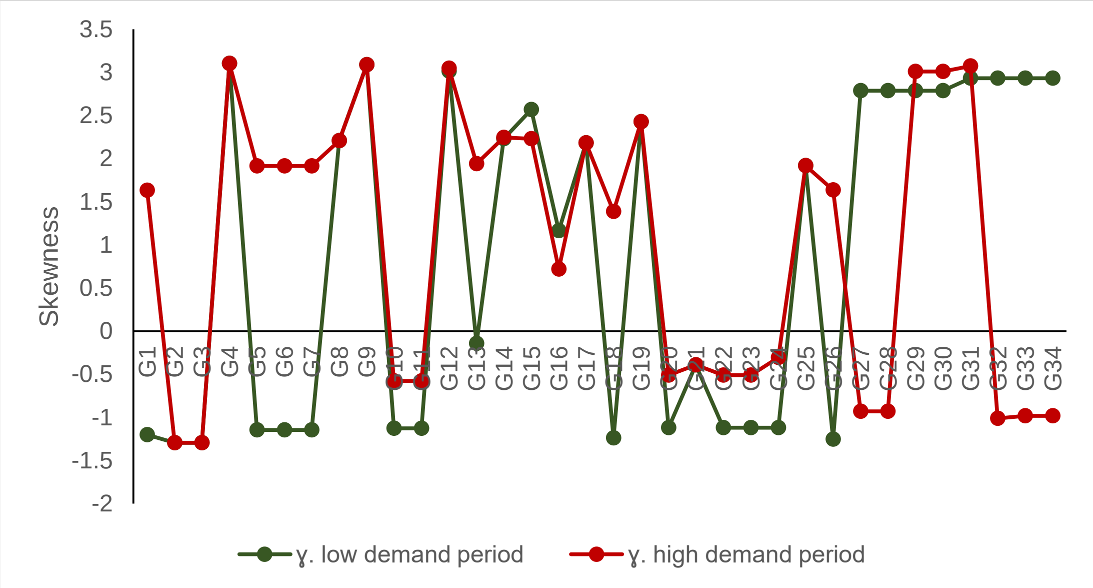


Figure 3.13. Skewness of distribution of volume offered at different price bands at low and high spot price period.

In general, the distribution of volume in the majority of generators' bid stack tend to approach bimodal distribution in the higher spot price periods. To show this, the bimodality coefficient $(BC)$

$$BC = \frac{\gamma^2 + 1}{k + \frac{3(n-1)^2}{(n-2)(n-3)}} \tag{3.6}$$

is calculated in a low and high spot price period for all 34 generators who participated in the market on 8th January 2010. Here $\gamma^2$ is the sample skewness and $k$ is the sample excess kurtosis. Values of $BC$ greater than 5/9 may indicate a bimodal or multimodal distribution.

The bimodality coefficient values for each of the 34 generators in low and high spot price period are illustrated in Figure 3.14. As that shows, generators tend to offer a more bimodal form of distribution of bid stacks offered in the higher spot price periods. For instance, the bimodality coefficient corresponding to $G27$'s bid stack has increased from 0.15 in a low spot price period to about 0.68 in a high spot price period.

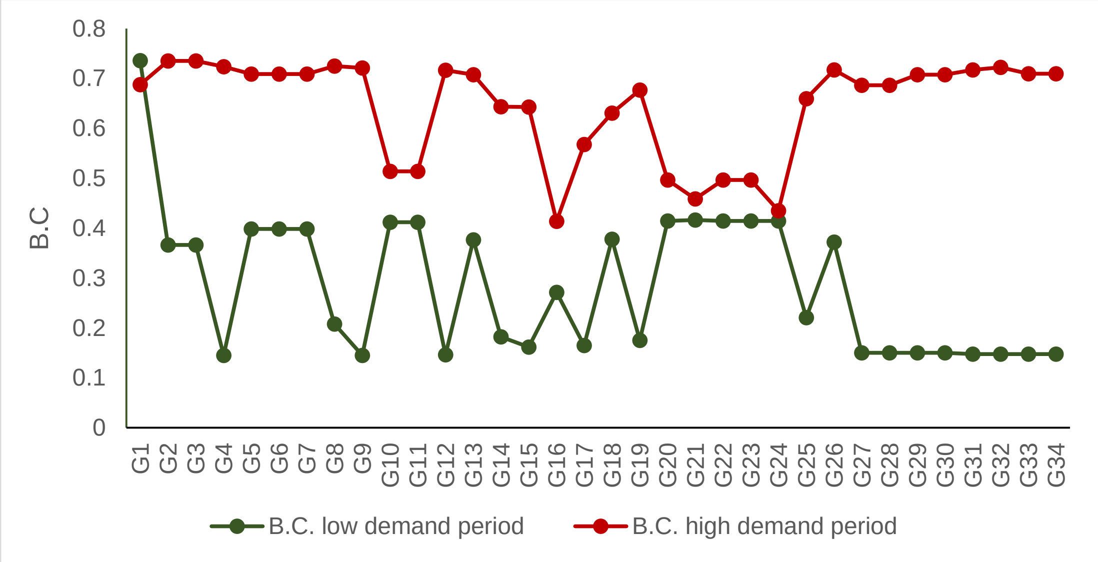


Figure 3.14. Bimodality coefficient at low and high spot price periods.

## 3.6 LOTTERY MODEL

In this section we consider generators' bidding strategy from another perspective. In particular, we consider whether it might be possible to view generators' bid offers as a betting strategy in a lottery constructed on the basis of historical data[23]. The lottery approach considered in this section, could be seen as a benchmark to test the extent to which generators are concerned about the risk of failing to win sufficient generation volume.

Suppose the market is a genuinely competitive market, where the spot price is essentially independent of any single generator's own bids. In such a case, any generator could consider their bid stack as a betting strategy in a lottery. The probabilities of the spot price falling in any range in such a lottery could then be estimated from historical data.

Consequently, in this section, we formally construct a lottery model – based on actual summer 2010, South Australia data – that will enable us to calculate a set of natural measures of risk. For the remainder of this section we shall use the following simplifying assumption.

A1. For generators, in any given trading intervals, the product of the volume of production won and the spot price constitutes their utility which they wish to maximise.

[23] Recall that the notation used for a bidding strategy of a single generator was $\boldsymbol{v}^g = \{v_i^g | i = 1,2, \ldots, M\}$.

A2. For consumers, in any given trading interval, the aggregate of the above products, across all generators actually producing electricity constitutes their cost which they wish to minimise.

Clearly, we recognise that the actual income and profit to generators is affected by many other factors (e.g., cost of production, fees, hedging contracts, etc.). Similarly, cost to consumers incorporates another set of factors (e.g., physical cost of maintaining the grid, and administrative cost of AEMO, changing prices of fuels, etc.). Nonetheless, it is indisputable that the products of volumes and spot prices mentioned in A1-A2 constitute a key component of both the income to generators and the cost to consumers. As such, we use them as convenient surrogates of utility and cost, respectively.

In what follows, we view generators' bid offer as betting strategies in a lottery model constructed on the basis of historical data. For instance, Table 3.12 shows price and volume offered by a gas turbine generator at 15:30 pm of 8$^{th}$ January 2010. It is possible to consider this bidding offer as a betting strategy in a lottery designed in the following way.

Table 3.12. Bid offered by a generator at 15:30pm of Jan 8th 2010.

| Band | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| Price | -976 | 0.98 | 96.62 | 141.52 | 292.8 | 575.84 | 976 | 9174.4 | 9564.8 | 9760 |
| Volume | 0 | 165 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 55 |

Recall that generators put 10 prices in a stack of 10 bands and assign a volume to each price. In this section we call these 10 intervals as "Price Interval". Based on historical spot price data, there is a positive probability that the final spot price, denoted by $S$, for this trading interval would lie somewhere between the boundaries of each band. In other words, each price interval has a probability of containing the final spot price for this trading interval. That is, these probabilities are defined as follows:

$$p_i = Pr(c_i < S \leq c_{i+1}); \quad for \ i = 1,2,\dots,9. \qquad (3.7)$$

For the final band, $i = 10$ this probability is defined using just lower price boundary.

$$p_{10} = Pr(c_{10} \leq S). \qquad (3.8)$$

Consequently, an approximation to the expected income can be derived out of this bid structure, or lottery, designed by the generator after selecting these price intervals and estimating the corresponding probabilities.

Of course, a generator's income depends on which price interval contains the spot price. For instance, if under the bid in Table 3.12, the spot price falls within the price interval of band 1 and 2, then this generator will not be dispatched to production as it has not assigned any volume to band 1. Suppose, however, that the spot price would take the value of \$300 per MWh, so it will lie within the interval of bands 5 and 6. Therefore, this generator has already won all volume that it bid from the first band to band 5. In other words, the cumulative volume of bands 1 to 5 is the volume that this generator has won.

Overall, the income random variable denoted by $I$ takes the value $I_i$

$$I_i = c_i \times V_i \,, \tag{3.9}$$

when the spot price falls in the $i^{th}$ price interval[24]. In the above, $c_i$ and $V_i$ are the price and comulative volume of bands $1,2,\dots,i$ respectively.

Note that

$$V_i = \sum_{j=1}^{i} v_j \qquad for\ i = 1,2,\dots,10. \tag{3.10}$$

As a result, the expected income from this lottery would be equal to,

$$\mu = E(I) = \sum_{i=1}^{10} I_i p_i \,. \tag{3.11}$$

The standard deviation of the generator's income is now given by,

$$\sigma(I) = \sqrt{\sum_{i=1}^{10} p_i (I_i - \mu)^2} \tag{3.12}$$

The usual coefficient of variation is now defined as $C_v = C_v(I) = \frac{\sigma(I)}{|\mu(I)|}$.

A numerical example is provided in Table 3.13 which shows the bid offered by generator $G1$ on Jan 8th, 2010 at 15:30 pm and the expected income out of this bid. The risk to the income for this trading interval is then examined with the standard deviation as defined above.

[24] This is a conservative estimation of the generator's income in this case because lower bound of the interval $(c_i, c_{i+1}]$ was used instead of its mid-point.

It is important to note that – under the assumptions of the competitive market and the lottery model – this generator would believe that the probability mass distribution represented by the $p_i$ row of Table 3.13 would apply in every trading interval of interest. Consequently, only the generator's bid stacks influence the lottery values.

Table 3.13. Expected income based on the bid stack offered by generator $G1$ on 8th Jan. 2010 at 15:30.

| Band | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| $c_i$ | -976 | 0.98 | 96.62 | 141.52 | 292.8 | 575.84 | 976 | 9174.4 | 9564.8 | 9760 |
| $p_i$ | 0.0013 | 0.9698 | 0.0081 | 0.0087 | 0.0020 | 0 | 0.0081 | 0 | 0 | 0.0020 |
| $v_i$ | 0 | 165 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 55 |
| $V_i$ | 0 | 165 | 165 | 165 | 165 | 165 | 165 | 165 | 165 | 220 |
| $I_i$ | 0 | 161.7 | 15942.3 | 23350.8 | 48312 | 95013.6 | 161040 | 1513776 | 1578192 | 2147200 |

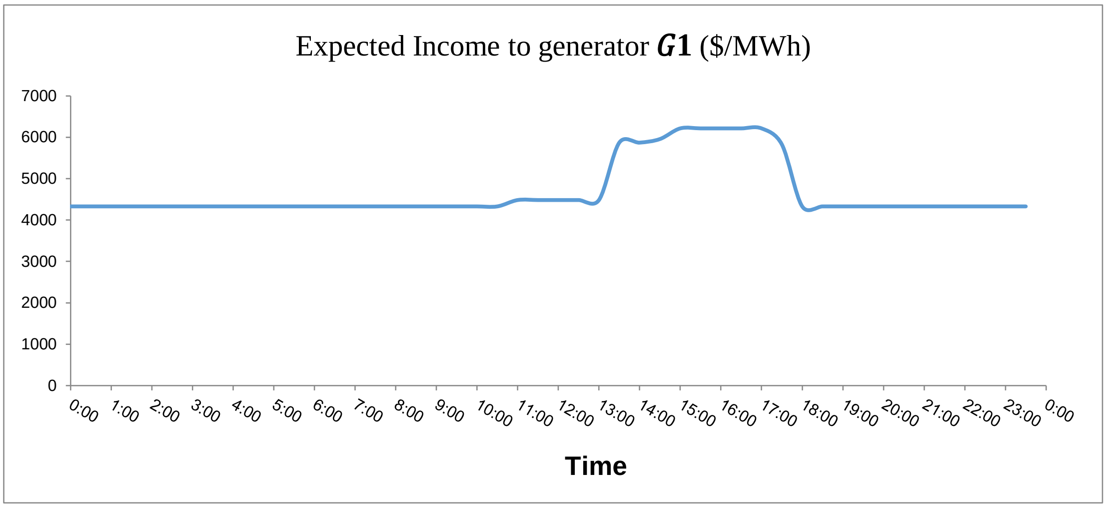


Figure 3.15. Average of income at Jan 8th 2010.

In view of this we considered the bid stacks this generator actually used in 48 trading intervals on January 8, 2010. For each of these trading intervals an analogue of Table 3.13 was computed and values of the mean, standard deviation and coefficient of variation were evaluated. In Figures 3.15-3.17 these three indices of the lottery performance were plotted for the 48 trading intervals on that day. Figure 3.15 shows that initially the expected income of generator $G1$ stays remarkably stable (at approximately $4300 per TI) but as we approach the high spot price trading intervals within that day, the expected income of this generator increases by more than 40%.

Similarly, we observe from Figure 3.16 that the standard deviation of the income of this generator is correspondingly stable (at approximately $96,000 per TI) during low spot price periods but as we approach the high spot price trading intervals within that day, the standard deviation increases but by only a little more than 1%.

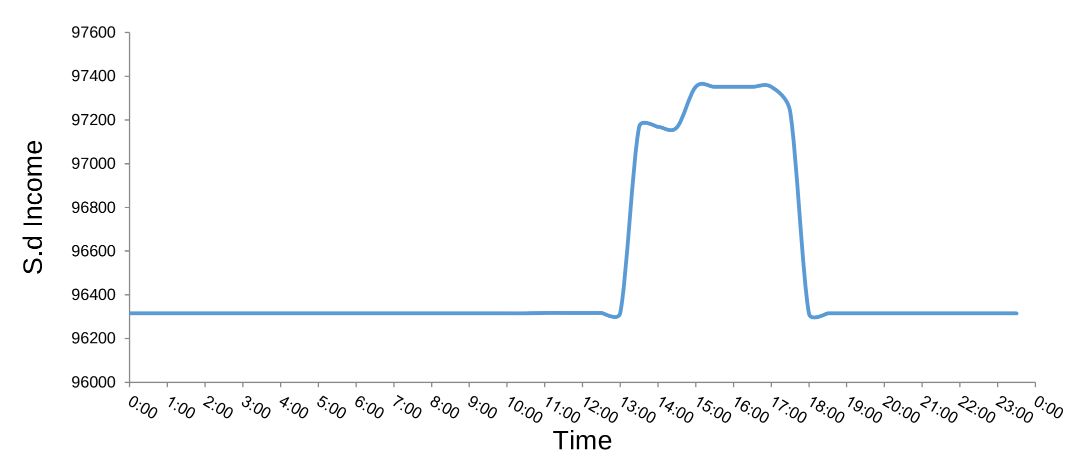


Figure 3.16. Standard deviation of income at Jan 8th 2010.

Hence, the generator's change of the bidding strategy during the high spot price periods seems to be beneficial (under the lottery model) in terms of the benefit versus risk trade-off. In particular, if we think of the coefficient of variation as capturing some of that trade-off, then we observe from Figure 3.17 that $C_v$ drops quite significantly during the high spot price periods from approximately 22.3 to 15.6, or about 30%.

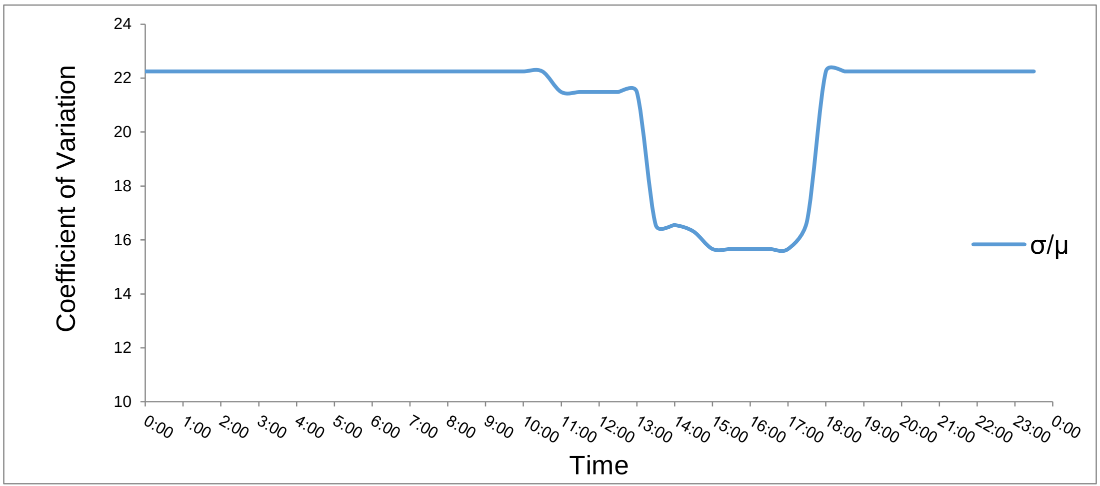


Figure 3.17. Coefficient of variation.

To an extent that Figure 3.17 highlights the amount of volatility, or risk, the generator is facing relative to the amount of return from his bids. Arguably, lower values of coefficient of variation correspond to better risk-return trade-offs for the generator.

These figures show that, statistically speaking, the generator's bidding strategy – during the high spot price periods - can be considered to be a well-designed lottery for such a generator. It seems to enable the generator to earn a large income with low risk. Of course, ultimately, the consumers pay for the generators' successes in playing such a lottery.

It is important to note that during the 48 trading intervals summarised in Figures 3.15-3.17, the generator exhibited an interesting transition in his bidding pattern. In particular, in the first 22 and last 12 trading intervals of January 8th, his bids had the structure corresponding to Figure 3.2 and – in reality – resulted in this generator failing to win any share of electricity generation. During only three trading intervals, from 3:30-4:30 pm, his bid structure corresponded to Figure 3.4 and resulted in this generator supplying nearly all of his capacity at the very high spot price of $9,999.71/MWH. In the remaining 11 trading intervals, his bid structures seemed to be in transition between the two extremes portrayed in Figures 3.2 and 3.4 and resulted in the generator winning some fractional parts of his capacity of 220 MW. This raises the natural question: What is a rational basis for such a changing bidding pattern?

