The Effect of Pricing Rules on a Constrained Wholesale Electricity Market: An Agent Based Approach

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Abstract

This thesis presents a comparative computational study of the performance of two different pricing mechanisms in a day-ahead wholesale electricity market, where performance is measured as the average level of payments made by the system operator to the generators. It focusses on two key pricing mechanisms: a uniform price based buy-back pricing model, defined as a short run approximation to the market design in Great Britain, and a nodal pricing model based on Locational Marginal Pricing rules. The research uses a game theory based approach for modelling themarket, allowing multiple rounds of the game to be played and statistically reliable results to be obtained.

The research develops an agent based simulation of the day ahead markets for both of the pricing mechanisms, and is simulated on a constrained electricity grid. The agents developed for the simulation each represent a generator and are designed to be profit maximising with respect to a parent generation company. Agents employ an evolutionary algorithm in order to create optimised bids for the generation of electricity based on the current market state. Simulations of the market are performed using a styalised 29-Node transmission grid.

A series of experiments are performed comparing the performance of the nodal and buy-back pricing mechanisms, under a series of different operating conditions. It is seen in all of the observed cases that the nodal market design averages a higher level of payments to its participants, and the indication is that the agents in a nodal market are able to explore the higher risk strategies more profitably than their buy-back counterparts. This work also highlights the value of creating evolutionary agents that are robust and flexible in analysing market designs.

This research demonstrates that the greater the level of competition in a market the more efficiently market participants act. In addition to this the agents competing with a uniform based Buy Back pricing system appears far more restricted by higher levels of competition than their Nodal counterparts.

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Chapter 1

Introduction

In recent years a major focus has been placed on almost every aspect concerning electricity, from the clean production and sustainability of the generation sources to the cost to an individual to 'light' their house. This research aims to look in depth at one of the intermediate stages in the supply of electricity, the wholesale electricity market.

1.1 Electricity Markets

Across the world there are a number of different wholesale electricity market designs implemented, using a variety of different bidding processes, market rules, regulations and pricing mechanisms. The interest in this subject area is in the way that these markets operate and the way those who participate in the market are able to make profit, especially as an electricity market is more constrained on it's production and delivery than most conventional markets. The major constraints that needs to be addressed concern the physical limitations of both the transmission grid and the capacities of the generators supplying to the network.

Although there are many different aspects of a wholesale electricity market that can be studied, the one that is focussed on here is the pricing mechanism. The pricing mechanism as referenced throughout this research is the way that the market decides how much each generator is paid for each MW of electricity that they produce.

For this research the base of the market in consideration is a wholesale electricity market using bilateral trading arrangements, where two different pricing mechanisms have been selected to be studied:

The first is the pricing mechanism used in Great Britain, called for reference in this research the Buy

Back market, which operates by selling back electricity that can not be supported from an initial schedule, to which all of those that are initially scheduled are paid at a single uniform price per unit (MW) produced. In the event of the system not being able to support the initial schedule, the generators buy back the generation at their bid price and this is replaced in the schedule by generation from an alternative source at the newly selected generator's bid price.

The second pricing mechanism, is a nodal based system and is referred to as the nodal mechanism, which pays for generation based on the cost to supply the electricity to each given location on the physical transmission grid, where each of these nodes has it's own price.

1.2 Historical Overview of Market Designs

With the move in many countries away from state run centralised electricity provision to liberalized electricity markets that allow for a number of different participants to actively compete for the supply of electricity markets, there are many issues that arise in creating the new markets. Prior to these changes Joskow[27] noted that "For nearly a century, the electricity sector in all countries has been thought of as a 'natural' monopoly industry, where efficient production of electricity required reliance on public or private monopoly suppliers subject to government regulation".

1.2.1 Previous Systems

The pool based market is centered around a day-ahead market that sets the price for a given period the next day. A pool operates by generators offering price and quantity bids for the supply of electricity. These bids are collated for all the generators and organised by the system operator to create the supply curve for the market based on merit order. This is used to create an unconstrained schedule based on the optimal dispatch, that can later be adjusted. The former England and Wales pool employs 48 half hourly bid schedule, where a bid consists of up to three levels of output.

In addition to the day-ahead market, a system of forward contracting was implemented that allowed for the trading of bilateral contracts between consumers and producers. Any forward contracts made were subject to price settlement through the mandatory day-ahead market.

Joskow)[28] identifies the key component of the effective monopolies that existed in the US, where the providers have a 'franchise' to provide electricity to retail customers (residential, commercial and industrial consumers) subject to pricing and reliability regulations imposed by the state. The provision of electricity is only a single part of a vertically integrated utility company that incorporates the generation, transmission and distribution of the generated electricity. The pricing of the electricity generated is defined by state regulations as the chargeable rate such that "both operating costs and capital costs are covered", with an aim to ensure that the revenue per unit is equal to the cost of provision. It should be noted that the author also comments by stating that "most state commissions act under fairly vague statutes", which reduces the efficiency and effectiveness of the charged rates to reflect the real costs.

1.2.2 Failures in the Previous Systems

After the privatisation of the electricity market in England and Wales that implemented a pool based market design, there was a number of problems that arose from this market design, most notable of these was that the pool based system offers prices that are too high and are effectively misleading in the signals that they are sending about the market. The case presented in a review of the pool covered by Newbery [40] states that "abolishing the present Pool as the price-setting mechanism would in fact itself reduce market power and hence lower prices", this is noted in the argument that a pool based system is too transparent and that the price is widely available to analysts and it is possible to create bids that are better profit maximising.

By moving towards a less transparent system the intention as noted by Newbery, is to create increased competition in the market and a reduction in the possible co-operative strategies and with this lower the price of electricity in the market.

An argument outlined by Joskow[28] highlights that the public interest rationale for electricity markets will cause the creation of a natural monopoly where the generation of electricity was typically integrated with the transmission and distribution. Further to this point it is noted that "regulated integrated monopoly distribution utilities are the efficient institutional response to obtain the cost savings of single-firm production without incurring the costs of monopoly pricing".

Having discussed the shortcomings of the pool based market previously implemented in England and Wales as well as the vertically integrated market design in the US, the main issue is how best to replace these markets.

1.2.3 Designing Electricity Markets

Green [23] presents a paper that identifies the shortcoming of two different market, the pool based market that existed in England and Wales prior to 2001 and the Bilateral Trading arrangements designed for the deregulated Californian market.

Green's paper on electricity market failure outlines some requirements for electricity market design. There are two distinct categories for these requirements 'needs' and 'wants', the needs are requirements for the electricity market to operate in a correct manner. The first need of an electricity market is that the supply and demand of electricity is equal; this point is reiterated often during the course of this thesis. The second need is that the all generation that is consumed is paid for, this means that no-one is receiving free electricity and those producers are being repaid for the service they provide.

The paper suggests that the price at which the generation is paid should be at a stable so as to ensure that participants can plan their generation and consumption accurately, which is in line with another desire for an effective market, that the prices paid in the market should reflect the costs of their respective market participants. The dispatch of the system should be efficient, which means that the generators who are able to produce electricity cheapest while fulfilling any constraints should be dispatched in order to minimise the short-run costs. In addition, the long-run costs of the market should be minimised by ensuring that adequate information should be available for investment. The final 'want' as described in the paper is that the market itself should be stable for those competing, which means that the market should not be subject to frequent rules changes that mean that the participants are not able to effectively plan for the future.

The needs describe the basic requirements of an effective electricity market, such that those who are generating are given the adequate incentive to produce electricity as well and that the laws of electricity transmission are maintained. The wants however are devices that are desired as a way to enhance the operation of the market that is used to promote efficient behaviour from the current market participants and to generate incentives for future investments.

Green[22] later defines a list of principles for effective electricity market design based on an updated version of work performed by Bruenkreeft et al.[9] that wholesale electricity markets should include:

1. The market needs to "ensure the efficient day-to-day operation of the generation sector", where the potential pitfall with a system that does not promote efficient operation in the market design is that it doesnâĂŹt have an alternative method to provide the stability of pricing.

2. The market needs to "Signal the need for investment in generation and demand-side management", where the investors need to be able to identify their potential future revenues in order to generate stable investment in the market.

3. The market should "Promote efficient locational choices for these investments"; this is specifically in respect to transmission constraints, where new generators should be placed on the side of a transmission

constraint such that they can be dispatched more frequently.

4. There is a requirement to "Compensate (sufficiently) the owners of existing generation assets", where the main point is that the generators are given a fair price for the service that they are providing.

5. The market should "Be as simple, transparent and stable as possible", which defines that the manner in which the market operates in terms of dispatch and pricing need to be easily understood by participants as well as investors.

6. The market should "Be Politically Implementable", where any new implementation of a market design needs to be acceptable to politicians and other stakeholders.

The key themes common across these design approaches is that the market should be designed such that it allows for each participant to be rewarded for acting in an optimal manner; it is this optimal manner of the participants' behaviour that this thesis is concerned with. The reasoning for this is that the most efficient methodology for a given participant is to maximise their profits, which where possible may require the exploitation of market power that a well-designed market should limit. This is noted in point one of Green's list, such that since there is no alternative method for price stabilisation outside of ensuring efficient basic operation, and consistent exploitation of market power will cause prices to fluctuate and the overall price stability to be greatly reduced.