Hence, we explore the possibility of answering the above question – within the framework of the lottery model – by exploiting Markowitz-type (Markowitz 1987) mean-variance optimization approach. In that approach, we postulate that the generator considers dividing his total capacity of 220 MW into a "portfolio" $v_1, v_2, \dots v_{10}$ of volumes of production offered in the 10 price bands. Hence, $\mu(I)$ and $\sigma(I)$ now become functions $\mu(v_1, v_2, \dots v_{10})$ and $\sigma(v_1, v_2, \dots v_{10})$ of these decision variables and the optimization problem takes the form

$$\begin{array}{ll} \min \sigma^2(v_1, v_2, \dots v_{10}) & \\ \mu(v_1, v_2, \dots v_{10}) \geq m & \\ 0 \leq v_i \leq 220\,; & i = 1,2, \dots 10, \end{array}$$

where $m$ is the acceptable lower bound on the expected income during a trading interval and forms a parameter that can be experimented with. Interestingly, perhaps, it turns out that low values of $m$ yield optimal $v_1, v_2, \dots v_{10}$ values that roughly correspond to the bid structure represented by Figure 3.2 (observed during low spot price periods). Furthermore, as $m$ increases the optimal $v_1, v_2, \dots v_{10}$ values begin to exhibit a shift toward the bimodal bid structures resembling that represented by Figure 3.4 (observed during high spot price periods).

However, perhaps, surprisingly the highest realistic value of $m$ results in a drastically different optimal $v_1, v_2, \dots v_{10}$ values, that concentrate all (or nearly all) capacity at the most likely, second, spot price band. These results can be observed from Table 3.14.

From the above it may appear, at first sight, that the bimodal bid structure observed during high spot price periods (see Figure 2.6) is a rational strategy resembling the third data row of Table 3.14. The latter simply minimizes the variance subject to the requirement that the mean is at least $6,500 in the trading interval.

Table 3.14. Optimal bids corresponding to a range of $m$ values.

| $m$ | $v_1$ | $v_2$ | $v_3$ | $v_4$ | $v_5$ | $v_6$ | $v_7$ | $v_8$ | $v_9$ | $v_{10}$ | $C_v$ | $\sigma$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 6840.00 | 0 | 220 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 14.35 | 98183.01 |
| 6800.00 | 0 | 216 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 4 | 14.43 | 98122.78 |
| 6500.00 | 0 | 190 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 30 | 15.03 | 97701.70 |
| 6000.00 | 0 | 146 | 0 | 0 | 0 | 0 | 0 | 15 | 15 | 45 | 16.19 | 97121.70 |
| 6500.00 | 0 | 190 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 30 | 15.03 | 97701.70 |
| 5000.00 | 0 | 59 | 0 | 0 | 0 | 0 | 0 | 11 | 11 | 139 | 19.29 | 96427.41 |
| 4500.00 | 0 | 15 | 0 | 0 | 0 | 0 | 0 | 0 | 22 | 183 | 21.40 | 96316.47 |
| 4399.91 | 0 | 6 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 214 | 21.89 | 96313.29 |

However, if the generator really believed that the lottery model were relevant to him, he would have assumed that the probability mass distribution displayed in Table 3.15 applies to spot prices at all trading intervals.

Table 3.15. Probability mass distribution of spot prices under the lottery model.

| **Band** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** |
|---|---|---|---|---|---|---|---|---|---|---|
| $c_i$ | -976.00 | 0.98 | 96.62 | 141.52 | 292.80 | 575.84 | 976.00 | 9174.40 | 9564.80 | 9760.00 |
| $P_i$ | 0.00 | 0.97 | 0.01 | 0.01 | 0.00 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 |

This reasoning leads to two, unexplained, questions:

(i) Why the generator did not use a bid structure corresponding to the first data row of Table 3.14 (which yields a better mean and a better coefficient of variation, in addition to being simpler)?

(ii) Why did the generator switch from one bid structure to another during the course of the day according to the pattern discussed earlier in this section?

The two, natural, explanations are that he either had information that is not captured by the lottery model and, therefore, did not believe that this model applies, or that he simply acted in a naïve way as a result of not knowing how to obtain best profit.

## 3.7 AUCTION & BID TO COVER RATIO

The bid to cover ratio is a measure used in auctions to express the public demand for a particular security such as shares and bonds. It compares the number of bids received in a Treasury security auction to the number of bids accepted. It also can be computed as the value of bids received divided by the value of bids accepted. As an example assume that the value of bids offered by the public for a security is $20 billion and the treasury offers $10 billion. This result in a bid to cover ratio of 2.

Bid to cover ratio is well-known as an indicator of the public interest in bidding and also a barometer of success of an auction. A higher ratio, above 2.0, would be an indication of a strong or "bought" auction. On the other hand, a low ratio is an indication of a weak auction where the bid-ask spread[25] is quite wide (Fabozzi & Leibowits, 2007).

In this section we examine the bid to cover ratio in the Australian electricity market. We compute this ratio by the value of money claimed from the electricity pool[26] by generators divided by the value paid to the generators by AEMO. Below we apply this ratio to the Australian electricity market using an example.

First, to explain the methodology, consider a small electricity market where just two generators bid to the pool. Suppose the bid stacks offered by these generators, G1 and G2 are as shown in Table 3.16 and Table 3.17 respectively.

Table 3.16. Bid stack offered by G1.

| **Band** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** |
|---|---|---|---|---|---|---|---|---|---|---|
| **Price** | -1000.8 | 28.79 | 33.8 | 38.8 | 45.81 | 55.81 | 75.83 | 100.85 | 2490.9 | 10007.77 |
| **Volume** | 30 | 0 | 0 | 0 | 0 | 0 | 0 | 20 | 70 | 10 |

Table 3.17. Bid stack offered by G2.

| **Band** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** |
|---|---|---|---|---|---|---|---|---|---|---|
| **Price** | -40 | 1 | 20 | 400 | 800 | 1000 | 1200 | 2000 | 5000 | 10000 |
| **Volume** | 90 | 0 | 0 | 0 | 100 | 0 | 0 | 0 | 20 | 30 |

For computing the bid to cover ratio first we need to calculate the value of money which has been claimed from the pool for cost of production. For this purpose,

$$M_B = \sum_{i=1}^{10} v_i c_i = 752858\,.$$

Next suppose the demand for this trading interval is $d = 130$, then the corresponding spot price for this trading interval is the price of the band at which the demand is

25 The bid–ask spread for a security is the difference between the prices quoted for an immediate sale (bid) and an immediate purchase (ask). It represents the difference between the highest price that a buyer is willing to pay (bid) for a security and the lowest price that a seller is willing to accept for it. A transaction occurs either when a buyer accepts the ask price or a seller takes the bid price.
26 In this we regard generators' bid stacks as claims.

satisfied and is equal to $S = 100.85/MWh$. Therefore, $M_P$, the value of money that these generators will receive is as follows

$$M_P = S * d = \$100.85 * 130 = \$13110.5 .$$

Hence, the bid to cover ratio, $R$, for this trading interval is

$$R = \frac{M_B}{M_P} = 57.4 . \qquad (3.15)$$

As this ratio is much higher than $2$, it shows that the assumed auction with two generators was quite competitive and the interest of generators in bidding in this market was high.

In the following, we demonstrate the bid to cover ratio in a more realistic situation, with respect to AEMO. Five trading intervals, both in low and high spot price periods, have been chosen in the state of South Australia. As shown in Table 3.18 the bid to cover ratio for the low spot price trading interval, 4:30 AM, is equal to 559.5 which shows a highly competitive auction in this period. However, as we approach to the high spot price trading intervals such as 3:30PM and 4:00PM, the bid to cover ratio decreases significantly to below one.

Table 3.18. Bid to cover ratio on January 8th 2010 in South Australia.

| Trading Interval | 4:30 AM | 10:00 AM | 3:00 PM | 3:30 PM | 4:00 PM |
|---|---|---|---|---|---|
| **Volume Offered** | 4403 | 4117 | 4897 | 4898 | 4898 |
| **Demand** | 1231.22 | 2151.89 | 2735.65 | 2736.7 | 2793.25 |
| **Volume / Demand** | 3.58 | 1.91 | 1.79 | 1.79 | 1.75 |
| **Spot Price** | **14.2** | **32.04** | **340.77** | **9999.71** | **9999.71** |
| **$ Paid by AEMO** | 17,483 | 68,947 | 932,227 | 27,366,206 | 27,931,690 |
| **Bid-Cover Ratio** | **559.5** | **120.9** | **4.9** | **0.37** | **0.36** |

The ratio below one indicates that, generators are paid much higher than they have bid to the market. This arises as all of the generators are paid equally based on the very high spot price, $9999.71, for this trading interval. For some generators, this price is even higher than the maximum price that they have offered in their bid stack. Luckily, similar to all other generators, they will also benefit from the high spot price in this trading interval.

As the bid to cover ratios illustrate in Table 3.18, it seems that in the high spot price trading intervals the competition among generators was not quite competitive and as a result the auction is considered to be relatively weak. The ratio of total volume of electricity offered by generators over the total demand in the fourth row of Table 3.18 is also an indication of lower generation capacity offered by generators in the high spot price periods.

## 3.8 RISK TO CONSUMERS

In view of the preceding discussion it is now natural to consider how different bidding strategies of generators affect the risk of loss to consumers. Consistently with the assumptions A1-A2, we shall now consider the income for generators as a loss to consumers. With this approach and using risk measures such as Value-at-Risk (VaR) and conditional Value-at-Risk (CVaR) (Rockafellar and Urysaev 2000) we can investigate the risk faced by consumers as a result of generators' bidding strategies in different trading intervals.

Table 3.19 shows income for generators, loss to end-users, in a month of January 2009. As in previous sections, all 1488 trading intervals in this specific month have been divided into three categories based on spot price values. It should be mentioned that January was chosen for investigation as there were a number of spikes in spot price of the electricity market in that period of time.

Table 3.19. Income for generators, loss for consumers, at January 2009.

| **Trading Interval** | **Number of TI** | **Ratio of TI** | **Sum of Income in the Category** | **Ratio of Income in the Category** |
|---|---|---|---|---|
| **Low spot price** | 1449 | 0.97 | 926,144,523 | 0.38 |
| **High spot price** | 39 | 0.03 | 1,495,246,025 | 0.62 |
| **Total** | 1488 | 1 | 2,421,390,548 | 1 |

Table 3.19 also shows the contribution to the income for generators corresponding to low and high spot price trading intervals. The labelled column "Ratio" is the ratio of the income of generators in each category to the whole income. We see that about 62% of the total income of generators is a result of about 3% of the 1488 trading intervals in January 2009. These are the intervals corresponding to the high spot price category. This can be seen even more clearly from the pie charts in Figure 3.18.

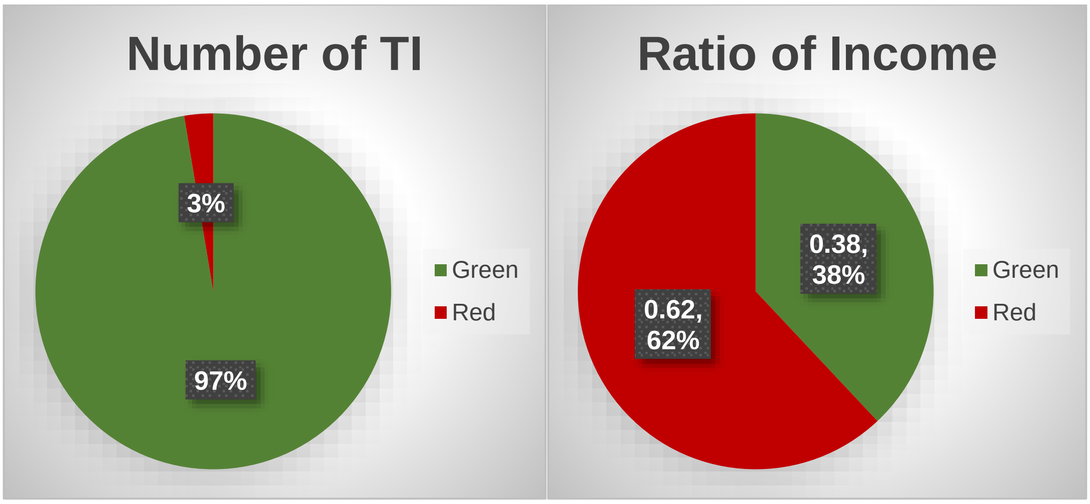


Figure 3.18 Income for generators in high and low spot price trading intervals, January 2009.

Since, the electricity cost during the high spot price periods is – in one form or another – passed on to the consumers, it is natural to consider the question: *what is the risk of loss that has been imposed on consumers as result of the underlying bidding behaviour of generators?*

Before we examine the risk of loss to consumers, we briefly introduce two risk measures, namely, "Value at Risk" and "Conditional Value at Risk", also called "Expected shortfall" (Hull 2008).

Value at risk is a tool for measuring risk that has been used by financial institutions since the late 1990's. It was initiated by J. P. Morgan in order to summarize the total risk of a portfolio in a single index. Basically, what VaR provides is a threshold for the loss in the portfolio in a specific time interval such that the probability that the loss exceeds this value in that time horizon will be given by a prescribed probability value, usually denoted by $\alpha$. Thus, VaR of loss can be calculated from the probability distribution of the loss in the interval $t$.

In our case, Figure 3.19 shows the estimated probability density function of loss to consumers in a a single trading interval. Intrinsically, what Figure 3.19 displays is how expensive electricity supply can become to consumers in just a single half hour period. This was done on the basis of real South Australian spot price and demand data collected over the 1,488 trading intervals in January 2009. The resulting, normalised, histogram is approximated by the continuous curve displayed in that figure. Note, that negative values on the horizontal axis can arise (with very small probability) as a consequence of the initial bands in some generators' bid stacks being negative. The maximum cost of nearly $33.5 million observed in just a single trading interval lies so far to the right of the origin that its inclusion would distort the display.

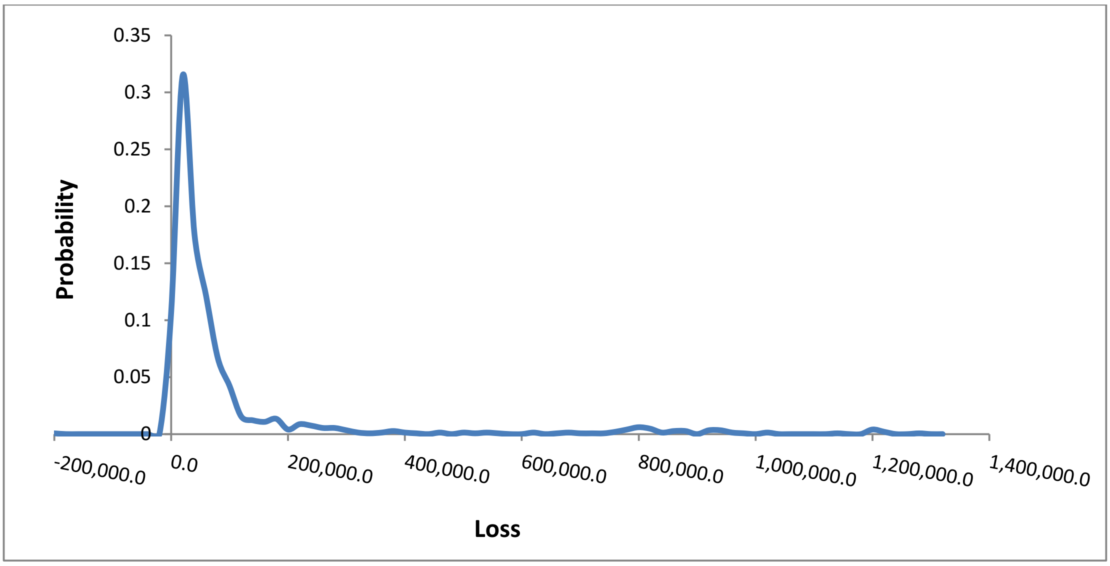


Figure 3.19. Probability density of loss in a trading interval.

However, we note that consumers may pay more than $33m in a trading interval albeit with a very low probability. Nevertheless, consumers could be legitimately concerned about their expected loss if, even with a low probability, that loss exceeds the VaR threshold in a trading interval. In order to answer this concern we employed the risk measure tool, sometimes called "Expected shortfall". What expected shortfall or CVaR determines is the average amount of loss over the mentioned time horizon, assuming that loss will exceed VaR (See Appendix 3.1). It has been argued that CVaR is a better measure of risk than VaR. Indeed, CVaR is what is known as a coherent measure of risk (Rockafellar and Uryasev 2000).

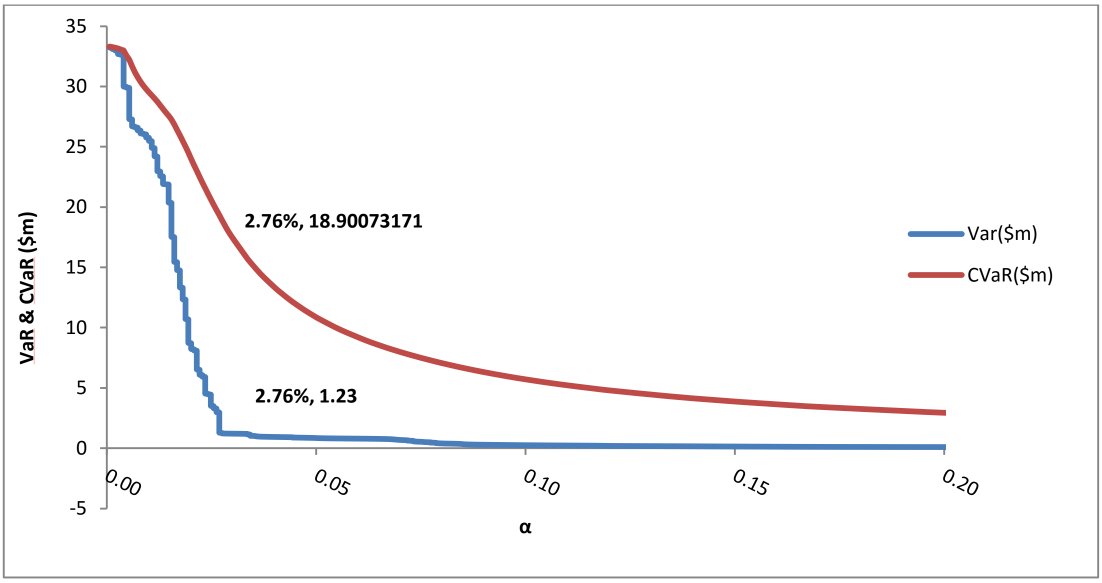


Figure 3.20. VaR and CVaR of loss in a trading interval.

Figure 3.20 compares the risk imposed on consumers in a trading interval based on two risk measures of VaR and CVaR. Naturally, at every value of $\alpha$ plotted on the horizontal axis VaR is less than or equal to CVaR, with the gap between the two indices diminishing as $\alpha$ tends to 0. As Figure 3.20 shows there is a low probability, $2.7\%$, that end-users lose more than \$1.23m in a trading interval but if they do, then the expectation of that loss will be approximately \$18.9m. If one regards $\alpha = 2.7\%$ as not an insignificant level of risk, then the width of this gap is a cause for concern.

Undoubtedly, that width is the direct consequence of the infrequent trading intervals where spot prices attain extremely high levels. The high spot price levels are clearly a consequence of the collective bid strategies by the generators, irrespective of whether the latter were intended to influence the spot price or not.

# CHAPTER 4. PARAMETRIC OPTIMISATION PROBLEMS AND MARKET POWER

In Chapters 1-3 we introduced the dispatch problem and the spot price calculation mechanism used by AEMO to pay generators for producing electricity. We saw that dual variables (shadow/marginal prices) of the linear program $LP(t)$ directly contributed to the spot price applied during every trading interval via the formula

$$\mathrm{y}_j(\hat{t}) = \frac{1}{6}\left[y_j(t_1) + y_j(t_2) + \cdots + y_j(t_6)\right]; \qquad j = 1,2,\ldots,5, \tag{4.1}$$

where $y_j(t_i)$ is the optimal value of the corresponding dual variable of $LP(t_i)$; $i = 1,2,\ldots,6$.

In this chapter we consider the potential consequences of the fact that generators can influence some parameters of the linear programs $LP(t_i)$. Indirectly, this opens the possibility of them being able to influence the marginal prices of electricity in each state and hence also the spot prices. We shall argue that this influence can potentially lead to at least two undesirable consequences:

C1: Spot price volatility

C2: Opportunity for generators to exercise market power.

## 4.1 DISPATCH PROBLEM IN GENERIC FORM

In this section, we express the dispatch problem in generic, mathematical, form. We explain why dependence of $LP(t_i)$ on parameters submitted by generators may cause instability in dispatch (and hence also) spot prices. Basically, from standard theory of linear programming (e.g. Luenberger, 1984) we know that $LP(t_i)$ and its dual can be written in the form

$$LP(t_i)$$

$$\min c(v, t_i)^T x$$

$$A(v)x \geq b(v, t_i)$$
$$x \geq 0,$$

and

$$DLP(t_i)$$

$$\max\ b(v, t_i)^T y$$

$$y^T A(v) \leq c(v, t_i)^T$$
$$y \geq 0,$$

where we now emphasize the dependence of the constraint matrix, cost function and right hand side bounds on a vector parameters $v$. Of course, $t_i$ still refers to the five minute time interval comprising a given 30 minute trading interval. In our context we restrict $v$ to only those parameters which can be influenced by stakeholders: generators, in our case. For instance $v_b^g$ the amount of electricity that generators $g$ is willing to produce in price band $b$ at time $t_i$ is such a parameter. Its value comes from the bid stack submitted by generator $g$.

Let $X(v)$ denote the feasible region of $LP(t_i)$ and $Y(v)$ the feasible region of $DLP(t_i)$. It is well known (e.g. Luenberger, 1984) that strong duality theorem implies that the set of all optimal pairs of solutions to $LP(t_i)$ and $DLP(t_i)$ is the set

$$\Omega(v) := \{(x, y) \in X(v) \times Y(v) \mid c(v, t_i)^T x = b(v, t_i)^T y\}.$$

**Remark 4.1** The cases when $\Omega(v)$ is empty or $LP(t_i)$ is unbounded are impossible in realistic situations. However, the cases where $\Omega(v)$ is a singleton or an infinite set may both arise.

It will be seen that there is an important distinction between the situation where $\Omega(v)$ contains multiple optimal solutions and the situation when $(z^0, y^0)$ is the unique pair of optimal solutions for $LP(t_i)$ and $DLP(t_i)$, respectively.

In particular, consider a function $u(v, x, y)$ that captures the benefit to certain stakeholders of an optimal solution pair $u(x, y) \in \Omega(v)$. For instance, if we think of generators in state $j$ as our stakeholders the simple projection function

$$u(v, x, y) = y_j,$$

where $y_j$ is the dispatch price in state $j$ at time $t_i$, demonstrates an example of such a benefit function, as large value of $y_j$ benefit these generators.

Let us define an "instability gap" of dispatch prices, for fixed parameter values $v$, as

$$I(v) := \max_{\Omega(v)} u(v, x, y) - \min_{\Omega(v)} u(v, x, y). \tag{4.2}$$

Clearly, if $\Omega(v) = \{(x, y)\}$ that is $LP(t_i)$ and $DLP(t_i)$ have unique optimal solutions, then $I(v) = 0$. However, the latter situation is not generic in applications of linear programming. Multiple optimal solutions frequently arise. In these cases $I(v) > 0$ is a possibility.

Furthermore, irrespective of whether $\Omega(v)$ is a singleton the fact that stakeholders can influence $v$ means that, in principle, $v$ can be seen as a vector of variables rather than parameters.

Hence if we let $V$ denote the set of all possible values of $v$, then we see that the benefit function $u(v, x, y)$ could have a much bigger range than $I(v)$ when considered over the entire domain

$$\Omega := \{(v, x, y) | (x, y) \in \Omega(v), v \in V\}.$$

Indeed, it is natural to now define the "overall instability gap" as

$$I := \max_{\Omega} u(v, x, y) - \min_{\Omega} u(v, x, y). \tag{4.3}$$

**Proposition 4.1:**

For a linear program $LP(t_i)$ whose parameters $v$ are supplied by stakeholders the instability gaps satisfy:

(i) $I(v) \geq 0$, with a strict inequality possible.

(ii) $I \geq I(v)$, for every $v \in V$, with a strict inequality possible, even if $I(v) = 0$ for each $v$.

**Proof:**

The inequality $I(v) \geq 0$ is obvious from definition and the fact that $I(v) > 0$ is possible when $\Omega(v)$ contains multiple optimal solutions also follows naturally. In Section 4.3 we supply examples of that fact.

For the second part note that

$$\max_{\Omega} u(v, x, y) = \max_{v} \max_{\Omega(v)} u(v, x, y)$$

and

$$\min_{\Omega} u(v, x, y) = \min_{v} \min_{\Omega(v)} u(v, x, y).$$

Hence, for each $v \in V$

$$I(v) = \max_{\Omega(v)} u(v, x, y) - \min_{\Omega(v)} u(v, x, y) \leq \max_{v} \max_{\Omega(v)} u(v, x, y) - \min_{v} \min_{\Omega(v)} u(v, x, y) = I.$$

Of course, strict inequality is possible in the above because

$$\max_{v} \max_{\Omega(v)} u(v, x, y) > \max_{\Omega(v)} u(v, x, y),$$

is certainly possible, and similarly for the minima.

Note that even if $I(v) = 0$ for every $v \in V$, the instability gap $I$ can still be positive. This is because the situation

$$I = \max_{\Omega} u(v, x, y) - \min_{\Omega} u(v, x, y) = u(v^*, x^*, y^*) - u\left(v^{\circ}, x^*, y^*\right) > 0,$$

can certainly arise.

**Remark 4.2** Arguably, both of the strict inequalities

$$I > I(v) > 0, \tag{4.4}$$

offer an opportunity for stakeholders controlling $v$ to exercise market power, albeit in somewhat different ways. In the case of electricity generation this will be demonstrated in the remainder of this chapter.

## 4.2 SIMPLIFIED DISPATCH PROBLEM

It should be mentioned that, constraints of $LP(t_i)$ include many considerations such as network structure, ancillary services, etc. and the exact coefficients and dimensions of matrix $A$ are not publically available. For this purpose, we use a simplified version of the dispatch problem, which we shall denote by $SLP(t_i)$, where we only consider the demand constraints and the bid stacks offered by generators. In this way, $SLP(t_i)$ can be written in the form

$$SLP(t_i)$$

$$\min \sum_{g,b} c_b^g(v, t_i) x_b^g$$

$$\sum_{g,b} x_b^g = d_j(t_i); \qquad j \in \{1,2, \dots ,5\}$$

$$0 \le x_b^g \le v_b^g(t_i); \qquad g \in G \; and \; b \in B.$$

Recall that, if the optimal solution is non-unique and considering the projection function of $u(v, x, y) = y_j$, there exists a gap between shadow prices of demand in different optimal solutions.

## 4.3 COMBINED MODEL

In this section, we investigate the possibility of non-uniqueness of the optimal solution in a combined model. For simplicity, we consider the primal dispatch problem of $SLP(t_i)$ for a single state $j$ . Suppressing the given argument $v$ and $t_i$ for every five minute time interval, the dispatch problem becomes

$$SLP$$

$$\text{Min} \sum_{g,b} c_b^g x_b^g$$

$$\sum_{g,b} x_b^g \geq d$$

$$-x_b^g \geq -v_b^g; \qquad g \in G \text{ and } b \in B$$

$$x_b^g \geq 0.$$

The dual variable corresponding to the demand constraint shows the dispatch price for the five minute time interval. We denote this dual variable by $y'$ in the dual linear problem below.

$$DSLP$$

$$\text{Max } [y'd - \sum_{g,b} y_b^g v_b^g]$$

$$y' - y_b^g \leq c_b^g; \qquad g \in G \text{ and } b \in B$$

$$y', y_b^g \geq 0; \qquad g \in G \text{ and } b \in B,$$

where, $y'$ and $y_b^g s$ are the corresponding dual variables of the demand constraint and the bid stack constraints, respectively.

Based on the strong duality theorem (e.g. Luenberger, 1984, P89), if the primal linear programming problem has an optimal solution, then so does the dual problem and also the objective function values are equal. Here we consider a combined model ($PDLP$) below which consists of all of the primal and dual's constraints and additional constraint which forces the equality of objective functions of primal and dual problem.

$$PDLP$$

$$\sum_{g,b} x_b^g \geq d$$

$$-x_b^g \geq -v_b^g; \qquad g \in G \text{ and } b \in B$$

$$y' - y_b^g \leq c_b^g; \qquad g \in G \text{ and } b \in B$$

$$\sum_{g,b} c_b^g x_b^g = y'd - \sum_{g,b} y_b^g v_b^g$$

$$x_b^g, y', y_b^g \geq 0.$$

Basically, we use the combined $PDLP$ model above to find the possible set of optimal solutions for the primal and dual linear programming problems indirectly. Any feasible solution $\{x_b^g, y', y_b^g\}$, which satisfies all of the constraints of $PDLP$ , will supply an optimal solution for the original primal and dual linear programming problems, in the corresponding variables. Each optimal solution includes the shadow price which is the optimal dual variable corresponding to the demand constraint in the primal $LP$ problem. This variable is the basis for all the financial transactions between AEMO and the stakeholders via equation (4.1).

**Remark 4.3** Relating the combined model to Proposition 4.1 we consider the projection function of $u(v,x,y) = y'$ as the objective function, where $y'$ shows the dual variable corresponding to the demand constraint. In this way, in case of non-uniqueness of the optimal solution, we discover the range for $y'$ by minimising and maximising objective function of $u(x,y,v) = y'$, respectively.

To simplify we assume that dispatch price remains the same for all of the six periods used to calculate the spot price. In this way, we refer to the first dispatch price as the ultimate spot price for the corresponding trading interval. In the real case examples, the values for the dispatch price for every five minute interval is not publically available. Therefore we used the available spot price for each of the half an hour trading interval instead.

As mentioned above, ultimately, we are interested in the minimum and maximum value for spot price, $y'$. Therefore, in the following, the combined $PDLP$ model is run twice with the two different objective functions of minimising $y_1$, $PDLP^l$ and maximising $y_1$ , $PDLP^u$.

| $PDLP^l$ | $PDLP^u$ |
|---|---|
| $Min\, y'$ | $Max\, y'$ |
| $\sum_{g,b} x_b^g \geq d$ | $\sum_{g,b} x_b^g \geq d$ |
| $-x_b^g \geq -v_b^g; \qquad g \in G \text{ and } b \in B$ | $-x_b^g \geq -v_b^g; \qquad g \in G \text{ and } b \in B$ |
| $y' - y_b^g \leq c_b^g; \qquad g \in G \text{ and } b \in B$ | $y' - y_b^g \leq c_b^g; \qquad g \in G \text{ and } b \in B$ |
| $\sum_{g,b} c_b^g x_b^g = y'd - \sum_{g,b} y_b^g v_b^g$ | $\sum_{g,b} c_b^g x_b^g = y'd - \sum_{g,b} y_b^g v_b^g$ |
| $x_b^g, y', y_b^g \geq 0.$ | $x_b^g, y', y_b^g \geq 0.$ |

In this way, if the optimal solution is non-unique in the original $LP$ problem, we will find the lower, $y'^{l}$, and upper, $y'^{u}$, boundaries of optimal shadow prices. For a fixed demand parameter $d$, the difference between maximum and minimum shadow prices, instability gap is

$$I(v) = y'^{u} - y'^{l},$$

where the dependence on $d$ is suppressed while this parameter is fixed. Sections 4.4.1 and 4.4.2 show examples under two different scenarios of a small electricity market with three generators and the South Australian electricity market with 34 generators, respectively. In each section, results are compared in low and high demand trading intervals.

### 4.3.1 Three generators examples

Consider, a small electricity market in which just three generators offer to produce electricity and instead of 10 bands, they only offer the volume and price of electricity in three bands, that is, $g \in \{1,2,3\}$ $and$ $b \in \{1,2,3\}$ as in the following table. Also assume that, all generators have the same total capacity of 20 MW.

As Table 4.1 shows, generator G1 allocates its total capacity of 20 MW into the three band bid stack and offers 10 MW at the price of \$-5 per MWh, 10 MW at the price of \$0 and 0 MW at the price of \$15 per MWh in the bands one, two and three, respectively. Recall that, the negative sign for the price (\$-5) indicates that this generator may even be willing to pay the market to produce some electricity.

Table 4.1. Three generators bid stack.

| Generators | Capacity | volume offered at each band | | | Prices offered at each band | | |
|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 1 | 2 | 3 |
| G1 | 20 | 10 | 10 | 0 | -5 | 0 | 15 |
| G2 | 20 | 7 | 3 | 10 | 0 | 10 | 20 |
| G3 | 20 | 5 | 10 | 5 | -2 | 6 | 14 |

Similarly, the last two rows of Table 4.1 give the volume and price bid stacks of generators G2 and G3. By considering just these three generators in the market, the primal $LP$ and the corresponding dual problem are as follows.

$$LP$$

$$Min\ (c_1^1x_1^1 + c_2^1x_2^1 + c_3^1x_3^1 + c_1^2x_1^2 + c_2^2x_2^2 + c_3^2x_3^2 + c_1^3x_1^3 + c_2^3x_2^3 + c_3^3x_3^3)$$

$$x_1^1 + x_2^1 + x_3^1 + x_1^2 + x_2^2 + x_3^2 + x_1^3 + x_2^3 + x_3^3 \geq d$$

$$x_1^1 \leq v_1^1$$

$$x_2^1 \leq v_2^1$$

$$x_3^1 \leq v_3^1$$

$$x_1^2 \leq v_1^2$$

$$x_2^2 \leq v_2^2$$

$$x_3^2 \leq v_3^2$$

$$x_1^3 \leq v_1^3$$

$$x_2^3 \leq v_2^3$$

$$x_3^3 \leq v_3^3$$

$$x_1^1, x_2^1, x_3^1, x_1^2, x_2^2, x_3^2, x_1^3, x_2^3, x_3^3 \geq 0.$$

$$DLP$$

$$Max\ (y'd - y_1^1v_1^1 - y_2^1v_2^1 - y_3^1v_3^1 - y_1^2v_1^2 - y_2^2v_2^2 - y_3^2v_3^2 - y_1^3v_1^3 - y_2^3v_2^3 - y_3^3v_3^3)$$

$$y' - y_1^1 \leq c_1^1$$

$$y' - y_2^1 \leq c_2^1$$

$$y' - y_3^1 \leq c_3^1$$

$$y' - y_1^2 \leq c_1^2$$

$$y' - y_2^2 \leq c_2^2$$

$$y' - y_3^2 \leq c_3^2$$

$$y' - y_1^3 \leq c_1^3$$

$$y' - y_2^3 \leq c_2^3$$

$$y' - y_3^3 \leq c_3^3$$

$$y', y_1^1, y_2^1, y_3^1, y_1^2, y_2^2, y_3^2, y_1^3, y_2^3, y_3^3 \geq 0.$$

Hence the combined $PDLP^l$ and $PDLP^u$ models are as follows.

$$PDLP^l$$

$$Min\, y'$$

$$\sum_{g,b} x_b^g \geq d$$

$$x_b^g \leq v_b^g; \qquad g \in \{1,2,3\} \,\&\, b \in \{1,2,3\}$$

$$y' - y_b^g \leq c_b^g; \qquad g \in \{1,2,3\} \,\&\, b \in \{1,2,3\}$$

$$\sum_{g,b} c_b^g x_b^g = y'd - \sum_{g,b} y_b^g v_b^g$$

$$x_b^g, y', y_b^g \geq 0.$$

$$PDLP^u$$

$$Max\, y'$$

$$\sum_{g,b} x_b^g \geq d$$

$$x_b^g \leq v_b^g; \qquad g \in \{1,2,3\} \,\&\, b \in \{1,2,3\}$$

$$y' - y_b^g \leq c_b^g; \qquad g \in \{1,2,3\} \,\&\, b \in \{1,2,3\}$$

$$\sum_{g,b} c_b^g x_b^g = y'd - \sum_{g,b} y_b^g v_b^g$$

$$x_b^g, y', y_b^g \geq 0.$$

Now for a single trading interval we illustrate the solutions of the models above assuming the demand is equal to 42 MW. As shown in Table 4.2 and Table 4.3, by solving the models $PDLP^l$ and $PDLP^u$, we obtain different values for the optimal $y'$, namely $y'^u$ and $y'^l$.