1.2.4 Reasons for Bilateral Trading

Bower and Bunn [7] state that there were three key components of the bilateral model proposed for use in Great Britain in 2000:

1. A voluntary over-the-counter forward market power exchange as required by consumers and generators.

2. A voluntary, half-hourly balancing market operated by the ISO from 3.5 hours before the particular half hour in question.

3. A mandatory settlement Process for imbalances.

These arrangements make the consumer and generators responsible for dispatching those contracts and a notification to the ISO of their expected generation or demand. It is the responsibility of the ISO to ensure system security and contracting that might be required to fulfil this responsibility.

The 2001 Ofgem report [42] supporting the reforms to the trading arrangement in Great Britain, where the main consideration is that the move to NETA is on the basis that electricity is treated as a single system-wide tradable commodity, where one of the major contributing factors is that the pricing of the forward contracts made for electricity are as transparent as possible. This transparency of the contractual arrangements is designed to promote liquidity and promote efficiency. In addition to increasing the transparency of the forward contracting market, the locational market power that can be exploited should also become more apparent under these conditions.

One of the main considerations made in the design is that in creating a market where the configuration of the transmission network is driven by the long term planning of the companies, which will "facilitate competition in generation and supply". The major factor to note is that bilateral trading arrangements should encourage efficient short term use of the transmission network and better planning for long term investment.

1.2.5 Reasons for Nodal Markets

Hogan [25] presents an argument for the desire to efficiently use the transmission system in a market, offering the concept that a "Contract Network" for transmission should be a fundamental part of the market design. The reason presented for the use of transmission contracting is that unlike other markets, the electricity market is bound by Kirchoff's Law, which divides the path taken by the electricity when distributed according to the resistance of all paths that the electricity can take. The criteria of following Kirchoff's laws for electricity transmission requires that the thermal limits and voltage tolerances are taken into consideration when contracting electricity.

Hogan notes that with the rise in the long distance power generation and transmission the requirement to have an economy focussed on the transmission grid is imperative to ensure the efficiency of the market.

Central to the discussion on long term investment in an electricity network, Hogan argues that the investors in high cost long term facilities such as power plants would require more than short term transmission access rights to make the investment feasible. This is given that without being able to provide the option to stabilise their income, the risk could potentially be too large for many to reasonably take. While contracting is an important part of generating electricity all the contracts must comply with the day-to-day operation of the market and as such not violate the thermal and voltage constraints of the transmission grid. One of the key aspects of ensuring price efficiency is that those with long term contracts should not be at a disadvantage when considering the short term congestion of a network.

The two main criteria Hogan considers with the definition of a contract network based design for transmission of electricity are 'Price Efficiency' and 'Capacity Rights'.

Price Efficiency as termed by Hogan should be represented by the generating of Spot Prices as defined by Schweppe et. al.(1988) [20], where the generators should be dispatched in order of economic merit, where those with the lowest marginal costs should be dispatched first. In a bid based system this will equate to those offering the lowest bid, which in an efficient market should optimally be at the marginal cost level. However it is by allowing a bid based system, there is room for market power to be employed by the market participants, which will affect the spot price of electricity in the market.

Capacity Rights are described as the means by which a market participant can state that their electricity has been transmitted to the location where it is required without the requirement that it is their electricity that has been delivered. By creating an implicit transfer system, the problem of congestion and loop flows are hidden within the market. In order to ensure this Hogan suggests the need for a central operator to organise the markets, this is to ensure that at all times the transmission rights are held by the correct parties at the time of dispatch. This is such that while the dispatched electricity may not be physically transmitted to the contracted location, the market operates in a manner that assumes it has.

1.3 Hypothesis

There are three principal market designs that have been considered across Europe and the US, which are Bilateral Contracts with countertrading (the GB market model), Locational Marginal Pricing (one of the US market models) and a Zonal Pricing System (implemented in parts of Europe).

A further study undertaken by Harvey and Hogan [53] aimed to tackle the comparison of two of the markets, being the Nodal and Zonal designs, where the authors argue that a Zonal design should never perform better than a representative Nodal market when attempting to exploit market power, taking the Californian market as a case study.

Harvey and Hogan offers a concise overview of the major points concerning the nodal-zonal debate, where the main issue concerning market power is that the expectation that zonal systems will be able to mitigate the issue of market power. The opinion offered by Hogan is that the dominant generators in zones will be able to exploit as much if not more market power, however the market power will be hidden as "favored generators could take advantage of the real physical constraints, but their higher charges would be socialized and averaged over all system users". One of the key points considerations that is noted in the rationale for design of the Californian market is over the problem of exercising local market power. The main argument presented is that if a generator is able to exercise locational market power, then they are able to raise the price above the normally competitive levels regardless of the pricing mechanism used (in the comparison case zonal, inter-zonal and nodal). The paper offers a number of scenarios designed to give as full a spectrum of possible market states as possible in order to effectively refute the claims made by CAISO (California Independent System Operator).

Having identified the case that the market design for Nodal model is functionally better than the Zonal model with regards to the exploitation of locational market power, the question still remains as to whether the bilateral trading arrangements with countertrading or the analogy of such a system is capable of performing better than a nodal system.

The hypothesis put forward in this research is that "a nodal pricing mechanism is more susceptible to the influence of market gaming than a buy back mechanism in a constrained electricity market".

Where a nodal market is a short run representation of the nodal systems described previously, and the buy back market is an analogy to a bilateral contract market operating efficiently in the short term(Section 1.6.5). Explanations of the operations of these markets are presented later in this chapter.

Within the scope of this research this means that, under equal market conditions, the nodal pricing mechanism will offer on average a higher level of system payments than it's buy back counterpart.

The issue is, why would a nodal market be more susceptible to gaming in the market than a buy back market? The expectationis that a market using a global value to set the price that an agent is paid will perform worse than one that uses a locationally sensitive method. This is a reasonable expectation that for every higher price offered in a global pricing structure, the impact of a higher price will affect the payments of more agents. However, this is only the case if the participants are bidding at a similar level in both mechanisms, which the influence of gaming and strategic bidding may cause to be different.

The thinking behind the proposed hypothesis is against the stated expectation, and is based on the reasoning that while the conditions of the market are the same, the market participants in the nodal market will on average bid higher than their buy back counterparts. This is to say that in the case of a buy back market most of the pricing influence is on the initial load, which requires a large number of market participants to push beyond a normal level to raise the price. As such there is little incentive for the participants to attempt to push the price high as the risk versus reward is potentially too high, it would take a large enough percentage of the generators to bid in excess of a normal market level to have any effect on the initial price. However with the nodal pricing mechanism, there is no initial level of payments, but the price paid for the generation at each node is influenced by the bids selected and that a requirement to change the generation schedule can cause more electricity to be sold at a higher price.

It is this potential influence that every nodal participant has over the price at every node as well as the limited individual influence that a single participant has over the initial global price in a buy back market, that leads to the proposed hypothesis.

1.4 Simulation

In order to see where this research fits in within the scope of work in the related field it is necessary to give an overview of the simulation that has been developed. Given that there are a number of different approaches that have been taken in this field which are covered in Chapter 2, it is important to be able to understand where there are similarities and differences in these approaches to understand where this research fits.

This research presents an agent based approach to simulating an electricity market using evolutionary algorithms for price determination. The Simulation presented in this research consists of a set of agents competing in a simulated single round wholesale electricity market.

1.4.1 Market Simulation

In looking at a complex real life system such as an electricity market, it is often very difficult to obtain real working data surrounding the operation of the market. In the market used in Great Britain the bids for the balancing mechanism are published, the strategic decision making processes the companies competing in the market implement are not readilly available. As such in order to understand these markets without being directly involved, as either a competitor or regulator, requires an alternative approach. One of the best approaches is to create a simulation of the market applying the rules and regulations, but in an artificial environment. By simulating a market, it is possible to see not only how a market works, but attempt different approaches to design and operation, which are vital in analysing the two pricing mechanisms.

It is difficult to compare two market models directly based upon the available empirical data as there are a large number of unseen factors that can potentially influence the outcome of the market and skew the comparison. As such a simulation with a fixed model is preferred as it reduces the number of inconsistencies that may exist between two real markets.

1.4.2 Agents

In addition to the simulating the market with a single fixed model, the bidding needs to be performed in a similar unbiased manner. The proposed method for this is an agent based system, where every agent is programmed to operate in an identical manner, with the aim of maximising their profits.

In order to adequately explain why an agent based system is useful, the first aspect that needs to be understood, is what exactly is meant by an 'agent'. Franklin and Graesser (1996) [19], "Workers involved in agent research have offered a variety of definitions, each hoping to explicate his or her use of the word 'agent'", after studying a variety of different definitions given by different project, they create their own definition:

"An autonomous agent is a system situated within and a part of an environment that senses that environment and acts on it, over time, in pursuit of its own agenda and so as to effect[sic] what it senses in the future." Franklin and Grasser(1996)

This is a clear and concise definition of what an agent is, and is expected to do. Although the reference to time is not as relevant within this work, this description of an agent stands as the base definition for the purposes of this work.