Table 4.2. Generators bid stacks and shadow prices ($PDLP^l$).

| Generators | Capacity | $v_b^g$ | | | $x_b^{g^*}$ | | | $y'^l$ | Demand |
|---|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 1 | 2 | 3 | | |
| $G1$ | 20 | 10 | 10 | 0 | 10 | 10 | 0 | 6 | 42 |
| $G2$ | 20 | 7 | 3 | 10 | 7 | 0 | 0 | | |
| $G3$ | 20 | 5 | 10 | 5 | 5 | 10 | 0 | | |

Columns 6-8 of Table 4.2 show the optimal dispatch variables, $x_b^{g^*}$, indicating the volumes of electricity ordered from each generator in each price band. For instance, after the bids are submitted and the regulator solves $PDLP^l$ , then the regulator will buy the whole volume offered by generator $G1$ in the bands one, two and three, $x_1^{1^*} = 10MW$, $x_2^{1^*} = 10MW$ and $x_3^{1^*} = 0MW$. From generator $G2$, the regulator only buys the whole volume of electricity offered in the first band and buys nothing from bands two and three, $x_1^{2^*} = 7MW$, $x_2^{2^*} = 0MW$ and $x_3^{2^*} = 0MW$, and finally the regulator will buy just the volumes of electricity offered in the fisrt and second band by generator $G3$, $x_1^{3^*} = 5MW$, $x_2^{3^*} = 10MW$ and $x_3^{3^*} = 0MW$.

Table 4.3. Generators bid stacks and shadow prices ($PDLP^u$).

| Generators | Capacity | $v_b^g$ | | | $x_b^{g^*}$ | | | $y'^u$ | Demand |
|---|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 1 | 2 | 3 | | |
| $G1$ | 20 | 10 | 10 | 0 | 10 | 10 | 0 | 10 | 42 |
| $G2$ | 20 | 7 | 3 | 10 | 7 | 0 | 0 | | |
| $G3$ | 20 | 5 | 10 | 5 | 5 | 10 | 0 | | |

Similarly, after the bids are submitted and the regulator solves $(PDLP^u)$, the optimal dispatch variables, $x_b^{g^*}$, are $x_1^{1^*} = 10MW$, $x_2^{1^*} = 10MW$ and $x_3^{1^*} = 0MW$. $x_1^{2^*} = 7MW$, $x_2^{2^*} = 0MW$ and $x_3^{2^*} = 0MW$, $x_1^{3^*} = 5MW$, $x_2^{3^*} = 10MW$ and $x^* = 0MW$ (See Table 4.2). Results from Table 4.2 and Table 4.3 show that the instability gap exists and is equal to,

$$I = y'^u - y'^l = 10 - 6 = 4.$$

**Remark 4.4** At first sight it may appear surprising that the values of $x_b^{g^*}$ are the same in Table 4.2 and 4.3. However, we note that the corresponding optimal solutions differ in the $y_b^{g^*}$ variable and also in $y'^*$.

### 4.3.2 South Australian size examples

In this section we investigate whether the instability gap can also arise in more realistic size situations. For this purpose, we consider the state of South Australia which at certain times, in 2010 had 34 generators participating in the pool. Using $PDLP^l$ and

$PDLP^u$ models and the bidding strategies of these generators during a high spot price trading interval, we determine the instability gap which is shown in Table 4.4.

As Table 4.4 demonstrates, the optimal value of $y'$, or the shadow price, possesses a wide instability gap and the width of this gap is increasing as the demand increases.

Table 4.4. Instability gap in shadow prices.

| Min Shadow Price | Max Shadow Price | Instability Gap | Demand |
|---|---|---|---|
| 0 | 19.7 | 19.7 | 2877 |
| 108 | 287.63 | 179.63 | 3360 |
| 551.25 | 1454 | 902.75 | 3665 |
| 1454 | 3740 | 2286 | 3739 |
| 3740 | 9000.1 | 5260.1 | 3754 |

Note that in practice, the generated electricity must be higher that the forecasted demand for each trading interval. This is due to electrical resistance and the heating of conductors in the network. Therefore, more electricity must be generated to allow for this loss during transportation. AEMO considers a loss factor to ensure the delivery of adequate supply to meet prevailing demand and maintain the power system in balance. For more details see (AEMO, 2012b and AEMO, 2015).

## 4.4 DEPARTURES FROM BEHAVIOURAL ASSUMPTIONS

The results above show that not only the value for the shadow price is non-unique, but also that it could lie in a wide interval. Therefore a question arises as to why would consumers pay a considerably higher price, particularly in the high demand periods, if optimal solutions to $LP(t)$ exist with lower shadow prices?

Clearly, the current market is based on a behavioural assumption concerning the generators' bidding strategies. Namely, that their desire to compete against one another would, somehow, lead to the optimal solution of $LP$ with the lowest value, namely, $y' = {y'}^l$. However, there is no formal mechanism in the market design to prevent an optimal solution with the highest possible value, namely, $y' = {y'}^u$.

Hence it is worthwhile to consider what alternative behavioural assumptions about the generators may lead to, in terms of shadow price, and whether some of the observed bidding behaviour is in concordance with one, or more, of these alternative assumptions.

Recall that, the price that AEMO is going to pay to all generators is the same and is equal to the spot price. Therefore, the bidding behaviour among generators is complex and related not only to winning as much volume of electricity as possible but, perhaps, also to influencing the spot price.

In view of the above, the volumes offered at different price bands can be regarded not as parameters but as variables with the potential to steer the spot price in a favourable direction. Consequently, in the remainder of this section we introduce two nonlinear programs which treat volumes in bid stack as decision variables under two extreme behavioural assumptions: antagonism and altruism.

**Remark 4.5** We alert the reader that the "trivial" solutions under these assumptions are obvious but totally unrealistic. On one hand, under the antagonistic assumption, all generators might demand $\$10{,}000/MWh$ for every unit of electricity. However, that would trigger a reaction from AEMO and accusations of blatant non-competitive behaviour. On the other hand, offering to produce all electricity at zero or unrealistically low price would lead to bankruptcies.

Interestingly, however, the nonlinear programs we formulated also contain many local minima and maxima and the form of the bid stacks corresponding to the latter, at times, resembles what is actually observed in the market. This raises the question of whether the generators are, implicitly, acting as such local maximisers.

### 4.4.1 Extreme antagonistic and altruistic scenarios

Here we consider the extreme antagonistic scenarios described below.

Arguably, generators could be viewed as an "aggregated agent" interested in maximising the spot price. To the "aggregated generator", $LP(t)$ may be viewed merely as a reactive pricing mechanism that AEMO's regulations are committed to follow, no matter what bids they supply. Thus, the "aggregated generator" could, theoretically, view their problem as the combined non-linear optimisation model $NPD^u$, stated below. Under this behavioural assumption, the aggregated generator solves $NPD^u$ to obtain an optimal solution $(x_b^{g^*}, y'^*, y_b^{g^*}, v_b^{g^*})$ which maximises the shadow price and consequently their profit. Then each individual generator $g$ uses the $v_b^{g^*},\ b \in B$ values to supply their bid stack to AEMO.

$$NPD^u$$

$Max\, y'$

$\sum_{g,b} x_b^g \geq d;$

$x_b^g \leq v_b^g;$ $\quad g \in G \; and \; b \in B$

$y' - y_b^g \leq c_b^g;$ $\quad g \in G \; and \; b \in B$

$\sum_{g,b} c_b^g x_b^g = y'd - \sum_{g,b} y_b^g v_b^g\,;$ $\quad (*)$

$\sum_b v_b^g = Cap^g;$ $\quad g \in G$ $\quad (**)$

$x_b^g, y', y_b^g, v_b^g \geq 0.$

In $NPD^u$ model, $v_b^g{}'s$ become decision variables from the aggregated generators' perspective. This means that the constraint $(*)$ in $NPD^u$ is now nonlinear in the decision variables $y_b^g$ and $v_b^g$. Moreover, the constraint $(**)$ is included in the $(NPD^u)$ model to make sure the summation of volumes offered at each band by a particular generator, $\sum_b v_b^g$, is exactly equal to that generator's maximum available capacity.

$$NPD^l$$

$Min\, y'$

$\sum_{g,b} x_b^g \geq d;$

$x_b^g \leq v_b^g;$ $\quad g \in G \; and \; b \in B$

$y' - y_b^g \leq c_b^g;$ $\quad g \in G \; and \; b \in B$

$\sum_{g,b} c_b^g x_b^g = y'd - \sum_{g,b} y_b^g v_b^g\,;$

$\sum_b v_b^g = Cap^g;$ $\quad g \in G$

$x_b^g, y', y_b^g, v_b^g \geq 0.$

Similarly, AEMO could be viewed as an "agent" interested in minimising the spot price on behalf of the consumers. Therefore, AEMO would prefer generators to offer their bid stacks in a way that minimises the cost to consumers. Hence, from AEMO's perspective, the optimal bid stacks that minimise the cost to consumers are the results of the non-linear programming problem, $NPD^l$.

Results in Section 4.4.2 and Section 4.4.3 show that difference in the allocation of bid stacks would result in considerable instability gap in the shadow price.

### 4.4.2 Illustrative examples

Similarly to Section 4.3.1 assume, a small market consisting of three generators who offer their available capacity and band prices as in Table 4.5. Both $NPD^l$ and $NPD^u$ models are solved in a low and a high demand period. We note that the solutions obtained may be only local (rather than global) optima.

Table 4.5. Three generators bid stack.

| Generators | Capacity | Prices offered at each band | | |
|---|---|---|---|---|
| | | 1 | 2 | 3 |
| G1 | 20 | -5 | 0 | 15 |
| G2 | 20 | 0 | 10 | 20 |
| G3 | 20 | -2 | 6 | 14 |

#### *4.4.2.1 Low demand period*

Assume the price bands offered by the generators are fixed as in Table 4.5 above and all generators have the maximum available capacity of 20 MW. If in a particular trading interval, the demand is 22 MW then AEMO would prefer the bid stacks to look as in columns 3-5 in Table 4.6 to minimise the cost for consumers.

Table 4.6. Optimal volume to be offered and bought in the minimisation and maximisation problems in a low demand period.

| Generators | Capacity | $NPD^l$ | | | | | | $NPD^u$ | | | | | | Demand |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | $v_b^{g^*}$ | | | $x_b^{g^*}$ | | | $v_b^{g^*}$ | | | $x_b^{g^*}$ | | | |
| | | 1 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3 | |
| G1 | 20 | 1.19 | 0.81 | 18.00 | 1.19 | 0.81 | 0.00 | 2.00 | 0.00 | 18.00 | 2.00 | 0.00 | 0.00 | 22 |
| G2 | 20 | 0.00 | 20.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 20.00 | 0.00 | 0.00 | 0.00 | 0.00 | |
| G3 | 20 | 0.00 | 20.00 | 0.00 | 0.00 | 20.00 | 0.00 | 0.17 | 19.83 | 0.00 | 0.17 | 19.83 | 0.00 | |
| $y'$ | | 6 | | | | | | 10 | | | | | | |

Assuming the price bands are as in Table 4.5 above, generator G1 needs to offer $v_1^{1^*} = 1.19$ MW at the price of $c_1^1 = \$-5$ , $v_2^{1^*} = 0.81$ MW at the price $c_2^1 = \$0$ and $v_3^{1^*} = 18$ MW at the price $c_3^1 = \$15$. Similarly, the optimum bid stack offered by generator G2 to minimise AEMO's cost would be $v_1^{2^*} = 0$ MW at the price $c_1^2 = \$0$ , $v_2^{2^*} = 20$ MW at the price $c_2^2 = \$10$ and $v_3^{2^*} = 0$ MW at the price $c_3^2 = \$20$. Similarly, generator G3 needs to offer $v_1^{3^*} = 0$ MW at the price $c_1^3 = \$-2$ , $v_2^{3^*} = 20$ MW at the price $c_2^3 = \$6$ and $v_3^{3^*} = 0$ MW at the price $c_3^3 = \$14$ to minimise AEMO's cost.

Then, as shown in columns 6-8 of Table 4.6, AEMO would gather all these bid stacks offered and will buy all volume offered by generator G1 in the first two bands so $x_1^{1^*} = 1.19$ , $x_2^{1^*} = 0.81$ MW and $x_3^{1^*} = 0$. AEMO buys nothing from generator G2 so, $x_1^{2^*} = 0$ MW, $x_2^{2^*} = 0$ MW and $x_3^{2^*} = 0$ MW. AEMO also buys 20 MW from the second band of bid stack offered by generator G3, namely, $x_1^{3^*} = 0$ MW , $x_2^{3^*} = 20$ MW and $x_3^{3^*} = 0$ MW.

Next the $NPD^u$ solutions are obtained. Similarly to the above, the corresponding $v_b^{g^*}$ and $x_b^{g^*}$ variables for the maximising problem are as shown in columns 9-14 in Table 4.6. Note that the allocation of optimum bid stacks in Table 4.6 accompany the shadow prices of $y'^l = 6$ and $y'^u = 10$ for the minimising and maximising problems respectively, which indicates that the instability gap exists and is equal to

$IG = y'^u - y'^l \geq 10 - 6 = 4 > 0.$

Note that the first inequality in the above is due to the fact that the solution algorithm used is not guaranteed to find global optima. However, these inequalities demonstrate that a sizable instability gap exists.

Comparing the results from the $NPD^l$ nd $NPD^u$ problems in Table 4.6 above reveals two notable differences;

(i) The values of $v_b^{g^*}$ show some shifts in the portion of volume offered at each band. For instance, to maximise the profit, generators G1 and G3 need to change the allocation of their total capacity $(20\ MW)$ and shift more volume to be offered in the less expensive bands.
(ii) These shifts increased the value of shadow price, since the instability gap of four occurs, which will result in a higher profit for generators.

It should be noted that, results in Table 4.6 may correspond to only local minima and maxima. Indeed, the multiplicity of local optima can lead to solutions that show little or no difference in either the shadow price variables $y'$ or in the $v_b^{g^*}$ values. However, the results above indicate that shifts in the bid stacks variables $v_b^g$ can result in significant shifts in the shadow price variable $y'$.

#### 4.4.2.2 High demand period

Consider the demand increased to $d = 42$ (out of total capacity of 40). Then Table 4.7 shows the optimum bid stacks to be offered in order to optimise AEMO and the aggregated generator's utility function, respectively. Results demonstrate that even very small shifts in the volumes offered by the generators in various bands may result in significant change in the shadow price variable $y'$.

Table 4.7. Optimal volume to be offered and bought in the minimisation and maximisation problems in a high demand period.

| Generators | Capacity | $NPD^l$ | | | | | | $NPD^u$ | | | | | | Demand |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | $v_b^{g^*}$ | | | $x_b^{g^*}$ | | | $v_b^{g^*}$ | | | $x_b^{g^*}$ | | | |
| | | 1 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3 | |
| G1 | 20 | 20.00 | 0.00 | 0.00 | 20.00 | 0.00 | 0.00 | 17.14 | 2.86 | 0.00 | 17.14 | 2.86 | 0.00 | 42 |
| G2 | 20 | 1.00 | 1.00 | 18.00 | 1.00 | 1.00 | 0.00 | 0.01 | 1.99 | 18.00 | 0.01 | 1.99 | 0.00 | |
| G3 | 20 | 15.49 | 0.00 | 4.51 | 15.49 | 0.00 | 4.51 | 17.78 | 0.00 | 2.22 | 17.78 | 0.00 | 2.22 | |
| $y'$ | | 14 | | | | | | 20 | | | | | | |

Similarly to the low demand period we observe that:

(i) The instability gap shows that the optimum shadow price in $NPD^u$ is greater than that in $NPD^l$. Furthermore,

$$IG = {y'}^u - {y'}^l \geq 20 - 14 = 6.$$

(ii) The behaviour of generators in offering the optimum bidding behaviour is different in the $NPD^l$ and $NPD^u$ models. Generators G1 and G2 need to shift small portions of their total capacity to the more expensive band to gain more profit in the $NPD^u$ model. Generator G3 three behaves in an opposite direction and shifts more volume to the less expensive bands (See Table 4.8).

Table 4.8. Comparison of optimal bids in min/max problems.

| Generators | Capacity | $NPD^l$ | | | $NPD^u$ | | |
|---|---|---|---|---|---|---|---|
| | | $v_b^{g^*}$ | | | $v_b^{g^*}$ | | |
| | | 1 | 2 | 3 | 1 | 2 | 3 |
| G1 | 20 | 16.14 | 3.86 | 0 | 2.03 | 16.78 | 1.19 |
| G2 | 20 | 16 | 0 | 4 | 0 | 0 | 20 |
| G3 | 20 | 0 | 0 | 20 | 11.13 | 0.64 | 8.23 |

### 4.4.3 South Australian size examples

For this section, we used the data related to the particular day, the 8th of January 2010, in South Australia. On that day, there were 34 generators who participated in the pool in South Australia. This means that now the number of variables in both $NPD^l$ and $NPD^u$ models is 1021. As a result, finding even a local optimum for these models is a time consuming task. Both $NPD^l$ and $NPD^u$ models were coded and run using MATLAB but the running times were prohibitive.

In order to improve the process speed we tried to transfer the nonlinearity of the constraints to the objective function and hence used the penalty method. That is, we included a variable $w$ in the model where, $\sum_{g,b} y_b^g v_b^g = w$. Then the minimisation $NPD^l$ model, changes to the $\overline{NPD^l}$ model, where $M$ is the penalty cost introduced in the objective function and assumed to have a suitably large value.

$$\overline{NPD^l}$$

$$Min\left\{y' + M\left(w - \sum_{g,b} y_b^g v_b^g\right)^2\right\}$$

$$\begin{aligned}
&\textstyle\sum_{g,b} x_b^g \geq d; && \\
&x_b^g \leq v_b^g; && g \in G \; and \; b \in B \\
&y' - y_b^g \leq c_b^g; && g \in G \; and \; b \in B \\
&-\textstyle\sum_{g,b} c_b^g x_b^g + y'd = w; && \qquad (*) \\
&\sum_b v_b^g = Cap^g; && g \in G \\
&x_b^g, y', y_b^g, v_b^g \geq 0. &&
\end{aligned}$$

In the $\overline{NPD^l}$ model, the nonlinearity only exists in the objective function, as deviations from satisfying the only non-linear constraint in $NPD^l$ model are now penalized in the objective function. Similarly the $NPD^u$ model would convert to the $\overline{NPD^u}$ model below, where $M$ is the penalty cost, as before.

$$\overline{NPD^u}$$

$$Max\left\{y' - M\left(w - \sum_{g,b} y_b^g v_b^g\right)^2\right\}$$

$$\begin{aligned}
&\textstyle\sum_{g,b} x_b^g \geq d; && \\
&x_b^g \leq v_b^g; && g \in G \; and \; b \in B \\
&y' - y_b^g \leq c_b^g; && g \in G \; and \; b \in B \\
&-\textstyle\sum_{g,b} c_b^g x_b^g + y'd = w; && \qquad (*) \\
&\sum_b v_b^g = Cap^g; && g \in G \\
&x_b^g, y', y_b^g, v_b^g \geq 0. &&
\end{aligned}$$

These models were coded and run using MATLAB software and this time it took less than an hour to find a local optimum solution. Thus the speed of the process was significantly enhanced.

**Remark 4.6** As we run both $\overline{NPD^l}$ and $\overline{NPD^u}$ models, we realize that many local optima exist for these problems. Therefore, in this section, we do not necessarily intend to find the global minimum or maximum $y'$ in the $\overline{NPD^l}$ and $\overline{NPD^u}$ models. Rather, we try to investigate which forms of bid stacks would benefit generators or consumers in different circumstances such as during low or high spot price trading intervals.

Table 4.9. Prices offered by the 34 generators in South Australia on January 8th 2010.

| Generator | Price offered at each band | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| G1 | -976 | 1 | 97 | 142 | 293 | 576 | 976 | 9174 | 9565 | 9760 |
| G2 | -958 | 0 | 97 | 240 | 288 | 431 | 8623 | 9533 | 9580 | 9581 |
| G3 | -958 | 0 | 97 | 240 | 288 | 431 | 8623 | 9533 | 9580 | 9581 |
| G4 | -962 | -605 | -505 | -405 | -305 | -205 | -105 | -55 | 0 | 9619 |
| G5 | -1006 | 0 | 70 | 100 | 301 | 503 | 1510 | 5031 | 8855 | 10062 |
| G6 | -1006 | 0 | 70 | 100 | 301 | 504 | 1510 | 5031 | 8855 | 10062 |
| G7 | -1006 | 0 | 70 | 100 | 301 | 503 | 1510 | 5031 | 8855 | 10062 |
| G8 | -975 | -89 | -39 | 0 | 39 | 73 | 98 | 976 | 8784 | 9750 |
| G9 | -949 | -99 | -75 | -25 | 0 | 80 | 99 | 199 | 497 | 8948 |
| G10 | -1011 | 0 | 30 | 50 | 70 | 149 | 300 | 2000 | 9100 | 9980 |
| G11 | -1011 | 0 | 30 | 50 | 70 | 149 | 300 | 2000 | 9100 | 9980 |
| G12 | -989 | -311 | -5 | 0 | 5 | 25 | 100 | 299 | 976 | 9891 |
| G13 | -969 | 0 | 67 | 96 | 290 | 485 | 1454 | 4844 | 8526 | 9689 |
| G14 | -965 | 0 | 11 | 24 | 35 | 48 | 75 | 108 | 258 | 3740 |
| G15 | -965 | 0 | 11 | 24 | 35 | 48 | 75 | 108 | 258 | 3740 |
| G16 | -1000 | 0 | 20 | 30 | 56 | 75 | 101 | 301 | 9500 | 9980 |
| G17 | -967 | 0 | 18 | 27 | 37 | 65 | 99 | 146 | 265 | 9402 |
| G18 | -916 | 0 | 274 | 280 | 536 | 1375 | 4580 | 7786 | 8061 | 9161 |
| G19 | -1000 | -5 | 13 | 20 | 30 | 36 | 299 | 1500 | 4999 | 9998 |
| G20 | -1000 | 0 | 55 | 75 | 150 | 200 | 300 | 1000 | 9000 | 9960 |
| G21 | -1000 | 0 | 55 | 75 | 150 | 200 | 300 | 1000 | 9000 | 9960 |
| G22 | -1000 | 0 | 55 | 75 | 150 | 200 | 300 | 1000 | 9000 | 9960 |
| G23 | -1000 | 0 | 55 | 75 | 150 | 200 | 300 | 1000 | 9000 | 9960 |
| G24 | -1000 | 0 | 55 | 75 | 150 | 200 | 300 | 1000 | 9000 | 9960 |
| G25 | -40 | 1 | 2 | 4 | 8 | 16 | 32 | 64 | 128 | 256 |
| G26 | -942 | 0 | 282 | 288 | 551 | 1413 | 4707 | 8002 | 8285 | 9415 |
| G27 | -1001 | 29 | 34 | 39 | 46 | 56 | 76 | 101 | 401 | 10008 |
| G28 | -1001 | 29 | 34 | 39 | 46 | 56 | 76 | 101 | 401 | 10008 |
| G29 | -1001 | 29 | 34 | 39 | 46 | 56 | 76 | 101 | 401 | 10008 |
| G30 | -1001 | 29 | 34 | 39 | 46 | 56 | 76 | 101 | 401 | 10008 |
| G31 | -1001 | 29 | 34 | 39 | 46 | 56 | 76 | 101 | 401 | 10008 |
| G32 | -1001 | 29 | 34 | 39 | 46 | 56 | 76 | 101 | 401 | 10008 |
| G33 | -1001 | 29 | 34 | 39 | 46 | 56 | 76 | 101 | 401 | 10008 |
| G34 | -1001 | 29 | 34 | 39 | 46 | 56 | 76 | 101 | 401 | 10008 |

Hereafter using $\overline{NPD^l}$ and $\overline{NPD^u}$ models we intend to answer the following questions.

(i) Assuming the price of the bands are fixed all the time[27], as in Table 4.9 below, what would be the optimum bidding stacks offered by the 34 generators to minimise the cost to consumers at this trading interval?

(ii) How would this behaviour change if they intend to maximise the shadow price for this trading interval?

(iii) How would bid stacks change if demand is related to a low or high spot price trading interval?

To answer questions (i) and (ii) above we need to determine the perspective from which we look at the $NPD$ problem. In other words by solving the $\overline{NPD^l}$ problem we are intrinsically, trying to find the optimum bid stacks associated with each generator that results in the best outcome for consumers and, albeit indirectly, the minimum shadow price. On the other hand, if we deal with the $NPD$ problem from generators' point of view, we basically need to solve $\overline{NPD^u}$ and find the optimum bid stacks that result in the "highest" shadow price, for that trading interval, in favour of generators.

Recall that, because of penalties resulting from repeated occurrence of maximum allowed price, in practice, generators could be searching for a local maximum. See Section 1.5.3 for more discussion.

#### *4.4.3.1 Consumers' point of view*

As we mentioned earlier, to achieve the best outcome in favour of consumers we need to solve $\overline{NPD^l}$ to find the optimum bid stacks associated with each generator which result in the minimum $y'$. In the following the $\overline{NPD^l}$ model is solved using MATLAB for January 8th 2010 in both low and high spot price trading interval.

(i) Consider a low spot price trading interval where demand is $d = 1295MW$. Then by solving $\overline{NPD^l}$ the optimum bid stacks associated with each generators are as shown in Table 4.10. These bid stacks offered by generators resulted in the minimum $y' = \$19.69/MWh$ .
In order to reach a better understanding of how, in general, generators shape their bid stack, we show the aggregated bid stacks in Table 4.11. In that table, the optimum volume offered by all generators is displayed at each price band, to achieve a local minimum shadow price in favour of consumers. In other

[27] Recall from discussion in Section 3.3 that, in practice, it was observed that generators do not change prices of the ten bands and merely adjust the volumes offered in each band.

words, if we consider AEMO as a representative for consumers then, considering the low demand value for this trading interval, AEMO prefers the aggregated bid stack to look as shown in Table 4.11.

Table 4.10. Volumes to be offered by the 34 generators in South Australia on January 8th 2010, low spot price trading interval.

| | Volume at each band | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Generator | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| G1 | 0.00 | 0.00 | 0.00 | 0.02 | 0.00 | 0.01 | 0.00 | 0.03 | 0.01 | 219.93 |
| G2 | 0.00 | 29.98 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| G3 | 0.00 | 19.96 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.02 |
| G4 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 57.00 | 0.00 |
| G5 | 0.00 | 104.80 | 0.02 | 0.02 | 0.02 | 0.04 | 0.04 | 0.04 | 0.01 | 0.01 |
| G6 | 0.00 | 104.86 | 0.03 | 0.03 | 0.00 | 0.00 | 0.03 | 0.01 | 0.02 | 0.02 |
| G7 | 0.00 | 104.67 | 0.03 | 0.02 | 0.15 | 0.02 | 0.03 | 0.05 | 0.01 | 0.01 |
| G8 | 0.00 | 0.00 | 0.00 | 94.92 | 0.02 | 0.01 | 0.01 | 0.01 | 0.02 | 0.02 |
| G9 | 0.00 | 0.00 | 0.00 | 0.00 | 70.99 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 |
| G10 | 0.00 | 0.17 | 0.01 | 0.00 | 0.01 | 0.01 | 0.00 | 0.09 | 87.66 | 0.05 |
| G11 | 0.00 | 0.06 | 0.01 | 0.01 | 0.00 | 0.00 | 0.00 | 0.19 | 87.70 | 0.02 |
| G12 | 0.00 | 0.00 | 0.00 | 143.71 | 0.01 | 2.94 | 1.56 | 2.21 | 7.89 | 0.68 |
| G13 | 0.00 | 0.00 | 0.00 | 26.84 | 145.49 | 31.59 | 0.00 | 0.05 | 0.01 | 0.00 |
| G14 | 0.00 | 105.12 | 0.01 | 0.01 | 0.01 | 0.02 | 0.01 | 50.11 | 0.01 | 124.71 |
| G15 | 0.00 | 106.57 | 0.03 | 0.03 | 0.03 | 0.00 | 0.00 | 0.00 | 0.01 | 173.32 |
| G16 | 0.00 | 0.00 | 0.00 | 68.02 | 0.00 | 0.00 | 0.00 | 0.00 | 161.96 | 0.00 |
| G17 | 0.00 | 109.40 | 0.00 | 0.01 | 0.01 | 0.02 | 8.61 | 0.07 | 0.01 | 133.86 |
| G18 | 0.00 | 54.95 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 | 0.01 |
| G19 | 0.00 | 60.32 | 0.00 | 116.78 | 5.40 | 148.89 | 0.01 | 0.06 | 45.11 | 133.41 |
| G20 | 0.00 | 0.03 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 44.91 | 0.04 |
| G21 | 0.00 | 0.02 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 46.94 | 0.02 |
| G22 | 0.00 | 0.02 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 44.93 | 0.03 |
| G23 | 0.00 | 0.03 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 44.93 | 0.03 |
| G24 | 0.00 | 0.01 | 0.00 | 0.00 | 0.01 | 0.01 | 0.01 | 0.01 | 242.73 | 5.22 |
| G25 | 0.00 | 0.02 | 0.02 | 0.00 | 21.60 | 12.64 | 16.41 | 14.68 | 15.50 | 18.13 |
| G26 | 0.00 | 92.36 | 0.01 | 37.53 | 0.07 | 0.01 | 0.02 | 0.00 | 0.00 | 0.01 |
| G27 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 130.00 |
| G28 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 17.83 | 112.17 |
| G29 | 0.00 | 9.15 | 0.01 | 18.98 | 84.52 | 14.80 | 2.54 | 0.00 | 0.00 | 0.00 |
| G30 | 0.00 | 0.00 | 0.00 | 91.73 | 38.27 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| G31 | 0.00 | 39.52 | 0.00 | 0.00 | 170.47 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| G32 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 210.00 |
| G33 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 210.00 |
| G34 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 210.00 |

As Table 4.11 shows, in order to achieve a local minimum value for $y'$ in this trading interval, for consumers sake, AEMO would hope that the aggregated bid stack offered by all generators were relatively evenly distributed. This form of bidding strategy by generators in this low demand period would result in a low spot price which benefits consumers.

Table 4.11. Aggregated volumes to be offered by the 34 generators in South Australia on January 8th 2010, low spot price trading interval.

| Volume | $v_1$ | $v_2$ | $v_3$ | $v_4$ | $v_5$ | $v_6$ | $v_7$ | $v_8$ | $v_9$ | $v_{10}$ |
|---|---|---|---|---|---|---|---|---|---|---|
| Sum | 0.00 | 942.01 | 0.2 | 598.7 | 537.1 | 211.0 | 29.3 | 67.66 | 905.20 | 1681.72 |
| $y'$ | $19.69/MWh | | | | | | | | | |

Next, we consider a number of alternate scenarios. For simplicity, we provide only the aggregated bid stacks in the other trading intervals. The details of volumes offered by each generator corresponding to each aggregated bid stack are shown in Appendix 4.1.

(ii) Now suppose that, demand increases to $d = 2793MW$. Consequently, to minimise the cost for consumers, the aggregated generator needs to offer higher proportion of the total capacity in lower prices.

Table 4.12. Aggregated volumes to be offered by the 34 generators in South Australia on January 8th 2010, high spot price trading interval.

| Volume | $v_1$ | $v_2$ | $v_3$ | $v_4$ | $v_5$ | $v_6$ | $v_7$ | $v_8$ | $v_9$ | $v_{10}$ |
|---|---|---|---|---|---|---|---|---|---|---|
| Sum | 79.50 | 3094.2 | 352 | 519.70 | 244.80 | 145.6 | 122.6 | 4.91 | 63.88 | 345.6 |
| $y'$ | $0.01/MWh | | | | | | | | | |

For instance, in a lower demand period, generators needed to offer about $942MW$ in the second band in order to reach the minimum shadow price. However, the total offer at the second band price now needs to increase to $3094MW$ so that we could achieve a low shadow price of $\$0.01/MWh$ in favour of consumers (See Table 4.12).

### *4.4.3.2 Generators' point of view*

Now consider the $NPD$ problem from generators' point of view. For generators, logically, the best outcome from the $NPD$ problem would be the maximum shadow price. Therefore they would search for the optimum bid stacks offered that will, at least locally, maximise their own profit at each trading interval. Below we consider three different scenarios for generators.

(i) Suppose that demand corresponds to a low spot price period and is equal to $d = 1295MW$. Then by solving $\overline{NPD^u}$ the optimum bid stacks that the aggregated generator needs to offer is as shown in Table 4.13. These bid stacks offered by generators resulted in the locally maximum shadow price of $y' = \$3740/MWh$. As Table 4.13 shows, in this low demand period, to reach that high shadow price, generators simply need to offer substantial portion of production at the higher price bands.

Table 4.13. Aggregated volumes to be offered by the 34 generators in South Australia on January 8th 2010, low spot price trading interval.

| Volume | $v_1$ | $v_2$ | $v_3$ | $v_4$ | $v_5$ | $v_6$ | $v_7$ | $v_8$ | $v_9$ | $v_{10}$ |
|---|---|---|---|---|---|---|---|---|---|---|
| Sum | 123.4 | 232.4 | 95.5 | 0 | 92 | 240.3 | 125.8 | 182.6 | 587.7 | 3012.5 |
| $y'$ | $3740/MWh | | | | | | | | | |

As demand increases, generators find more opportunities to offer strategically to maximise their own profit. In the following we provide two forms of bidding behaviour which both result in a very high shadow price in this trading interval.

(ii) Considering the demand increased to $d = 2793MW$, Table 4.14 shows that generators are able to maximise their profit, by maximising shadow price, if they again offer a large portion in the high price bands. As shown in Table 4.14, these generators need to offer 2497 MW in the highest price band, band 10, to be able to achieve a high spot price for this trading interval. This form of bidding behaviour results in the shadow price of $y' = \$9581/MWh$.

Table 4.14. Aggregated volumes to be offered by the 34 generators in South Australia on January 8th 2010, high spot price trading interval.

| Volume | $v_1$ | $v_2$ | $v_3$ | $v_4$ | $v_5$ | $v_6$ | $v_7$ | $v_8$ | $v_9$ | $v_{10}$ |
|---|---|---|---|---|---|---|---|---|---|---|
| Sum | 99 | 662 | 71 | 0 | 69 | 171 | 105 | 159 | 570 | 2497 |
| $y'$ | $9581/MWh | | | | | | | | | |

However, in high demand periods, a more subtle "bimodal" bidding behaviour has been observed in practice (see also Section 3.2). Interestingly, that behaviour also corresponds to some local maxima of $\overline{NPD^u}$ .

Table 4.15. Aggregated volumes to be offered by the 34 generators in South Australia on January 8th 2010, high spot price trading interval.

| Volume | $v_1$ | $v_2$ | $v_3$ | $v_4$ | $v_5$ | $v_6$ | $v_7$ | $v_8$ | $v_9$ | $v_{10}$ |
|---|---|---|---|---|---|---|---|---|---|---|
| Sum | 54 | 2457 | 60 | 607 | 98 | 20 | 53 | 64 | 175 | 1369 |
| $y'$ | $9000/MWh | | | | | | | | | |

For instance, when demand was increased to $d = 3510MW$ , MATLAB solver generated a solution that yielded a shadow price $y' = \$9000/MWh$ and the aggregated bidding behaviour given in Table 4.15. Note the high volumes offered both in the low price band 2 and in the high price band 10.

# CHAPTER 5. DISINCENTIVES TO STRATEGIC BIDDING

In the preceding chapters we have demonstrated that AEMO's current method of arriving at electricity spot price does not contain a mechanism to prevent generators from strategic bidding that may result in spot price spikes. Indeed, bimodal bid stack structures have been observed during times when spot price attained (or approached) the highest permissible level (see Section 3.2).

If public consensus were reached that such extreme oscillations in spot price are undesirable, then AEMO may wish to consider changes to its pricing mechanism aimed at creating disincentives to strategic bidding. Furthermore, it may be desirable to consider structurally "minimal changes" in the sense that the bulk of the existing mechanism remains in place. Arguably, these might be considered least disruptive to the ongoing operations.

Consequently, in this last technical chapter of the thesis we propose a new approach to create disincentives to strategic bidding. This mean-value approach is inspired by the famous concept of Aumann-Shapley Prices (e.g., see Tauman 1982) to determine the spot price. We shall demonstrate that this approach has the potential for discouraging strategic bidding and for reducing the ultimate spot price for electricity.

## 5.1 BACKGROUND

Since the Aumann-Shapley pricing schemes have their roots in research in Economics and Game Theory, for the sake of completeness, we briefly review some relevant literature addressing the potential problems with achieving truly competitive behaviour in the electricity market.

Since 1980's traditional state monopoly paradigm of power industry has changed in order to increase competition. However there is still doubt about the degree of genuine competitiveness in electricity markets. Some researchers believe that deregulation in electricity markets changed these markets to some kind of oligopoly markets (Borenstein and Bushnell 2000).

Literature discusses some possible reasons behind this. The latter included factors such as limited number of producers, barriers to entry as a consequence of large investment size, transmission constraints that make it hard for consumers to reach many generators and finally transmission losses that discourage end-users from purchasing their electricity from suppliers far away (David and Wen 2001).

The above factors create a situation where a small number of generators serve a specific geographic area. These generators may also be able to maximize their own profit by some specific behaviour in bidding which we call "Strategic Bidding".