Part of the reason for wanting to use agents is that they are autonomous, such that they are able to act and interact with the environment, in this case a market, without the requirement of a person giving them information and instructions, that could influence their behaviour.

The agents within this research are as important as the results obtained, since we hope to obtain an additional insight into how agents act in similar complex environments. Although the agents themselves will be the same, the market that they are operating on in each case is slightly different giving a slightly different method of calculating payments, causing a change in the way the fitness is calculated.

While the change in behaviour that may be seen in a single agent as a result of a change in the market rules is of interest, however it is equally interesting to note the change in behaviour of the collective of agents.

Due to the fact that market rules are often changed, with additional regulations added and removed, it istherefore imperative for the research field of agent based computational economics, that a set of agents are able to effectively respond to a series of new scenarios in a given market without the need for specified tailoring and modification in order to be able to draw clear comparison.

As such this research additionally aims to show that, "agents using an evolutionary search methodology are ideally suited as tools for market analysis".

1.4.3 Validation

In addition to evaluating the results of the simulation with respect to the experimental questions and the proposed hypothesis, a look needs to be taken at how valid the simulation and the model used are for drawing relevant conclusions. Part of the problem is how to effectively establish the relationship between the simulation and the real world, stating that the real world data is "not only standard empirical evidence (e.g. datasets, stylized facts), but also qualitative and quantitative evidence regarding the setup of the economy and agents' cognitive repertoires gathered from laboratory experiments, case studies and inductive analyses"[17]. The following considers the main factors that will pose the main questions for discussing the success of the agent based model presented in this research:

1. How closely does the data set used reflect the real world?
2. How closely does the market set-up reflect the reflect the real world?
3. How effective are the agents in their role within the simulated environment?

The first two questions define the critical components of the whole model that is used in running the experiments, where the emphasis is on how this relates to the real world. The third question is a qualititive assessment of the way that the agents operate, this is mainly due to the alternative approach taken in the design of the agents. Due to the evolutionary based design there is no requirement for the agents to act with the same rationale as a human bidder, meaning that a direct comparison of strategy is not possible. It is with this view that a slightly broader approach needs to be taken, examining the extent to which the agents are able to perform their task of exploring different strategies within the market.

1.5 Experimentation

In order to test the hypothesis, three different comparative experiments have been devised. The first experiment is the direct comparison between the two different market mechanisms when operating with no restrictions. This is designed to be the main experiment for drawing the conclusions about how well each of the pricing mechanisms perform in the simulation when considering different market demand scenarios. By identifying how the operation of the market changes at different demand levels a more indepth study of the market dynamics can be performed.

The remaining experiments introduce some different operating conditions in order to further explore the market and augment the findings of the primary results. The first of these conditions is based on a more realistic scenario, where the smaller or conventionally less competitive agents do not attempt to influence the market, but instead bid just above cost price. This is performed to see if under a different strategy those agents that are still acting competitively are capable of generating the same market outcomes and in what sense they differ from the initial experiment.

The second of the conditions placed on the agents is that instead of acting as part of a collective representing one of the generation companies where they are trying to maximise the profits of the whole company by their actions, they attempt to only maximise their own profits. Since the experimentation proposed by this research, not only aims to test the market rules, the final experiment is performed to further the understanding of how the agents operate under different conditions, despite no direct change to the agents themselves.

In order to perform this study, a model has been developed based on the Great Britain's National grid, taking into account as much of the real world data that is available, although for processing reasons some aspects have been simplified. The aim of developing such a model is to test the techniques in a more stretching environment. This is done in order to question in greater detail the way that the agents operate in the market and the effectiveness of the market rules as opposed to whether the market design is relevant or not.

1.6 Market Overview

The following section outlines the basic operation of a constrained wholesale electricity market, with a focus on the technical challenges that are central to the operation of an electricity market.

A wholesale electricity market is the market in which the generators of electricity sell their capacity to satisfy the demand across the geographical region that the market represents. In the case of a constrained electricity market, the sale and distribution of electricity is restricted by the physical limitations of a transmission grid.

1.6.1 Market Basics

The basis of a wholesale electricity market operates similar to most other markets, in that the generators (suppliers) offer to supply a certain quantity of electricity at a given unit cost and Load Serving Entities (the effective consumers in this market) state the amount they are willing to pay for certain quantities. In this case the unit considered is megawatt hours (MWh), which is the supply of a megawatt of electricity for the duration of one hour.

This research often refers to the bids made by the generators, a bid in this case is an offer to supply electricity at a certain price. In this work a bid is represented as stepped supply function. A stepped supply function is a supply function in which a series of stepped price quantity pairings are offered as opposed to a single supply function. Figure 1.1 shows a two step supply function.

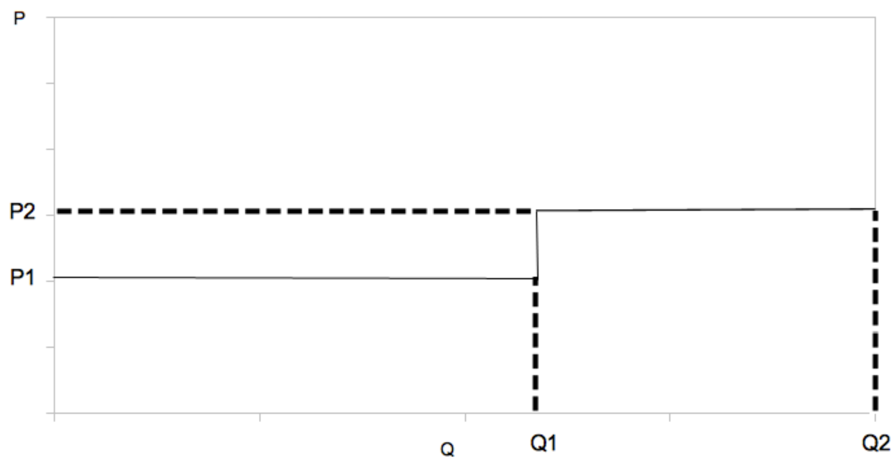


Figure 1.1: A Bid in the form of a Stepped Supply Function

The example in figure 1.1 relates to the way in which bids are represented in this research. This represents a bid made by a generator to supply Q1 MWh of electricity at a price P1 and the rest of their electricity (Q2 - Q1) at a price P2. In this case the number of steps is limited to two, different markets allow for different numbers of steps in bids.

The bids supplied by each of the generators are collated to give the supply curve for the market. Similarly all bids from the Load Serving Entities (LSE) are compiled to form the demand curve. The Equilibrium point gives the predicted demand in the system given the bids made by the generators. Functionally this creates an initial generation schedule, where all the generators left of the equilibrium point form this schedule. The demand left of the equilibrium point shows the location and amount of electricity to be served.

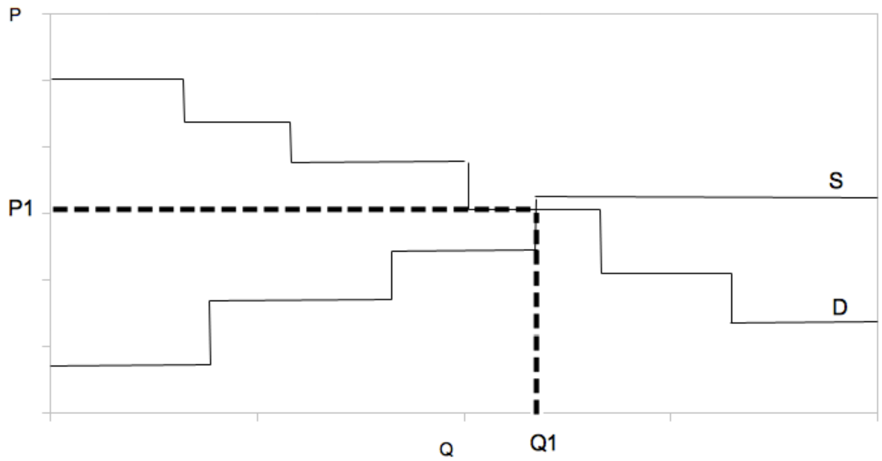


Figure 1.2: Sample Market State with Stepped Supply and Demand Functions

Figure 1.2 shows an example of a simple supply and demand graph representative of an electricity market, where all the bids from the generators have been aggregated and the demand from the LSE also represented by stepped bids. In this research the LSEs do not individually offer bids, as such their demand curve is represented as a fixed minimum (baseload) and an inelastic slope (peak demand), this is shown in figure 1.3.