Essentially, the performance of market is measured by the economic notion called "Social Welfare". Social welfare is a combination of the cost of a commodity and the benefit of that commodity to the society. Real markets always operate at a lower than maximum levels of social welfare. The difference in social welfare between a perfect market and a real market is a measure of the inefficiency in the real market (David and Wen 2000).

In a perfect electricity market, any power supplier would be a price taker. Microeconomic theory stipulates that the optimal bidding strategy for a supplier is to simply bid the marginal cost. When a generator bids other than marginal cost (in an effort to exploit imperfections in the market to increase profit) this behaviour is called strategic bidding (David and Wen 2000).

If for a number of generators their profit grows as a result of their strategic bidding or by any means other than lowering their costs, then they are exercising market power. In David and Wen (2001) the authors claim that there are essentially only three ways by which generators could possibly exercise market power.

The first way for increasing profit for generators is the estimation of marginal cost of production, where generators can increase their profit by offering a price just a little bit less than the marginal cost of production. Second way is through estimation of the bidding behaviour of other generators in the market. Most of the methods until 2000 for estimating bidding strategies of other parties include techniques such as statistics, probability analysis and fuzzy sets. The third way is by using Game Theory to analyse the behaviour of generators (Exelby 1993, Ferrero et al 1997, Green et al 1992, Von Neumann and Morgenstern 1944, Jones 1980).

## 5.2 AUMANN-SHAPLEY INSPIRED PRICING MECHANISM

In the economics literature there is a well developed theory of pricing mechanisms of commodities that stems from the seminal work of Aumann and Shapley (1974). Billera et al. (1978) were the first to introduce the AS prices as an application of the theory of values of nonatomic games developed by Aumann and Shapley (1974). They proposed equitable telephone billing rates that share the cost of service.

That theory has evolved to supply pricing mechanisms that satisfy desirable properties. Indeed, in many situations, a closed form formula is available that supplies the unique price mechanism with prescribed properties. We refer the reader to a comprehensive survey of this field by Tauman (1988). Somewhat loosely, we shall call these pricing mechanisms, Aumann-Shapley prices.

In the case of a single commodity, assume that $F(\alpha)$ is a differentiable cost function, where $\alpha \neq 0$ is a specific production level of that commodity. Let $AC(F,\alpha) = {F(\alpha)}/{\alpha}$ be the average cost pricing rule for the single product case and consider four properties of $AC(F,\alpha)$

(i) Cost sharing: $\alpha AC(F,\alpha) = F(\alpha)$ for each $\alpha > 0$.

(ii) Additivity: $AC(F+G,\alpha) = AC(F,\alpha) + AC(G,\alpha)$.

(iii) Rescaling: If $G(x) = F(\omega x)$, then $AC(G,\alpha) = \omega AC(F,\omega\alpha)$.

(iv) Continuity: $AC(.,\alpha)$ is continuous with respect to the $C^1$ norm. (i.e., if $F_n \to F$ in the $C^1$ norm on $[0,\alpha]$ then $AC(F_n,\alpha) \to AC(F,\alpha)$ as $n \to \infty$.

Based on Mirman and Tauman's theorem (1982), the Aumann-Shapley price mechanism that satisfies all these properties is given by the formula

$$P(F,\alpha) = \int_0^1 \frac{\partial F}{\partial x}(t\alpha)dt, \qquad (AS)$$

where $F(x)$ is the cost of producing $x$ units of the commodity and $\frac{\partial F}{\partial x}$ is the marginal cost of producing one additional unit.

We observe certain, important, similarities and differences between an Aumann-Shapley pricing mechanism and AEMO's pricing of electricity in Australian electricity market. In particular, recall the simplified dispatch linear programming problem $LP(d)$, for a single state, where $d$ is the demand for electricity.

$$
\begin{aligned}
& LP(d) \\
& \text{Min} \sum_{g,b} c_b^g x_b^g \\
& \textstyle\sum_{g,b} x_b^g \geq d \\
& -x_b^g \geq -v_b^g; \qquad\qquad g \in G \; and \; b \in B \\
& x_b^g \geq 0.
\end{aligned}
$$

This program uses generators' bids and determines the shadow price $y'(d)$ for different values of $d$. Note that $y'(d)$ can be regarded as the marginal cost of supplying $d\ MW$ of electricity in the time interval in question.

However, it should be noted that when generators submit their bid stacks into $LP(d)$, they do not know the value of the demand d which is a realisation of the demand random variable $D$. Hence, it is not automatically clear why they should be paid the shadow price of $y'(d)$ for all the electricity they generate during that period. To some extent the current AEMO pricing mechanism acknowledges this by calculating the spot price for a half an hour long period as the average of six consecutive shadow prices (see Section 1.6.1.2). On the other hand, the latter seems like an ad hoc resolution to the problem that researchers working on the Aumann-Shapley price mechanisms had investigated since 1980's.

Consequently, in this section we propose an alternative pricing mechanism that is similar to Aumann-Shapley pricing. The main difference arises from the fact that – in order to keep the overall structure as similar as possible to the current AEMO operations – we still wish to treat the shadow price $y'(d)$ as the marginal cost of production when the demand is $d$ even though the latter need not be differentiable with respect to $d$ (because of possible jumps of optimal bases when $d$ changes).

Despite the above difference, numerically, it is still possible to calculate $y'(\mu d)$ for values of the parameter $\mu$ ranging from 0 to 1 and to numerically approximate

$$AP_1(d) = \int_0^1 y'(\mu d) d\mu, \qquad (AP_1)$$

where $AP_1(d)$ denotes average (or mean value) marginal price per unit of electricity generated.

The next issue concerns the value of the demand $d$ that should be used in the equation $(AP_1)$. As indicated above, in a given time period on a given day of the week (in a particular season of the year) the demand $D$ is a random variable whose distribution and realistic minimal and maximal values $d_l$ and $d_u$ can be accurately estimated. Hence we shall argue that a natural choice for the average marginal price is either $(AP_1)$, or

$$AP_2(d) = \frac{1}{\mu_u - \mu_l} \int_{\mu_l}^{\mu_u} y'(\mu d) d\mu, \qquad (AP_2)$$

where $\mu_u$ and $\mu_l$ are chosen so that $d_u = \mu_u d$ and $d_l = \mu_l d$, respectively. While $(AP_1)$ is closer to Aumann-Shapley mechanism in the sense that it considers marginal costs for all possible outputs, in the case of electricity production outputs below $d_l$ are so unlikely that it seems unreasonable to consider them and hence $(AP_2)$ may be preferable. Illustrations below demonstrate that in likely applications $AP_2(d) > AP_1(d)$, making $(AP_2)$ preferable for generators. However, both mechanisms tend to yield much lower prices than the currently used $y'(d)$, during periods of high demand.

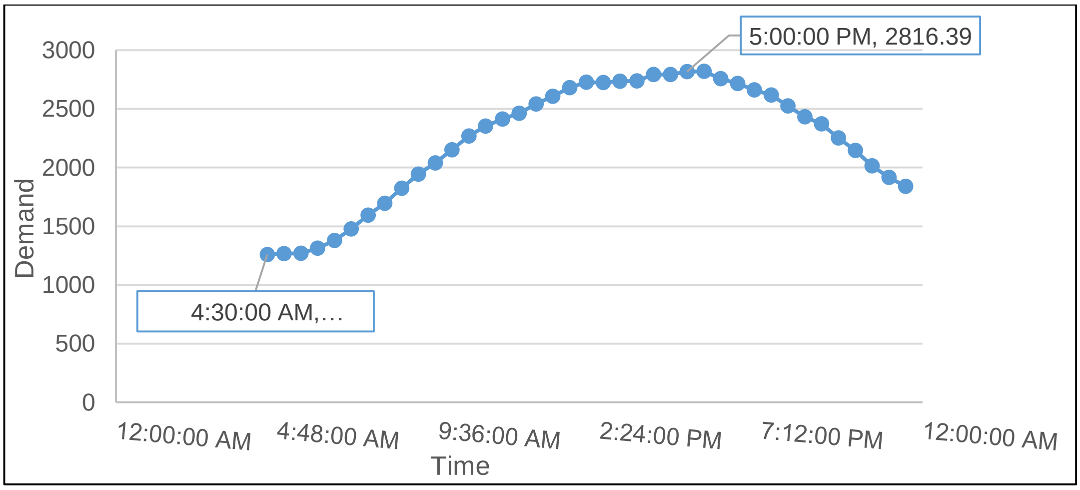


Figure 5.1. Electricity demand in January 8th 2010.

In the following we determine the electricity price using two approaches of $AP_1$ and $(AP_2)$. Figure 5.1 shows the variation in the electricity demand on the 8th January 2010. As shown in Figure 5.1 the minimum and maximum demand for electricity occur at the 4:30 AM where $d_l = 1259.48MW$, and at 5:00 PM where $d_u = 2818.68MW$, respectively.

### 5.2.1 Average price based on $(AP_1)$:

Here, we apply $(AP_1)$ to find the electricity price in two selected low and high demand trading intervals of 10:00 AM and 4:30 PM in January 8th 2010. All itegrals in the remainder of this chapter are evaluated numerically.

(i) Consider the selected trading interval of 10:00 AM in January 8th 2010. We let $\mu$ vary in the interval of $0 \leq \mu \leq 1$, and using generators bid stacks offered in $LP(d)$ model we determine $y'(\mu d)$ in this trading interval. Figure 5.2 shows the shadow prices $y'(\mu d)$ for different values of $\mu$. As shown in the Figure, the actual demand for the trading interval 10:00 AM, $d = 2151.89$, corresponds to $\mu = 1$ where the shadow price is $y'(d) = \$38.80/\text{MWh}$.

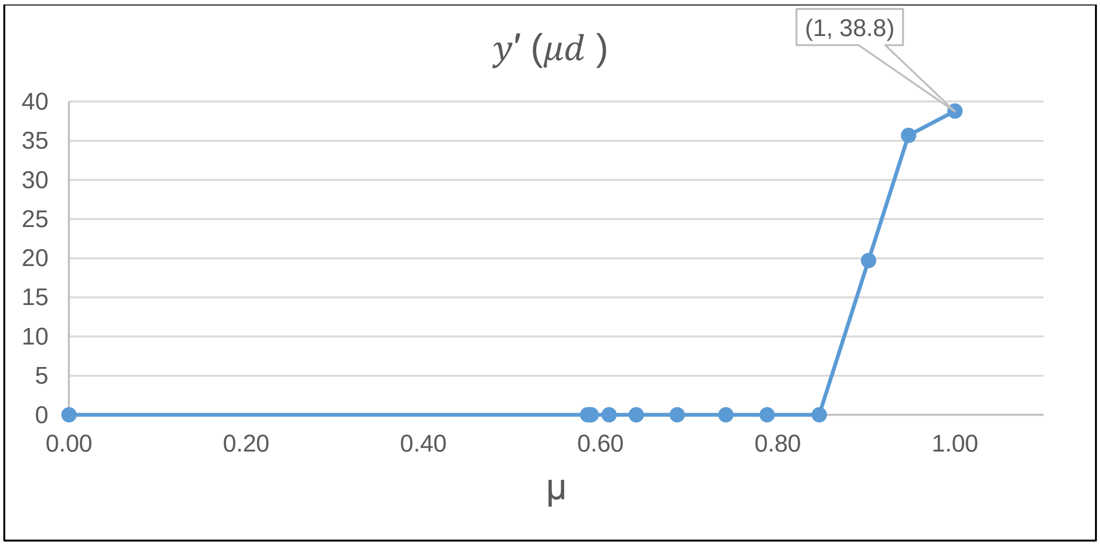


Figure 5.2. Shadow prices corresponding to different values of μ. Low demand trading interval.

Then $AP_1(d)$ price for electricity in this trading interval is determined by,

$$AP_1(d) = \int_0^1 y'(\mu d)d\mu, \approx \$3.75/MWh,$$

which is significantly lower than $\$38.80/\text{MWh}$ mentioned above. It will be seen that this difference is narrowed when $AP_2(d)$ is used instead of $AP_1(d)$.

(ii) Similarly, we apply $(AP_1)$ approach to find the electricity price in a high demand trading interval of 4:30 PM, where $d = 2793.33MW$[28]. Figure 5.3 shows the shadow prices $y'(\mu d)$ for different values of $\mu$.

As shown in the Figure 5.3, $y'(\mu d) = 0$ corresponding to the $\mu < 0.93$, that is $d < 2605MW$. As described in Sections 3.2 and 3.5 the distribution of volumes offered is positively skewed. Therefore, the majority of total electricity production offered by generators are in very low price bands. This results in an even lower price average $(AP_1)$, for electricity in this trading interval, namely

$$AP_1(d) = \int_0^1 y'(\mu d)d\mu, \approx \$1.77/MWh.$$

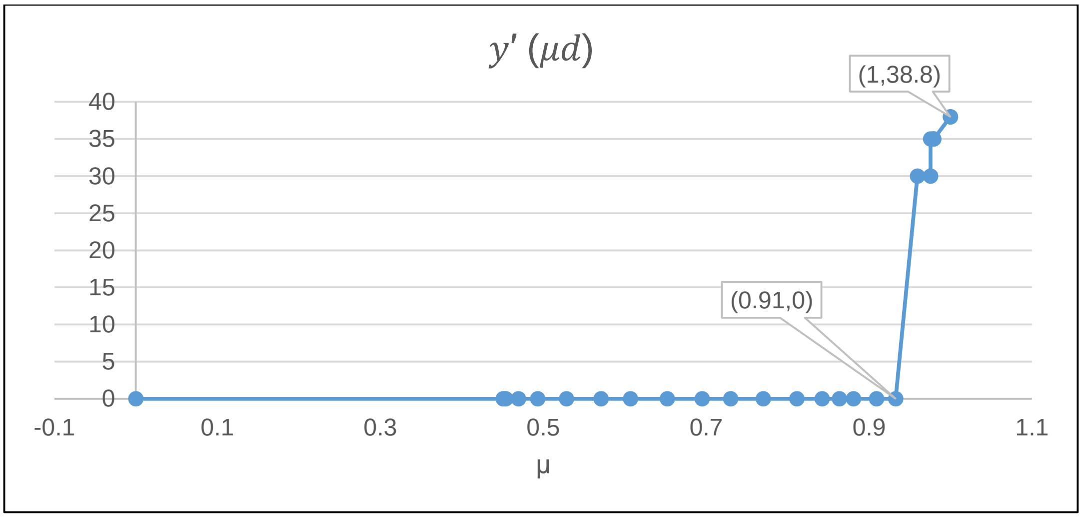


Figure 5.3. Shadow prices corresponding to different values of μ. High demand trading interval.

Note that the shadow price determined by $LP(d)$ model with the demand value $d = 2793$ for this trading interval was again $\$38.80/\mathrm{MWh}$.

### 5.2.2 Average price based on $(AP_2)$.

Next, we consider the situation where capture demands that can change from the minimum to the maximum possible demand in the summer 2010 at the corresponding trading interval. As before, we calculate the $(AP_2)$ price for two selected low and high demand trading intervals of 10:00 AM and 4:30 PM on January 8th 2010 .

[28] It should be mentioned that, an extra 10% of MW s added to the demand in this high demand trading interval to overcome the possible loss in network (see (AEMO, 2012b) and (AEMO, 2013a) for more information).

Here we let $\mu$ vary within the interval of $\mu_l \leq \mu \leq \mu_u$ where $\mu_l = \frac{d_l}{d}$ and $\mu_u = \frac{d_u}{d}$, and determine the values of $y'(\mu d)$ for $\mu \epsilon [\mu_l, \mu_u]$.

(i) Figure 5.4 shows $y'(\mu d)$ for the corresponding $\mu$ values for the trading interval of 10:00 AM on January 8th 2010. Here we selected data set of all $10AM$ trading intervals within summer 2010. The minimum and maximum demand level corresponding to the trading intervals within this data set are $d_l = 1091.2$ and $d_u = 2861.16$ respectively. Therefore, $\mu$ varies in the interval of $0.56 \leq \mu \leq 1.3$.

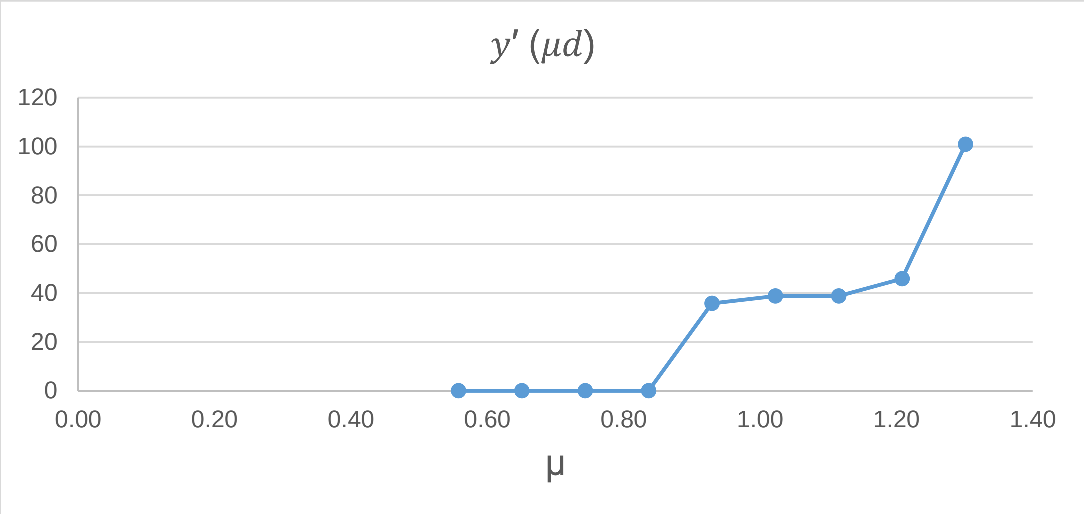


Figure 5.4. Shadow prices corresponding to different values of μ. Low demand trading interval.

Then $AP_2(d)$ price for electricity in this trading interval is determined by,

$$AP_2(d) = \frac{1}{\mu_u - \mu_l} \int_{\mu_l}^{\mu_u} y'(\mu d) d\mu \approx \$19.47/MWh.$$

(ii) Similarly to the above, to find the electricity price for a high demand period at 4:30 PM where $d = 2793.33$. The minimum and maximum demand level corresponding to the trading intervals within this data set are $d_l = 1150$ and $d_u = 3150$ respectively. Based on $AP_2$ approach, we let the $\mu$ vary in the interval of $\mu_l \leq \mu \leq \mu_u$, where $\mu_l = \frac{d_l}{d} = 0.40$ and $\mu_u = \frac{d_u}{d} = 1.13$, and find the $y'(\mu d)$. Figure 5.5 shows $y'(\mu d)$ for the corresponding $\mu$ values.