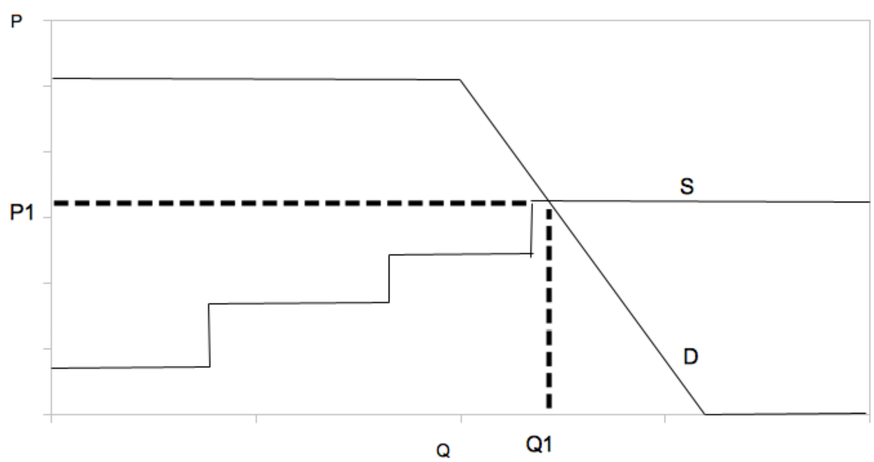


Figure 1.3: Sample Market State with a Stepped Supply Function and a Simplified Demand Function

In an electricity market the equilibrium point is critical, as a system operator has to make sure that supply is equal to demand in order to ensure system stability. System instability that results from a loss of voltage on the system can result in blackouts, as such this supply and demand equilibrium is maintained within a stated tolerance. For a day ahead market the demand value used is only a predicted demand, and so the supply can exactly match the demand, it is at the point of delivery that this tolerance is critical.

1.6.2 Transmission Overview

With an electricity market, the electricity that is generated has to be transported from the location that it is generated to the location that its is demanded at the time of production. The transportation of electricity is the sending of electric current along power lines from a source to a destination. The collective of all these lines in termed here as the 'Transmission Grid'.

The transmission grid consists of a number of power lines that connect the locations where where electricity is supplied or demanded, termed 'Nodes'.

When dispatching electricity, the load placed on the network has to follow the laws that govern electrical transmission. There are two important aspects to consider:

The electricity that flows down a line is inversely proportional to the resistance of the lines that it travels down to reach the destination.

The flow of electricity along a line is directional.

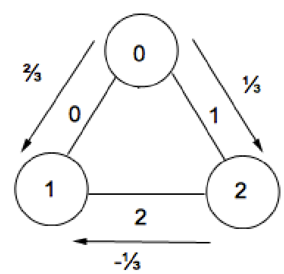


Figure 1.4: Sample 3 Node Network

Figure 1.4 shows a sample three node network and identifies the flows that each of the line would have on them should electricity be generated at node 0 and be required at node 1. Given that every line has the same resistance, the flows on line 0 will consist of two thirds of the total generation and the remaining load that must travel along lines 1 and 2 will consist of the other third. This split is due to the ratio of the relative resistances, which are 2:1

The directionality of the lines is such that on both lines 0 and 1, since they are flowing from the designated start point to the end point. In the case of the proposed flow on line 2, the value is negative to signify that the flow on the line is flowing from the end node to the start node. The negative value has no functional impact on the operation of the transmission system and serves only as signal to those operating a balancing mechanism.

1.6.3 Constraints and Rebalancing

When scheduling the generation of electricity, the physical transmission lines may not be able to physically support the proposed load without the risk of causing long term damage to that line. In this case the schedule needs to be rebalanced such that the lines are capable of supporting the loads placed on the network.

Using the same sample three node network as figure 1.4, a capacity of $C_{\max}$ MW has been placed on line 0. For the flows to be valid, the flow on line 0 (X) must not exceed $C_{\max}$ MW.

$$-C_{max} <= X <= C_{max} \tag{1.1}$$

If X is greater than Cmax, then the total inputs onto the grid must be adjusted such that the inequality in equation 1.1 is true. In the example shown the minimum required reduction in output at Node 0 is equal to:

$$\frac{3}{2}(X - C_{max}) \tag{1.2}$$

.

The stated reduction in this case is equal to the overload on the line multiplied by the inverse of the proportion of flow from the generator along the line.

In addition to reducing the generation, the excess demand must be met from alternative sources. In the example, either all excess generation can be made up from generators at node 1 or node 2. In the case that generators at node 2 are selected to rebalance the system there will be a further requirement for the output at Node 0 to be reduced; This id due to the case that a third of the electricity generated at node 2 will be transferred along line 0 in a positive direction.

The process of rebalancing is the reduction of output at one location and the increase in generation in response at another location. The result of a rebalance should have two effects:

The first effect should be that the demand should still be filled as required at each of the nodes. This is to maintain the equilibrium of supply and demand.

The second effect is that the resultant change in supply should impact a constrained line in order to reduce the proposed flow of electricity on the given line.

A number of changes to the schedule may be required in order to create the required stable equilibrium, as each change will likely impact a number of transmission lines.

1.6.4 Payments and Pricing

In this research, the market mechanism studied is based on the day ahead market, where a day ahead market is the arrangements for electricity production made during the day prior to delivery.

The buy back market described in this research is based on the British Electricity Trading and Transmission Arrangements (BETTA) [35]. A buy back market offers a uniform price across the market for all of the initial load, where initially scheduled electricity capacity can be bought back by the system operator in rebalancing at bid price. Following the buying back of capacity addition electricity required in the new scheduled is then paid for at bid price.

The nodal pricing system pays each generator based on the cost of generation as given at each node. A Locational Marginal Pricing system that calculates a price for each of the nodes based on the cost of generation for the last MW of electricity at that node. An overview of the operation of a Nodal Market is given in Lesieutre and Eto (2003)[32].

This section will give an overview of the different markets as well as the considerations made for their implementation and operation.

1.6.5 Buy Back Pricing Mechanism

The Buy Back market designed for this simulation is an analogy to of the bilateral trading arrangements set out in 2005 in the BETTA policy implemented in the Great Britain, based on the original 2001 NETA policy.

The Buy Back market design presented here can be seen in many ways as a short run approximation to the Bilateral Contract based system seen in Great Britain under NETA. In a Bilateral Contract based market, the contracts for production are traded between various competing entities up to the point of market closure, at which point those contracts are then used to form the initial schedule. The assumption made is that the market will reach an optimal level as given by the uniform price paid for the initial schedule to those contracted to produce. The bids in the market can then be used to define the price that generators are willing to buy back their generation in the case of those scheduled for production or the price at which a generator is willing to sell.

The rationale for the assumption that the uniform price being a stable contract price level, is that the long term trading of these contracts for a single production window will initially be valued at a wide range of prices for different generators, however closer to the scheduled time, contracts will have been exchanged, where the contracts for production should become more balanced due to the increase in information about the markets. The changing prices for these contracts should theoretically create a uniform or close to uniform price for the generation for a time period.

The buy back market process involves the scheduling of the full requirement of electricity that is demanded, in the cheapest manner possible. Where the price that everyone is paid is decided at the price of the last MW supplied in the initial schedule. Should it be required for the purposes of balancing the line loads, the System Operator can sell back any electricity to the supplier at the value stated in the bid.

The process works by first calculating the single global price as a form of the System Operator's initial schedule, where the bids are searched for the highest price offer, which will be the cost of supplying the final MW of the demand; This value become the initial global price, for which all generators are paid the same per MW produced.

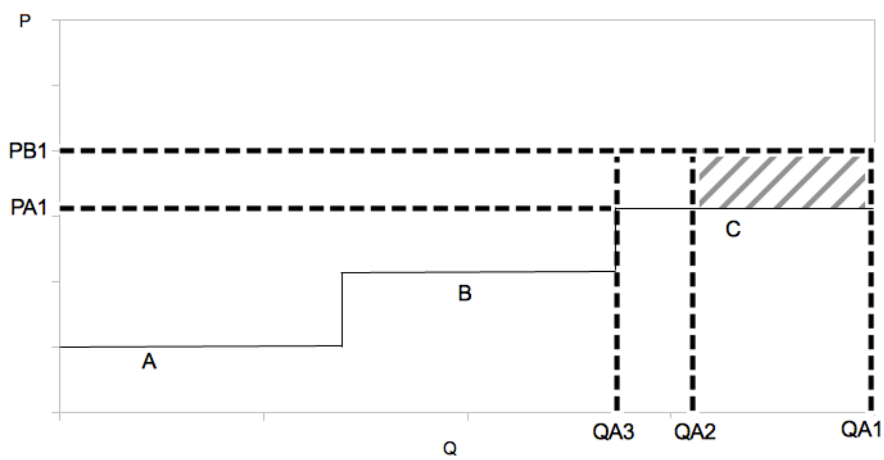


Figure 1.5: Example of the Bids and Payments made at an Exporting node in a Buy Back Market

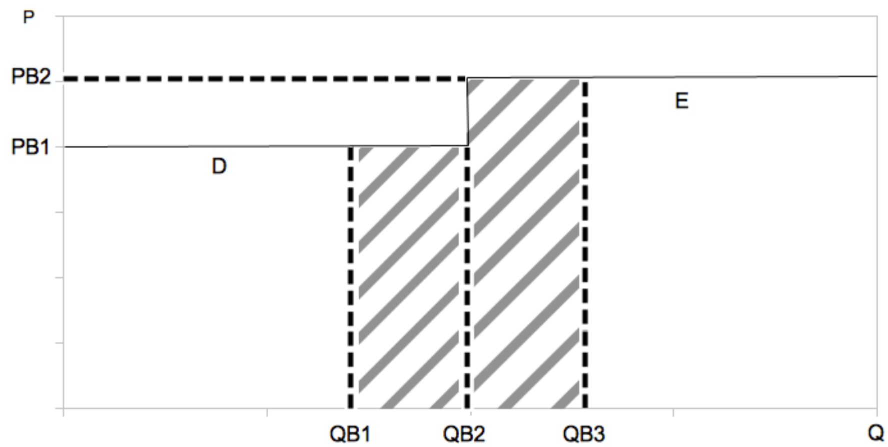


Figure 1.6: Example of the Bids and Payments made at an Importing node in a Buy Back Market

Figures 1.5 and 1.6 show the supply and demand on a sample two node network. Node A has three comparatively cheap generators, each offering to supply electricity to Node B at a price less than each of the generators at Node B. In this example, the initial schedule is comprised of all the generation of the three generators at Node A and a partial load of the cheapest generator at Node B. In this case the uniform system price for each MW is calculated to be the maximum price of all the bids that form the schedule. In the example, the uniform price will be set at PB1 and each of the generators at both nodes A and B.