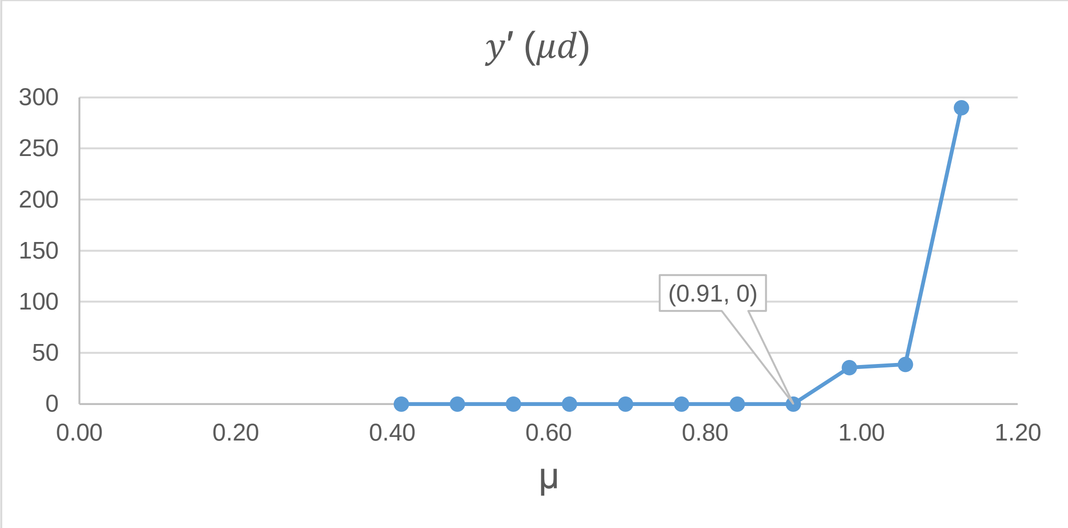


Figure 5.5. Shadow prices corresponding to different values of μ. High demand trading interval.

Then $AP_2(d)$ price for electricity in this trading interval is determined by,

$$AP_2(d) = \frac{1}{\mu_u - \mu_l} \int_{\mu_l}^{\mu_u} y'(\mu d) d\mu \approx \$15.70/MWh.$$

Note that the lower average price of $\$15.70/MWh$ is caused by the fact that comparing to the lower demand trading interval above, a higher proportion of the generators' bids had the bimodal structure (see Section 3.2). That structure ensures that when $\mu \leq 0.91$ the low (essentially zero) marginal price of electricity is sufficient to meet the demand. As Figure 5.5 confirms, the area under the graph of $y'(\mu d)$ is small. Nonetheless, this phenomenon is positive in the sense that the use of $AP_2(d)$ would tend to discourage generators from submitting such bimodal bids.

Next, we show how generators would benefit by offering a uniformly distributed bid stack. Assume that in the above trading interval, a high demand trading interval, all generators offer $10\%$ of their total capacity equally at each band. This means that, Generator $G$ with the capacity of $220\ MW$ should offer the bid stack shown in Table 5.1 to the market.

Table 5.1. Uniformly distributed volume bid stack offered by generator g.

| Band | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| Volume | 22 | 22 | 22 | 22 | 22 | 22 | 22 | 22 | 22 | 22 |

Then, similarly to the above, $y'(\mu d)$ for the corresponding $\mu$ values are as shown in Figure 5.6.

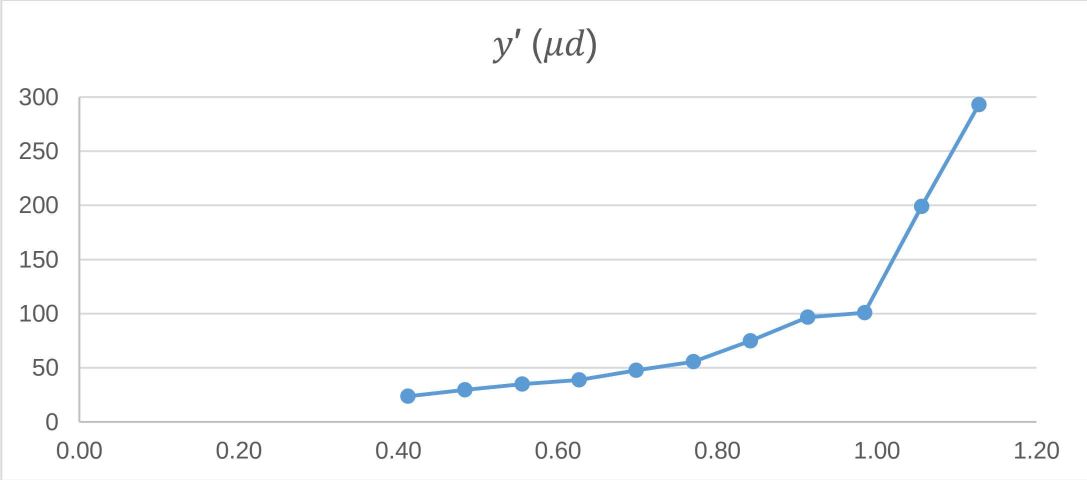


Figure 5.6. Shadow prices corresponding to different values of μ. Uniform bidding strategy.

In this way, $AP_2(d)$ price for electricity in this trading interval is determined by,

$$AP_2(d) = \frac{1}{\mu_u - \mu_l}\int_{\mu_l}^{\mu_u} y'(\mu d)d\mu \approx \$59.91/MWh.$$

Note that the average price of $\$59.91/MWh$ is significantly higher than $\$15.70$ above, which was a result of bimodal bidding behaviour. In other words, the uniform bidding strategy will result in moderate increase/decrease in $y'(\mu d)$, for the corresponding $\mu$ values, which could benefit all the stakeholders in the market.

### 5.2.3 Average price based on observed distribution of demand.

We observe that formulae $AP_1(d)$ and $AP_2(d)$ represent mean values of $y'(\mu d)$ with respect to the Lebesgue measure (uniform distribution) on the $\mu$-intervals $[0,1]$ and $[\mu_l, \mu_u]$, respectively.

However, in view of the availability of extensive data on historical demands, it is possible to accurately estimate the empirical distribution function $F_D(d) \coloneqq P(D \leq d)$ in a period of interest. The latter is in one-to-one correspondence with $F_M(\mu) \coloneqq P(M \leq \mu)$, where $M$ is the random variable taking values in $[\mu_l, \mu_u]$, corresponding to the demands in the interval $[d_l, d_u]$, as described earlier.

Hence it is reasonable to propose a third version of the mean-value Aumann-Shapley like pricing formula

$$AP_3(d) = \int_{\mu_l}^{\mu_u} y'(\mu d)\, dF_M(\mu), \tag{$AP_3$}$$

where, $dF_M(\mu)$ is the measure induced by the empirical distribution of $M$.

In practice, $[\mu_l, \mu_u]$ can be subdivided into $n$ small sub-intervals $J_k$ with mid-points $\mu_k, k = 1,2, \dots, n$.

Then, if we set for each $k$, $p(\mu_k) \approx F_M\left(\mu_k + \frac{\varepsilon}{2}\right) - F_M\left(\mu_k - \frac{\varepsilon}{2}\right)$, where $\varepsilon$ is the width of the interval $J_k$, we see that approximately

$$AP_3(d) \approx \sum_{\mu_k} y'(\mu_k d) p(\mu_k). \tag{$\widehat{AP_3}$}$$

We calculate the $(AP_3)$ price for two selected low and high demand trading intervals of 10:00 AM and 4:30 PM on January 8th 2010. For each trading interval, we let $\mu$ vary within the interval of $\mu_l \leq \mu \leq \mu_u$ where $\mu_l = \frac{d_l}{d}$ and $\mu_u = \frac{d_u}{d}$, and determine the values of $y'(\mu d)$ for $\mu \epsilon [\mu_l, \mu_u]$.

(i) Recall that Figure 5.4 shows $y'(\mu d)$ for the corresponding $\mu$ values for the trading interval of 10:00 AM on January 8th 2010. Note that, the actual demand for the trading interval $10{:}00\ AM$, $d = 2151.89$. Here we selected data set of all $10AM$ trading intervals within summer 2010. The minimum and maximum demand level corresponding to the trading intervals within this data set are $d_l = 1091.2$ and $d_u = 2861.16$ respectively. Therefore, $\mu$ varies in the interval of $0.56 \leq \mu \leq 1.3$.
Then we determine the probability density function corresponding to each $\mu$ level (see Figure 5.7).

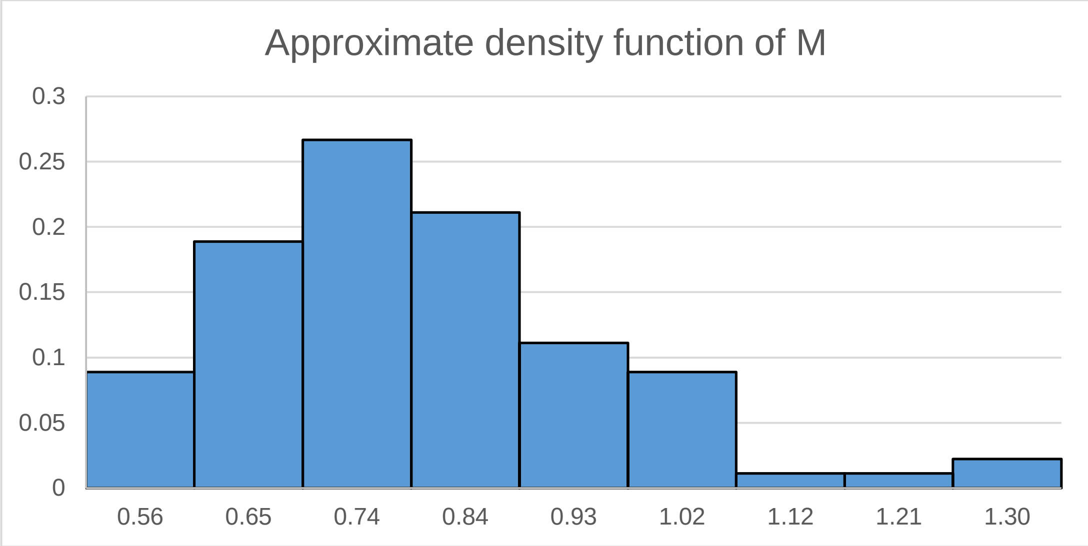


Figure 5.7. Probability density function corresponding to different values of μ. Low demand trading interval.

Using the approximate probability density function, the electricity price for this trading interval can be approximated by

$$AP_3(d) = \int_{\mu_l}^{\mu_u} y'(\mu d) dF(\mu) \approx \sum_{\mu_k} y'(\mu_k d) p(\mu_k) = \$10.59/MWh.$$

(ii) Here we find the electricity price for a high demand period at 4:30 PM, where $d = 2793.33$, based on $AP_3$ approach. Similarly to above, we selected a data set of all $4{:}30\ PM$ trading intervals within summer 2010.

We let the $\mu$ vary in the interval of $\mu_l \leq \mu \leq \mu_u$, where $\mu_l = \frac{d_l}{d} = 0.4$ and $\mu_u = \frac{d_u}{d} = 1.13$, and find the $y'(\mu d)$ (Figure 5.5 shows $y'(\mu d)$ for the corresponding $\mu$ values).

Then we determine the approximate probability density function corresponding to each $\mu$ level (see Figure 5.8). Using Probability density function, the electricity price for this trading interval can be approximated by

$$AP_3(d) = \int_{\mu_l}^{\mu_u} y'(\mu d) dF(\mu) \approx \sum_{\mu_k} y'(\mu_k d) p(\mu_k) = \$9.35/MWh.$$

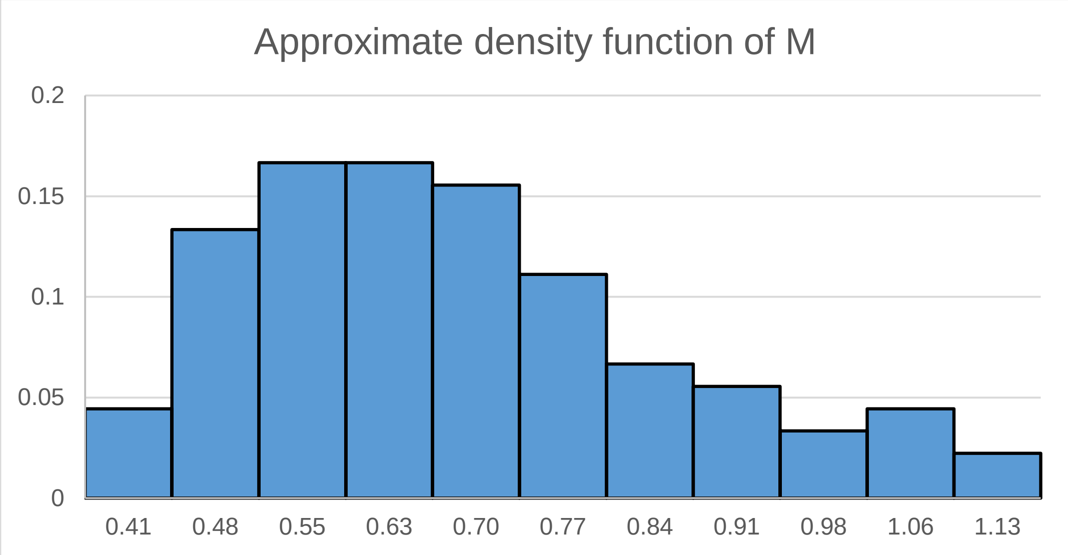


Figure 5.8. Probability density function corresponding to different values of μ. High demand trading interval.

## 5.3 EXTENSION TO MULTI-REGIONAL MEAN VALUE PRICING

In previous sections of this chapter, the shadow price variable $y'(d)$ was treated as the marginal price of one $MWh$ of electricity at an optimal solution of $LP(d)$, with a single demand constraint in a single region model. However, AEMO's dispatch linear program contains five demand constraints, one for each of the five geographic regions. In this section, we point out that the mean value pricing mechanism proposed above can be easily generalised to the whole network in NEM which consists of 5 interconnected regions. However, because the details of the coupling of the five regions is not accessible to us, we cannot easily construct numerical examples that might capture, in a realistic way, the combined effect of the coupling and the mean value pricing approach. If there were interest, in exploring the benefits of this approach – and access to the detailed AEMO model were provided – it would be relatively straightforward to continue to explore this approach.

Mathematically, the main difference between the multi-regional situation and Section 5.2 is that instead of dealing with $d$ as the demand corresponding to one single state, we have a vector $\boldsymbol{d}$, where $\boldsymbol{d} = (d_1, d_2, \dots, d_5)$ represents the corresponding demand values for the 5 regions in NEM. In this way, $LP(\boldsymbol{d})$ is

$$Z(d_{1,}d_2, \dots, d_5) \coloneqq \min \ C^T(\boldsymbol{x}) \qquad (1)$$

$$s.t. \quad (\boldsymbol{x}, \boldsymbol{u}, \boldsymbol{\omega}) \in \boldsymbol{\mathcal{F}},$$

which includes regional demand constraints

$$\Delta_j(\boldsymbol{x}, \boldsymbol{u}, \boldsymbol{\omega}) \geq d_j, \qquad for\ j = 1,2, \ldots, 5. \qquad (2)$$

In the above, decision variable vectors $\boldsymbol{u}$ and $\boldsymbol{\omega}$ have entries that represent amounts of electricity exported from region $j$ and, respectively, imported into region $j$, for each $j$.

In the multi-regional case we may still regard the shadow price $y_j'(\boldsymbol{d})$ of the constraint $(2)$, for $j = 1,2, \ldots, 5$, as $y_j'(\boldsymbol{d}) = \frac{\partial}{\partial d_j}[Z(\boldsymbol{d})]$. Hence it is possible to generalise the Aumann-Shapley like pricing schemes $(AP_1) - (AP_3)$ and $(\widehat{AP_3})$ in the natural fashion.

In particular, in a typical period, we will have the demand $D^j$ in region $j$ lying in an interval $[d_l^j, d_u^j]$ and the corresponding scaling random variable $M^j$ taking values in the interval $[\mu_l^j, \mu_u^j]$, where $\mu_l^j = \frac{d_l^j}{d_j}$ and $\mu_u^j = \frac{d_u^j}{d_j}$ for $j = 1,2, \ldots, 5$. Then clearly, $AP_2(d)$ can be naturally generalized.

For instance, for $j = 1$ we shall have

$$AP_2{}^1(\boldsymbol{d}) = \frac{1}{\mu_u{}^1 - \mu_l{}^1} \int_{\mu_l{}^1}^{\mu_u{}^1} y'_1(\mu^1 d_1, d_2, d_3, d_4, d_5) d\mu^1,$$

and similarly for $j = 2,3, \ldots, 5$.

It is reasonable to expect that, similarly, to the single region situation the mean-value multi-region pricing schemes will penalize bimodal bidding strategies of generators and thereby result in reduced spot price volatility. An interesting area for future investigations is whether more uniform bid stacks of generators (e.g., resembling those proposed in Conticini et al (2010)) would result in overall increase or decrease in the cost of electricity.

# CHAPTER 6. CONCLUSION AND FUTURE WORK

Australian electricity market has accepted deregulation since the early 1990's. The aims of deregulation of electricity supply included promoting market competition and ensuring reliable supply of electricity at stable prices to consumers. However, it has been observed that spot price for electricity can be volatile and occasionally spikes to extremely high levels. This thesis examines the latter phenomenon with the help of quantitative techniques of operations research and statistics.

Closer examination shows that bidding behaviour of generators is affecting the price volatility in Australian electricity market especially in high demand periods. In particular, our analyses suggest that some of the observed volatility may be due to the underlying structure of the optimisation model's design that does not exclude the possibility of generators being able to exercise market power. We also propose a novel pricing mechanism designed to discourage strategic bidding.

In the preliminary analysis, history of price volatility and possible exercise of market power in Australia mentioned by literature were discussed. According to Australian Energy Regulator the significant increase in the number of price spikes occurred in South Australia during the years 2008-11 where "disorderly bidding strategies" by generators were addressed as one of the underlying reasons for this high electricity price fluctuations.

Exploratory analysis of data from South Australian electricity market identified and exhibited a number of phenomena which, arguably, contribute to the high cost of electricity supply to consumers and volatility in spot prices. It identified certain characteristic bidding behaviours of generators during the periods when spot price spikes occurred.