The Buy Back aspect of the market only comes into consideration should it become necessary to adjust the schedule from the cheapest possible supply schedule to an alternative schedule due to line constraints. It is in this case, that the System Operator will sell back a generator's capacity at the price bid and will then replace that with the electricity supplied from a different generator, who will be paid at their bid price.

Within the simulation this process is broken down into three stages. The first stages is to purchase the initial load at the agreed global market price. The next stage is to calculate the difference in supply for each each of the bids, this is to calculate not only where supply has decreased, but also where it has increased, this relates not just to new bids brought in, but the increase in supply from other currently utilised generators. The final stage is to process the additional payments, where the System Operator is refunded money from the generators not used and pays for the additional required generation.

In more detail, the process of buying back electricity requires a calculation of the difference between the bids used initially and the bids in the revised schedule. By calculating the difference, the amount to be bought back is calculated, where the price that the electricity is bought back at is the difference between the initial global price and the original bid price. The new generation brought in to the schedule to replace the generation removed in the rebalancing process is paid at the price that the generator bid.

Returning to the examples in figures 1.5 and 1.6, in the case that a constraint becomes binding, such that the electricity generated at Node A that is to be exported to Node B is greater than the capacity of the line, then the system needs to be rebalanced. In the example, the rebalancing causes a shift from QA1 to QA2 and QB1 to QB3. In figure 1.5, the Quantity is bought back at the bid price of the Generator C, which is at price PA1, giving that generator a payment of PB1 - PA1 for not generating electricity they were scheduled to. Given the reduction in generation, Generator C is still producing QA2 - QA3 MWh of electricity in this schedule at the price PB1.

In figure 1.6, Generator D is now producing the remainder of it's capacity, up to BQ2, this is paid at it's bid price, which is PB1. In the revised schedule Generator E is now required to generate, and since they offered a price at PB2 they are paid at that price for producing PQ3 - PQ2 MWh of electricity.

1.6.6 Nodal Pricing Mechanism

The second pricing mechanism design being considered in this research is the nodal pricing mechanism. The nodal mechanism uses a vastly different method of calculating the pay that a generator receives for supplying electricity than the buy back mechanism, however the system operator process and rescheduling mechanism remain the same.

The nodal mechanism operates by calculating calculating a price for supplying electricity to each node on the network. This price is calculated based on which generators are used to supply each of the nodes, where the price is the cost of the most expensive MW of electricity used to fulfil the demand at that particular node.

In this system, if all of the electricity for a node is supplied at a high price, then the price per MW will be relatively low and if all of the electricity is supplied at a high price, then the price will also be high. However if most of the generation is supplied at a low price, but in order to fill the demand the node needs more expensive generation, then the price per MW at that node will increase to the level of that more expensive generation. Figures 1.7 and 1.8 show an overview of how the nodal pricing mechanism works.

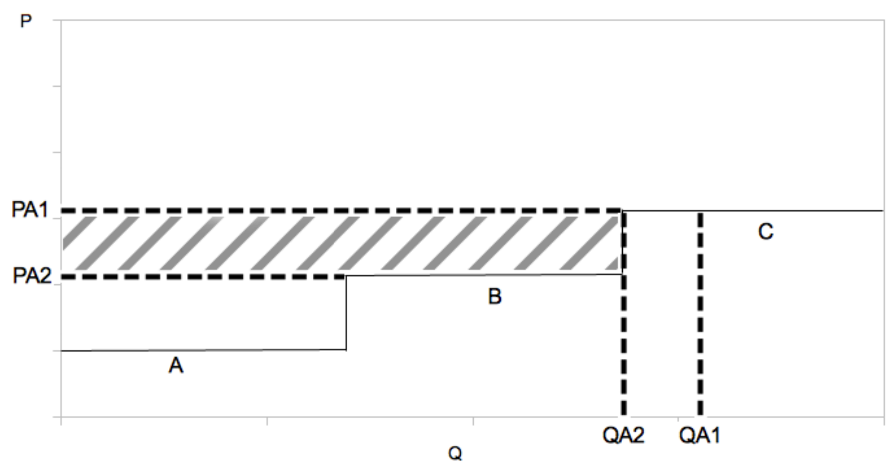


Figure 1.7: Example of the Bids and Payments made at an Exporting node in a Nodal Market

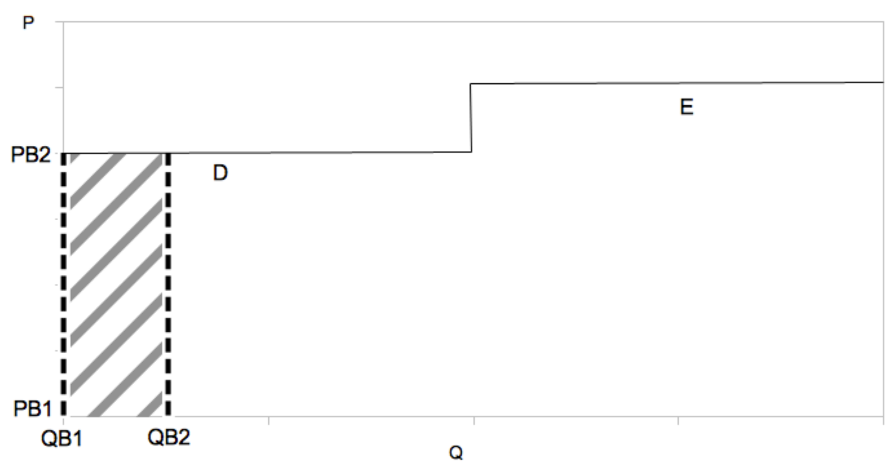


Figure 1.8: Example of the Bids and Payments made at an Importing node in a Nodal Market

Figures 1.7 and 1.8 show the supply and demand on a sample two node network. Node A has three comparatively cheap generators, each offering to supply electricity to Node B at a price less than the generation at Node B. Under a condition where there is no binding constraint on a line between Nodes A and B, all of the generators would be paid at the price PA1. This price is the highest price offered by all generators at Node A, that is selected for use, additionally no generation is scheduled at Node B.

If the constraint on the line becomes binding, then a change in output is required in order to balance the system. In the example shown in Figures 1.7 and 1.8, the quantity produced at Node A falls from QA1 to QA2, and the quantity at Node B rises from QB1 to QB2. This results in a fall in price of generation at

Node A from PA1 to PA2 and a rise in price at Node B from PB1 to PB2.

In this case, despite the new nodal price at Node B being higher than previously seen, a rise from PA1 to PB2, the Nodal price at A falls to PA2. For the purposes of this research, the prices that the generators are paid is the key aspect, where despite the higher price at Node B, only the generation at Node B is paid at this price (PB2). The remainder of the electricity, which is generated at Node A is paid at the price PA2.

Within the market simulation, the payments to the generators are derived from the highest cost of production for a given node, where the most expensive generator scheduled gives the price paid for all of the generation at that node. This action is performed for each of the nodes on the network.

There are two considerations made with the nodal pricing mechanism to simplify the process as handled by the computer. Firstly, the distribution is always ordered such that cheapest generation is supplied first, and proceeds in increasing price up to the most expensive generation required to complete the schedule. The second factor is that the generation is allocated geographically based on the minimum distance needed to be traveled where there is still demand that needs to be supplied.

This process ensures that the cheapest generation is supplied to the nodes surrounding the cheapest generators and the more expensive generation is effectively used to top up nodes that otherwise would lack supply needed to fulfil demand.

1.7 Summary

This chapter presented an overview of the workings of a constrained wholesale electricity market, displaying the basic market operation.

A wholesale electricity market should maintain an equilibrium of supply and demand. In addition, the generation schedule should be set such that for every line the predicted load of electricity does not exceed the stated maximum capacity. In the case that the schedule would cause a line capacity to be exceeded, then a rebalancing procedure is performed to reduce the predicted load on a given line to below the operational capacity.

Payments are made according to the market rules, this research covers two different pricing mechanisms for operation with a day ahead market, these are buy back and nodal pricing mechanisms.

The remainder of this research is divided as follows, Chapter 2 dentifies relevant research in the related field of electricity market based computational economics, with a focus on agent based systems in whole sale energy markets. Chapters 3 and 4 cover the design of the simulation and the agents respectively. Chapter

5 details a small scale example of the simulation that was used for the purposes of testing the operation of the agents and simulation, where some basic results are taken to provide an insight into the expectations of operation on the larger scale. Chapter 6 notes the process undertaken in defining the model to be used in the main experiments. Chapter 7 outlines the experiments that were performed, with the results and discussion. This work is closed in Chapter 8 with the conclusions drawn from the preceding research.

Chapter 2

Background

The use of agents to effectively recreate human behaviour is one of the key features of most agent based economics, as it gives a clear insight into the operation of a market. There have been a number of different approaches that have looked at the behaviour of the agents as related to their real world counterparts. Although there is a disparity between the proposed agents and those reported on in this section, the success of such systems has quite clearly been established, especially in the longevity of the field and has become an integral part of Electricity Market Analysis.

This section aims to look at not only electricity market research, but also models that have been created large systems capable of analysing these markets in greater detail. In addition, other aspects of non-electricity market related game theory aspects are considered along with other relevant work for this research.

2.1 Agent Based Approaches to Analysing Electricity Markets

The concept of Agent Based Computer Economics (ACE) has developed into a relatively large area of research, with an increasing interest in modeling and simulating electricity markets. While much of the early work was based simply around modeling the markets, it became imperative to model the physical systems as well as the market. A paper by Widergren et al. (2004) [61] approaches the problem of designing ACE simulations across different levels of the market. Of note for wholesale electricity market, the difficulty highlighted is the development of the decision making process, given that even agents that appear to have a similar profile may have different "functions and responsibilities". This is one of the key factors that drives the preference for a form of adaptive system in these simulations and one of the contributing factors towards using a Genetic Algorithm to create the agents presented in this research.

Bower and Bunn (2001)[8], proposed an agent based approach to analysing market power in an oligopolistic electricity market. The approach uses agents that analyse their previous market state to modify their bids by either raising or lowering the bid price in order to better achieve their objective, where the portfolio utilisation is to achieve at least their target rate of utilisation for their whole plant portfolio and they achieve a higher profit on their own plant portfolio, than for the previous trading day. One of the key outcomes that this paper gives for this research concerns the information available to bidders, where they state that: "the case study presented here, it seem that more transparent publication of competitors' prices would increase competition in the bilateral model while not make any difference in the Pool". This conclusion is interesting as the agents proposed in this work are given a high level of competitor information and so the expectation would be that the competitiveness of these agents will rise and that the prices will be impacted accordingly.

In addition to this work, Bunn and Oliveira (2001)[10] developed an agent based simulation of the newly proposed trading arrangements that a version of is implemented in this research. The key outcome of this work was to identify potential strategic bidding behaviour that could be seen in advance of the system's introduction. The companies with a diverse portfolio are able to create a dominant position are obtain higher profits than others, as such the paper concludes that the market for generation capital is going to rise such that each company will actively be striving to improve their portfolio diversity and market position is order to improve their profitability.

The difficulties of trying to build a realistic energy market simulation are highlighted by Bernal-Agustin et al. (2007) [5], with the requirement of creating a useful training tool for those working with the market. The paper is not looking to scientifically prove a specific hypothesis beyond verification of the system's operation. This is done by creating "sufficiently complex" case-studies to test that the results obtained by simulation are in line with those found in the relevant real market (Spanish Mainland Day-Ahead Market).

Camerer and Ho (1999)[11] use Experience Weighted Attraction (EWA) by utilising what the agents hold as their 'belief' of the expected situation to formulate their profit-maximising bids. The paper combines the belief-based methodology with a reinforcement approach, which prior to the time of the paper were considered "fundamentally different". However the EWA model utilises the common feature of one time learning combined with the given knowledge that thee information they require is different, reinforcement looks at itself while belief looks at their opponents. They conclude that the EWA model better fits the class of problems tested than either of the generic cases, with specific note of it's superior performance against reinforcement learning.

A number of papers written by Cau have involved looking at collusion between participants in markets. The papers present a number of different scenarios in which the tacit collusion, information garnered through multiple interactions, of more than one agents can be used in an attempt to influence the system price. Work with Anderson (2002)[12], uses a co-evolutionary approach to create the tacit collusion in an representation of the New Zealand electricity market. The finding show that the stable outcome to a collusive game seems to be a Nash Equilibrium, with no agent able to make a better move from the best solution even if purely in self interest. A follow-up paper (2011) [1] look at the constraints of an electricity market more and specifically the spare capacity. They find that with a high excess of supply the price is forced into being lower by competition, even if the agents are acting in a collusive manner.

Peter Cramton (2003) [14] covers competitive bidding behaviour in uniform price electricity auctions, stating that it is expected that "suppliers should be bidding to maximize their profits, which, as this paper explains, will inevitably involve bidding above marginal cost". The key conclusions drawn in his study is that although the agents are profit maximising and achieving above marginal cost levels of profit, they are doing so with their own individual actions and are not colluding to get these results, but these prices that are offered do have a natural limit, which is determined by the actions of the other participants in the market. Both of these conclusions are instrumental in the rationale of this work, since this work is not only interested in pushing the boundaries of the market to the limit, but is also interested in the way in which different agents interact. It should be noted that Cramton's paper only reflects a uniform market (represented in this research by the Buy-Back Market) and not a discriminatory pricing system (as seen in the Nodal Market presented in this work), however it can be expected that although the actual behaviour of each individual market participant is different, the conclusions about the overarching form of the collective of market participants will still hold true.

Work undertaken by Ernst et. al. studies a simplistic electricity market model and agent based interactions within this environment. Their focus is on the development of the agents' behaviour rather than the actual market equilibrium. The agents that are considered are: consumers, producers and the ISO. A detailed representation is created for both the producers and ISO to maximise the understanding of behaviour, additionally a static inelastic demand is used to represent the consumer agents. They show that under limited transmission capacities that their agents are not able to make as large a profit as the unconstrained case. They conclude that the agents can not produce as much electricity as in the unconstrained case without entering into direct competition with other generators competing for use of the limited transmission. Surmising that, "the limited transmission capacity prevents the portfolio from using the bids of the generators it owns at the different locations of the system to exercise its market power"; identifying a key point, that at least in this simplified system the constraints on an electricity market seem to be directly able to reduce the market power that a collection of generators at a number of locations (the aforementioned portfolio) is able to effectively excerpt on that market.

The component agents defined in Ernst et.al.'s paper (2004)[39] reflect the decisions taken in this research, taking a simplistic view of the consumer stance in order to focus on the producers and their interaction with the ISO. They include not only the producers, consumers and ISO, but the transmission owners in their model, showing that with "an active transmission constraint" the agents on the export side of the constraint are unable to achieve the same levels of profit as opposed to a market running a simple Locational Marginal Pricing (LMP) system. By adding in a new actor into the market (in the form of the transmission company), the dynamic of the market are affected such that the previously more profitable agents are not able to exert the same market pressure.

2.2 Alternative Artificial Intelligent Approaches

One of the alternative approaches when using artificial intelligence in simulating electricity markets is put forward by Cincotti et al (2005) [13] uses a simulation centred on learning in games, as opposed to the evolutionary methods used for this work. The paper looks at two different algorithms to simulate a day-ahead auction. Of note is the result that in a Nash Equilibrium strategy setting, the sellers are able to obtain a higher profit in a uniform pricing setting over a discriminatory pricing auction, stating that "it is easier to learn to collude in the uniform rather than in the discriminatory auction context", a point that is fundamental to this research.

A comparative study into different approaches to the analysis of equilibria in a constrained pool based electricity market was undertaken by Krause et al. [30], who use both a Nash Equilibrium Analysis and Agent Based Modelling approach. The simulation operates a matrix based game and implements a Q-Learning system for the agents. The study looks at two different cases, one with a single equilibrium and a case with two equilibria. The results of this study show that with a single equilibrium the system converges upon this point, but it is in the case where there are two equilibrium points that an interesting result is found. In the two equilibria market, the agents behaviour causes the game to cycle between the two points. Even in a simplistic setting, the cyclical nature of the results is an important feature to note, and with a larger system, this behaviour could potentially not only be repeated, but with the inclusion of more equilibria, such as present in a real market, there could be even more unpredictable behaviour.

Bakirtzis [4] offer a Q-learning based approach to creating bidding behaviour in their agents, this is done by using a simulated annealing (SA) approach created by Guo et al. The approach uses the reduction in 'temperature' to work towards convergence, within the structure of the algorithm this is used to reach an optimum strategy. The application of this strategy in the paper is to look at the comparison of pay-as-you-bid and uniform pricing systems to clearly identify the effects of market power, pay-as-you-bid systems take the exact value that is bid and that is the value that is paid, whereas a uniform pricing system pays at the market clearing price. The paper demonstrates that high pricing is common to both pricing system when market power can be exercised, but when there is only minor market power available uniform pricing seems to achieve lower overall prices.

Another similar project using Q-Learning based agents in an electricity market was undertaken by Ly-Fie Sugianto (2010) [33]. Sugianto takes a look at the Java-Bali region of Indonesia as a case study, taking a particular look at how generators interact in the market, when they are able to offer less than maximum capacity. The author concludes that in this scenario there is often a trade-off that the agents have to make between offering a substantial quantity of electricity at a lower price versus offering less electricity but at a much higher price. At any given time, it is imperative to identify which of these strategies is the best, however for the research proposed here, the concept of a two step bid is implemented, that allows for a great depth of strategy to be implemented, including the effective removal of supply that can be obtained by pricing some of the electricity beyond a normally reasonable range.