For this reason, the bidding behaviour by generators was investigated in more detail in Chapter 3. We began the discussion by exhibiting distinct bidding patterns by some generators which occurred in trading intervals corresponding to low and high electricity spot prices. Our analysis showed that, observed bid structures exhibit bimodal form in higher demand trading intervals. Moreover, clusters of generators seem to behave in same patterns in offering their bidding stacks to the market in the higher demand periods.

Consequently, characteristic bidding behaviour by generators seems to be one of the underlying reasons for the price spikes in Australian electricity market. This is highlighted by the fact that, a significant spot price increase in electricity market is not necessarily a result of demand increase as the correlation between electricity demand and spot prices on days when spot price spikes are observed were considerably low.

Moreover, to examine the effects of strategic bidding in generators' income, we considered the competition among generators as a lottery model. In this way, the choice of offering price and volume of electricity production would be a tool for designing this lottery at each trading interval. The lottery approach is seen as a benchmark to test the extent to which generators are concerned about the risk of failing to win sufficient generation volume. Results showed that, the generator's bidding strategy during the high spot price periods seems to be beneficial (under the lottery model) in terms of the benefit versus risk trade-off.

It is now natural to consider how different bidding strategies of generators affect the risk of loss to consumers. In other words, the high income to generators can be considered as a loss to consumers. We used risk measures such as Value-at-Risk (VaR) and Conditional Value-at-Risk to investigate the risk faced by consumers as a result of generators' bidding strategies in different trading intervals (see Section 3.8).

Since disorderly bidding by generators was highlighted to be one of the underlying reasons including the price spikes, in the remainder of this thesis, we investigated how the dependence of the spot price on the generators' bids in the pool may contribute to electricity price fluctuations.

In particular, we considered the potential consequences of the fact that generators can influence some parameters of the dispatch linear program $(LP)$ that is used to determine shadow prices of demands which, in turn, determine the spot price. Indirectly, this influence opens the possibility of them being able to impact the marginal prices of electricity in each state and hence also the spot prices. Indeed, due to the non-uniqueness of solutions to linear programs, a phenomenon that we call “instability gap” may arise whereby some optimal shadow prices favour the generators and some favour consumers.

Numerical results in Chapter 4 showed that, in low demand period consumers are more likely to benefit from the designed market structure of setting the ultimate price. However, as demand increases, generators seem to find opportunities to benefit from higher spot price by bidding strategically in the market. In other words, the system works more in favour of generators than consumers in higher demand periods where generators can even reach the highest permitted price per MWh, in some trading intervals.

We do not attribute the above, undesirable, phenomena to any intentional actions of any stakeholders in the Australian electricity market. However, we believe that these findings demonstrate the need to re-examine the design of the market with the dual goal of reducing the volatility in the spot prices and the overall cost to consumers.

Therefore, AEMO may wish to consider changes to its pricing mechanism aimed at creating disincentives to strategic bidding. For this purpose, in Chapter 5 we proposed a Mean-Value approach to determine the spot-price that is inspired by the famous concept of Aumann-Shapley Prices. We demonstrated that this approach has the potential for discouraging strategic bidding and for reducing the ultimate spot price for electricity.

We treated the shadow price as the marginal cost of production when and we considered three approaches that use the Aumann-Shapley like mechanisms as the basis for pricing electricity. The three approaches differ on the basis of the way that possible values of the demand random variable are treated in order to calculate the price at which generators are paid for the electricity they produce.

In the first of these, all possible demands between zero and the actually observed demand are considered as equally likely. In the second approach all possible demands between realistic lower and upper bounds (in a given trading interval) are considered as equally likely. In the third approach, all possible demands between realistic lower and upper bounds (in a given trading interval) are considered with respect to an empirical probability distribution calculated for that period. In all three cases, the mean value of marginal shadow price is taken as the “proper price” to be paid for all the electricity produced by the generators during that period.

Numerically, it was shown that all three mean value price mechanisms tended to yield much lower prices than the currently used shadow price, during periods of high demand. This is caused by the fact that comparing to the lower demand trading intervals, a higher proportion of the generators’ bids had the bimodal structure. That structure ensures that the low marginal price of electricity is sufficient to meet the demand. This resulted in a very low mean value price of electricity for higher demand periods. Nonetheless, this phenomenon is positive in the sense that it would tend to discourage generators from submitting such bimodal bids.

Furthermore, we showed how generators would benefit – under a mean value pricing scheme - by offering a uniformly distributed bid stack. Results showed that, the uniform bidding strategy will result in moderate increase/decrease in shadow price which could benefit all the stakeholders in the market.

Finally, we showed that the mean value pricing mechanism proposed above can be easily generalised to the whole network in NEM which consists of 5 interconnected regions. It is reasonable to expect that, similarly, to the single region situation the mean-value multi-region pricing schemes will penalize bimodal bidding strategies of generators and thereby result in reduced spot price volatility.

Naturally, there are many issues arising from this thesis that could be investigated in greater depth. Some of the most obvious ones include:

1. Subject to the availability of the detailed mathematical formulation, and source code, of AEMO’s dispatch linear program; the analysis of Chapter 4 relating to the instability gap of shadow prices should be repeated with real constraints for the entire 5-region network;
2. Inclusion of a “consumer oriented generator” into the market should be investigated. This new generator would play a role analogous to a central bank which steps in to protect a country’s currency. In the electricity market, perhaps, this could take form of AEMO incorporating all the electricity produced by solar panels into the dispatch model and – at strategic times – releasing it at a price below that at which home owners were paid.

Investigating alternatives to the current structure of using shadow prices from six $LP$-based dispatch models as a basis for determining the spot price. For instance, further regulations on the permitted bid stacks, or new pricing mechanisms such as those considered in Chapter 5 could be investigated. More radically, a completely new quantitative mechanisms such as auctions could be considered.

# APPENDIX

### Appendix 3.1. Value at Risk (VaR) and 'Conditional Value at Risk' (CVaR)

In financial risk management, value at risk ($VaR$) is a statistical technique used to measure the risk of loss on a specific portfolio of financial assets. It assist managers to control the level of risk which the firm undertakes.

For this purpose, value at risk ($VaR$) is used to calculate the maximum loss expected on an investment, over a given time period and given a specified degree of confidence. In other words, the "$VaR$ question" has three elements: a level of confidence $(1-\alpha)\%$, a time period and an estimate of investment loss (Rockafellar, 2006).

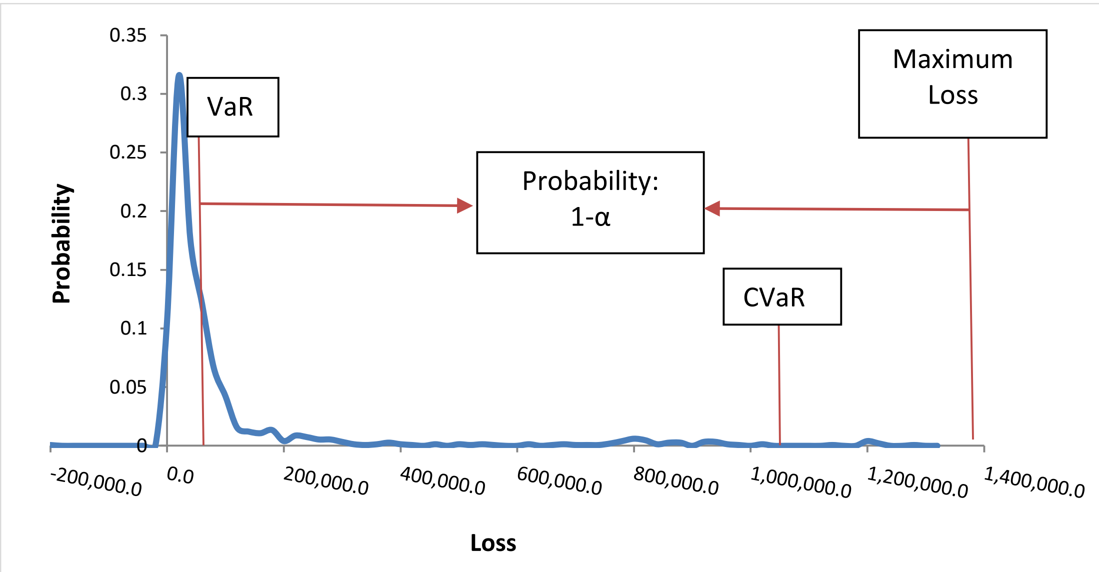


Figure 3.21. Probability density function of loss to consumers.

Similarly to Section 3.8, Figure 3.21 shows the probability density function of loss to consumers in a trading interval in January 2009. Given a confidence level $\alpha \in (0,1)$, the VaR of the portfolio at the confidence level $\alpha$ is given by the smallest number $l$ such that the probability that the loss $L$ exceeds $l$ is at most $(1-\alpha)$.

Mathematically, if $L$ is the loss of a portfolio, then $VaR_\alpha(L)$ is

$$VaR_\alpha(L) = \inf\{l \in \mathbb{R} : P(L > l) \leq 1 - \alpha\}.$$

A more recent approach for optimization of Conditional Value-at-Risk ($CVaR$) was suggested and tested with several applications. For continuous distributions, CVaR is defined as the expected loss exceeding Value-at Risk (VaR) (Rockafellar, 2002).

$$CVaR_\alpha = \mathrm{E}(L|L > VaR_\alpha(L)).$$

Fundamental properties of conditional value-at-risk ($CVaR$), as a measure of risk with significant advantages over value-at-risk ($VaR$), are derived for loss distributions in finance that can involve discreteness. Such distributions are of particular importance in applications because of the prevalence of models based on scenarios and finite sampling. $CVaR$ is able to quantify dangers beyond $VaR$ and moreover it is coherent. (Krokhmal, P., et al, 2002).

## Appendix 4.1.

Table 4.12. Aggregated volumes to be offered by the 34 generators in South Australia on January 8th 2010, high spot price trading interval.

| | v1 | v2 | v3 | v4 | v5 | v6 | v7 | v8 | v9 | v10 |
|---|---|---|---|---|---|---|---|---|---|---|
| G1 | 0.00 | 36.79 | 31.53 | 31.40 | 34.08 | 0.00 | 29.63 | 0.00 | 0.00 | 56.57 |
| G2 | 0.00 | 30.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| G3 | 0.00 | 20.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| G4 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 57.00 | 0.00 |
| G5 | 0.00 | 105.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| G6 | 0.00 | 105.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| G7 | 0.00 | 105.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| G8 | 0.00 | 0.00 | 0.00 | 95.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| G9 | 0.00 | 0.00 | 0.00 | 0.00 | 71.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| G10 | 0.00 | 80.21 | 0.43 | 1.86 | 2.19 | 3.25 | 0.00 | 0.00 | 0.00 | 0.05 |
| G11 | 0.00 | 81.43 | 3.19 | 0.34 | 2.79 | 0.09 | 0.00 | 0.00 | 0.00 | 0.15 |
| G12 | 0.00 | 0.00 | 0.00 | 159.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| G13 | 0.00 | 204.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| G14 | 0.00 | 280.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| G15 | 0.00 | 280.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| G16 | 0.00 | 230.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| G17 | 0.00 | 252.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| G18 | 0.00 | 55.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| G19 | 0.00 | 510.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| G20 | 0.00 | 38.55 | 0.10 | 2.64 | 2.14 | 1.29 | 0.15 | 0.13 | 0.00 | 0.00 |
| G21 | 0.00 | 41.64 | 0.01 | 3.65 | 0.00 | 1.15 | 0.08 | 0.47 | 0.00 | 0.00 |
| G22 | 0.00 | 40.17 | 0.00 | 0.47 | 1.63 | 1.99 | 0.48 | 0.26 | 0.00 | 0.00 |
| G23 | 0.00 | 39.94 | 0.20 | 1.99 | 1.77 | 1.09 | 0.00 | 0.00 | 0.00 | 0.00 |
| G24 | 0.00 | 165.61 | 10.12 | 9.89 | 9.15 | 9.94 | 10.19 | 3.96 | 0.00 | 29.14 |
| G25 | 79.50 | 2.50 | 0.00 | 0.00 | 0.00 | 8.27 | 1.76 | 0.08 | 6.88 | 0.01 |
| G26 | 0.00 | 130.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| G27 | 0.00 | 36.50 | 43.88 | 14.74 | 2.64 | 32.24 | 0.00 | 0.00 | 0.00 | 0.00 |
| G28 | 0.00 | 38.61 | 50.57 | 26.39 | 7.98 | 0.02 | 6.43 | 0.00 | 0.00 | 0.00 |
| G29 | 0.00 | 14.43 | 19.70 | 0.01 | 0.00 | 27.40 | 66.95 | 0.00 | 0.00 | 1.51 |
| G30 | 0.00 | 35.56 | 42.88 | 12.20 | 0.56 | 31.94 | 6.86 | 0.00 | 0.00 | 0.00 |
| G31 | 0.00 | 33.67 | 36.04 | 39.23 | 36.92 | 0.00 | 0.03 | 0.00 | 0.00 | 64.10 |
| G32 | 0.00 | 33.46 | 35.65 | 39.44 | 37.25 | 0.00 | 0.00 | 0.00 | 0.00 | 64.19 |
| G33 | 0.00 | 34.71 | 38.12 | 39.90 | 33.67 | 0.00 | 0.00 | 0.00 | 0.00 | 63.59 |
| G34 | 0.00 | 34.50 | 39.58 | 41.54 | 1.04 | 27.02 | 0.00 | 0.00 | 0.00 | 66.33 |

Table 4.13. Aggregated volumes to be offered by the 34 generators in South Australia on January 8th 2010, low spot price trading interval.

| | v1 | v2 | v3 | v4 | v5 | v6 | v7 | v8 | v9 | v10 |
|---|---|---|---|---|---|---|---|---|---|---|
| G1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 221 |
| G2 | 0 | 30 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| G3 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 21 |
| G4 | 0 | 83 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| G5 | 0 | 0 | 0 | 0 | 0 | 80 | 0 | 0 | 0 | 0 |
| G6 | 0 | 0 | 0 | 0 | 0 | 80 | 0 | 0 | 0 | 0 |
| G7 | 0 | 0 | 0 | 0 | 0 | 80 | 0 | 0 | 0 | 0 |
| G8 | 0 | 120 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| G9 | 0 | 0 | 96 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| G10 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 52 | 0 |
| G11 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 52 | 0 |
| G12 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 183 | 0 | 0 |
| G13 | 0 | 0 | 0 | 0 | 0 | 0 | 126 | 0 | 0 | 0 |
| G14 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 295 |
| G15 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 295 |
| G16 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 221 | 0 |
| G17 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 253 |
| G18 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 57 |
| G19 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 510 |
| G20 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 27 | 0 |
| G21 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 49 | 0 |
| G22 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 27 | 0 |
| G23 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 27 | 0 |
| G24 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 130 | 0 |
| G25 | 123 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| G26 | 0 | 0 | 0 | 0 | 92 | 0 | 0 | 0 | 0 | 0 |
| G27 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 130 |
| G28 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 130 |
| G29 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 130 |
| G30 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 130 |
| G31 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 210 |
| G32 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 210 |
| G33 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 210 |
| G34 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 210 |

Table 4.14. Aggregated volumes to be offered by the 34 generators in South Australia on January 8th 2010, high spot price trading interval.

| | v1 | v2 | v3 | v4 | v5 | v6 | v7 | v8 | v9 | v10 |
|---|---|---|---|---|---|---|---|---|---|---|
| G1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 220 |
| G2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 30 |
| G3 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 20 |
| G4 | 0 | 57 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| G5 | 0 | 0 | 0 | 0 | 0 | 57 | 0 | 0 | 0 | 0 |
| G6 | 0 | 0 | 0 | 0 | 0 | 57 | 0 | 0 | 0 | 0 |
| G7 | 0 | 0 | 0 | 0 | 0 | 57 | 0 | 0 | 0 | 0 |
| G8 | 0 | 95 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| G9 | 0 | 0 | 71 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| G10 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 50 | 0 |
| G11 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 50 | 0 |
| G12 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 159 | 0 | 0 |
| G13 | 0 | 0 | 0 | 0 | 0 | 0 | 105 | 0 | 0 | 0 |
| G14 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 280 |
| G15 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 280 |
| G16 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 220 | 0 |
| G17 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 252 |
| G18 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 55 |
| G19 | 0 | 510 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| G20 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 25 | 0 |
| G21 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 47 | 0 |
| G22 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 25 | 0 |
| G23 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 25 | 0 |
| G24 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 128 | 0 |
| G25 | 99 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| G26 | 0 | 0 | 0 | 0 | 69 | 0 | 0 | 0 | 0 | 0 |
| G27 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 130 |
| G28 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 130 |
| G29 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 130 |
| G30 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 130 |
| G31 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 210 |
| G32 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 210 |
| G33 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 210 |
| G34 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 210 |

Table 4.15. Aggregated volumes to be offered by the 34 generators in South Australia on January 8th 2010, high spot price trading interval.

| | v1 | v2 | v3 | v4 | v5 | v6 | v7 | v8 | v9 | v10 |
|---|---|---|---|---|---|---|---|---|---|---|
| G1 | 0 | 12 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 207 |
| G2 | 0 | 12 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| G3 | 0 | 20 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| G4 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 10 | 14 | 33 |
| G5 | 0 | 105 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| G6 | 0 | 105 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| G7 | 0 | 105 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| G8 | 0 | 0 | 57 | 19 | 0 | 19 | 1 | 0 | 0 | 0 |
| G9 | 0 | 0 | 0 | 0 | 71 | 0 | 0 | 0 | 0 | 0 |
| G10 | 0 | 88 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| G11 | 0 | 88 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| G12 | 0 | 0 | 0 | 159 | 0 | 0 | 0 | 0 | 0 | 0 |
| G13 | 0 | 204 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| G14 | 0 | 280 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| G15 | 0 | 280 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| G16 | 0 | 230 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| G17 | 0 | 144 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 108 |
| G18 | 0 | 55 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| G19 | 0 | 262 | 0 | 14 | 26 | 0 | 49 | 52 | 45 | 61 |
| G20 | 0 | 45 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| G21 | 0 | 47 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| G22 | 0 | 45 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| G23 | 0 | 45 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| G24 | 0 | 142 | 0 | 0 | 0 | 0 | 0 | 0 | 106 | 0 |
| G25 | 54 | 12 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 32 |
| G26 | 0 | 130 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| G27 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 129 |
| G28 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 129 |
| G29 | 0 | 0 | 0 | 112 | 0 | 0 | 1 | 0 | 3 | 14 |
| G30 | 0 | 0 | 0 | 112 | 0 | 0 | 1 | 0 | 2 | 14 |
| G31 | 0 | 0 | 0 | 190 | 0 | 0 | 1 | 0 | 4 | 14 |
| G32 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 209 |
| G33 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 209 |
| G34 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 209 |

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