Xiong et al. [64], also implement the popular Q-Learning approach to agent design, in order to test uniform versus pay-as-you-bid market designs. Using a system of ten generator agents, and a single merit based ISO, the system runs over a number of repeated trading days. The conclusions drawn from this simulation show that a pay-as-you-bid pricing rule is vastly less volatile in the distribution of the price, although on average from the sample given the average price of the uniform system is lower (Figures 2.1 and 2.2). Despite not using a constrained electricity market, the results of Xiong et al's study give an important insight into the expectations of the results that will be obtained in this research.

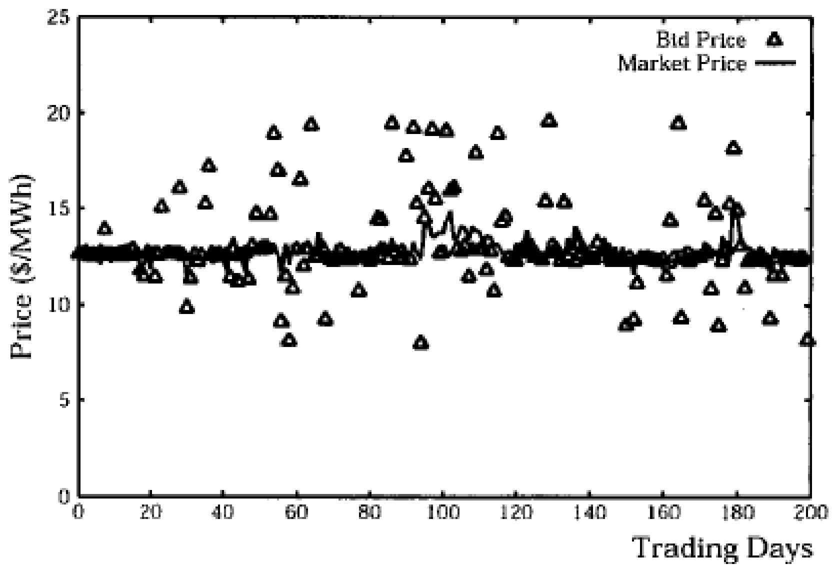


Figure 2.1: An example of market prices and bid prices of an agent at a given hour under the pay-as-bid pricing rule. Xiong 2004 [64] Figure 4

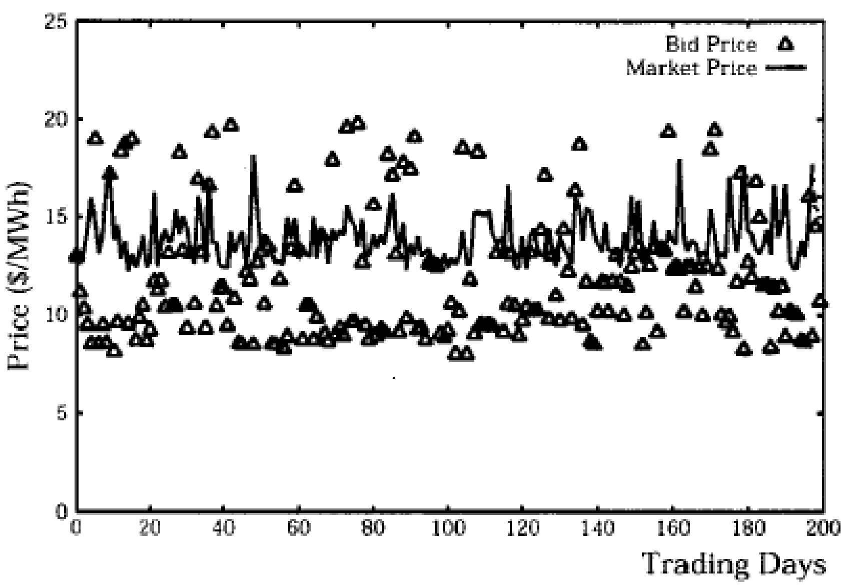


Figure 2.2: An example of market prices and bid prices of an agent at a given hour under the uniform pricing rule. Xiong 2004 [64] Figure 5

Before the introduction of the new electricity market regulations in California, Richter and Sheble [47] studied the proposed market and built an adaptive agent system with the aim that it could be used by those with an interest in the new market. The Genetic Algorithm based agents used for their system implement a very similar basic process, as can be seen in figure 2.3.

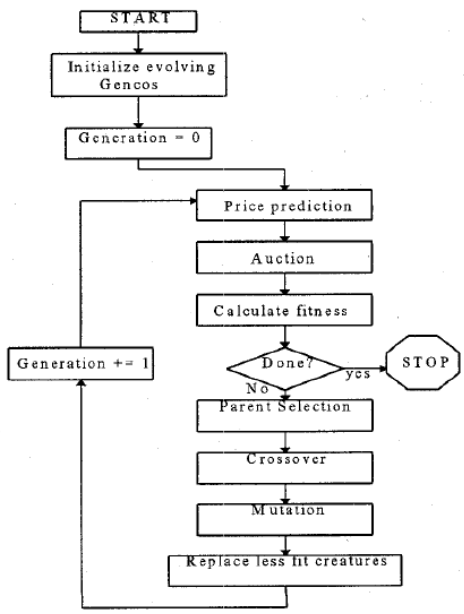


Figure 2.3: The GA agent evolution process. Richter 1998 [47] Figure 2

Most noticeably different from the market design that is present in Richter and Sheble's work and the one described for this research is the actual market design being used. While their paper implements an auction based system, the proposed approach uses the bilateral trading arrangements, that have been introduced in Great Britain since the publication of Richter and Sheble's paper. The authors do note the success of the developed system and note that not only has it succeeded in it's primary operation, but would also be relevant as a tool for future use in the electricity market. It is with this the success of Genetic Algorithm based agents, in earlier systems such as theirs, that confidence can be gained that such systems are a useful tool for analysing electricity markets.

2.3 Additional Electricity Market Considerations

One major factor that is important in studying electricity markets, is the fact that although each individual instance of the market is a 'one-shot' deal, the real systems happen hour to hour and day to day. Rothkopf [48] offers a look at the daily repetition process that is often overlooked, noting that the repetition of the auctions is imperative to gain a true perspective of the real workings of the market. Although at one point a perpetual market state was considered to view the progress of agents across a year of operation, which would follow Rothkopf's desire for the daily repetition of the market, the scope of error or inaccuracy that could come from a single event could propagate and possibly invalidate many future results. Knowing the possibility that a look at a one-shot event could not be conclusive and using states resulting from previous runs could prove unreliable, the decision was taken to have a number of test cases and perform multiple runs taking the average and noting where the runs differ and by how much. This is increasingly important given the use of evolutionary based agents that have randomised initial states.

In relation to the problem that is considered by Rothkopf at the heart of electricity market simulation and analysis, that of repeated daily events not being represented, Ilic and Vishudiphan (1999) [58] developed a system that aims to have generators learn the behaviour of daily repeatable events in order to obtain higher levels of profit in subsequent iterations of the market. The market used is a pool based system, in which the generators repeatedly attempt to sell their electricity on either an hourly or daily basis. The generators are able to use one of two different strategies, Estimated Profit Maximisation (EPM) or Competition to a Base-Load Generator (CBG), The two different methods are desingned based on the uncertainty that a generator might have over it's own classification, base, mid or peak load generators, with each calculating between the two methods so as to optimise it's own strategy at any given time.

This work is extended into a more complex model that Vishudiphan presents in his thesis [59], applying it to the study of the New England Electricity market. The thesis offers a different set of agent strategies from those in the previous work, focussing on a more generalised case. The major issue raised with the strategies is the problem of imperfect information, which is a major factor in economic analysis and games. The main focus of the thesis is on developing a simulation with the potential use in the real world, stating that it serves specific roles for both regulators and planners, but much like other tools, is wary of the validation required before serious market participants would want to use it, although this validation method is clearly identified for those wishing to take the approach.

The multiple strategy approach that is offered is one that was considered during the development of the agents in this research. As an approach it can offer a wide range of options for a variety of classes of generator, which would be imperative to show a true reflection of the operation of the electricity market.

Juselius and Stenbacka [29] have produced a study on the Nordic market, undertaking a long term study of the pricing areas, it could be seen that some areas create effective markets on their own, while others seem to integrate to form larger connected markets. Of particular interest is the consideration of the transmission capacity bottlenecks, which cause substantial problems in keeping competition available in all countries (With Finland-Sweden acting as their main case study). It is important to note that there are some considerations made about market power when considering the bottlenecks and transmission constraints.

Foroud et al. [18] have identified a similar approach to the one proposed by this research, splitting the task of a generator into two sub-problems identifying the maximisation of generator profit and the minimisation of System Operator cost as the primary operation. The approach is similar in working, but takes into account distribution companies as well as generation companies. The system uses a constrained 8-bus grid and seems to achieve success in reaching a Nash Equilibrium in favour of the distribution companies.

A similar study has been undertaken by Pozo et al.[44] into the Nash Equilibrium of electricity markets, however this has a focus on the long term equilibrium over the short term equilibriums considered in many other approaches. Although the model used is capable of working on a short term basis, the duration is considered in the long term, as such it is by iterating through the equivalent of a year's worth of short term cycles that the long term is calculated.

Boonchuay and Ongsakul [6] have produced an approach to look at risky bidding strategies using a particle swarm optimisation algorithm. By taking risk into account the added factor of how well the bid is likely to perform is made part of the deciding factor. A reliability aspect is an interesting addition to the work and although has been considered in the simulation created for this research as an extension of simply taking the average of results of various System Operator runs, no advantage has been seen t including it thus far.

A paper presented by Singhal and Swarup [52], looks at how to forecast electricity prices using an artificial neural network. The system works very well for the majority of cases, but suffers when the demand spikes beyond the normal level. The system uses historical data (for up to four weeks) as inputs in order to get the best results, the use of such historical data could be incorporated into this work should time need to be factored into the simulation at any point.

When looking at equilibria strategies in repeated games, Roth and Erev [16] performed a study of three different games, using a variety of learning algorithms. Through experimentation they show that their 'Best-Shot' and 'Market' games conform to predictable and observable equilibrium, where-as the 'Ultimatum' game, in which two players are attempting to find an agreeable level of demand, where the maximum amount of production an agent will allow of it's competitors directly reflects their own payments.

The ultimatum case that is presented is of particular interest when considering the interactions between agents. This kind of game is helpful in looking at constrained electricity markets, as there can often be a level of payoff that is directly attributed to the required actions of competitors. An Ultimatum Game is expected to be a more marginal case within this research, however there is significant room to acknowledge that allowing an opponent access to the 'limited' demand they want, might allow for more profitable strategies. The best measure of how this kind of game is played within a larger simulation is to identify the different strategies that are played between high and low demand levels, trying to identify where if at all an Ultimatum Style Game is played within this work

Work by Viet, Weidlich et al. [15] into simulated electricity markets, their first paper defines a simulation that looks at both the forward contracting and spot market for a two settlement electricity market. The simulation uses a reinforcement based learning methodology in their agent based system and is modeled on a stylised version of the Belgian high-voltage transmission grid. The authors note in this paper that the inclusion of forward contracts as a market to create significant incentives for the agents to compete in advance so as to influence their behaviour in the spot market, which they ultimately report lowers the energy price.

A follow-up work by Viet and Weidlich[57], looks at two different aspects of the market, the first is using a day-ahead system, similar to the system used in this research, with the second being the market for supplying the reserve power. They take the same approach to the agents as in the previously reported paper, using a reinforcement learning technique. They look at two different market mechanisms, a 'pay as you bid' mechanism and a uniform pricing mechanism. The outcome generated using these different systems is dependent on the order in which the markets are prioritised, where the scenario in which agents must offer reserve capacity first yields higher prices in a uniform pricing market, where in the reverse case both mechanisms obtain lower prices than the previous order.

In addition to their other work, one of the best overview of related research available was produced by Weidlich and Viet (2008) [60]. The review shows the wide range or research and approaches taken, with a note that at the time the field was beginning to really take shape and so a few conclusions were drawn across all of the considered approaches at the time, these conclusions can be used to see how the field has moved on since the 2008 review and specifically what is relevant to the work presented in this thesis.

The 2008 review considers that not much of the work carried out had considered transmission constraints, however now a greater amount of the work is considering the need to include transmission constraints to see the effect of many simulations on the markets. The work presented in this thesis also considers transmission constraints in order to better understand the effect on a market under more realistic conditions.

2.4 Large Scale Elcetricity Market Models

One of the major systems that has been developed in recent years concerning the simulation and operation of an electricity market on a constrained transmission grid, is the AMES (Agent Based Modelling of Electricity Markets) platform that was created by Tesfatsion et al [56].

The model set out in a 2005 paper [31] was developed with regards to a set of proposed new guidelines made by the US Federal Energy Regulation Commission (FERC), where the aim was to in the long term test the economic reliability of these new designs. The main focus of this work was to address the proposed Locational Marginal Pricing (LMP) system, a nodal pricing variant, that was a key component of the proposal.

From this initial outline of the platform, the AMES model was developed and the components and algorithms that formed the platform were compiled in a 2007 paper [54]. where the process is a daily repeated two stage process, where both a day ahead and real time market are run concurrently, the process of which can be seen in Figure 2.4.

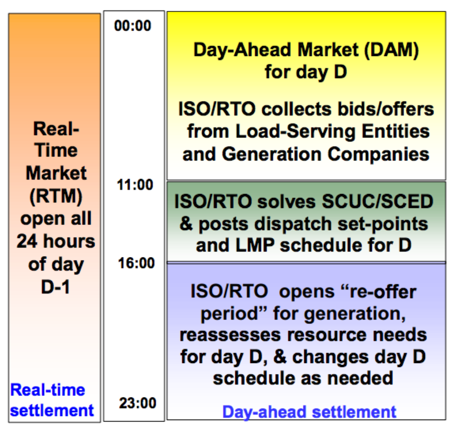


Figure 2.4: AMES Time Constrained Market Operation [56]

The AMES platform was test in a 2008 paper [34], where demand sensitivity and price caps were both considered while looking at the LMP system. One of the key aspects of this was looking at how the generators adapted their bids over time in this complex environment as a reaction to the market dynamics. The results show that the competing generators when they are able to learn about the market are able to push the system price up even at the potential loss of demand and thus increased competition.

There are a number of notable aspect with relation to this research, is that the test platform has become a very well documented open source system, that was considered as the platform for this research. Details of the decision making process surrounding the consideration for using the AMES system can be seen in Chapter 4.

Along with the AMES project, the EMCAS (Electricity Market Complex Adaptive System) project is one of the major research platforms used to date in the use of Agent based systems for electricity market analysis. A large amount of detailed study has gone into the development the detailed commercial system [36]]. The system aims to emulate the market at all the different levels of interaction and has beed primarily used "to study restructuring issues in the U.S., Europe, and Asia".

The agent system developed for EMCAS reflects the decision process made by a Genco and combines three approaches in order to make it's decisions, each of which is based on a perception of time. Initially the agents look back at it's own previous behaviour to see which bids were accepted, including profit levels and utilisation, in both the short and long term. Then the system analyses the current market, noting which generators it is competing against, and finally it attempts to predict the market round that it is bidding in. Taking into account each of these analyses, it then process them in order to create it's offers, Figure 2.5 shows the overall agent decision making process for a day ahead market.

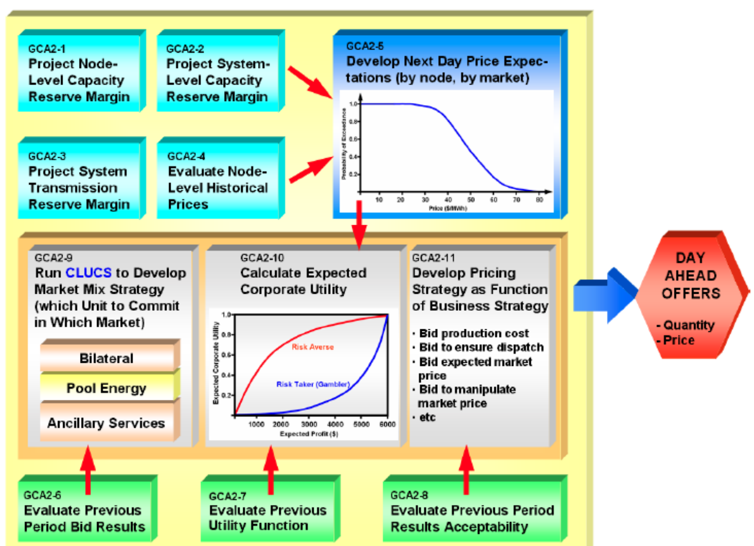


Figure 2.5: EMCAS - Generation Company Agent Decision Process (North 2002 [36] Figure 4)

One of the major considerations for this work is the validation of the agents, the three conditions defined in this work for agent validation as adapted from Fagiolo's work are a concise and easily understood set of guidelines, however there has been work that goes to a greater depth. Macal and North [37] take an approach to validating the EMCAS model that has limited access to real world comparable data, such that it is able to hold up to the scrutiny of interested parties within the industry along with policy makers. In order to validate the model, without empirical data they create a seven point process (figure 2.6) to minimise the possibility that any given aspect is invalid.

- **Data Validation**
  - Data Gaps and Inconsistencies
  - Data Currency
  - Third-Party Data Verification
  - Proprietary Data
  - Data Visualization
- **Subject Matter Expert (SME) Judgment**
  - Developer SMEs
  - Independent SMEs
- **Participatory Simulation**
- **Model-to-Model Comparison**
- **Critical Tests and Key Indicators**
- **Comprehensive Test Cases**
  - Parameter Space
  - Agent Strategies
- **Invalidation Exercises**

Figure 2.6: EMCAS - Model Validation Framework (North 2005[37] Table 1)

Testing the EMACS system against this criteria, they draw a number of conclusions concerning the agents, the main point of interest is that they found it 'easy' to convince policy makers of the use of agents, primarily due to the way they act in correspondence to the real world. This clear conveyance of the real world becomes one of the major challenges in the agents proposed in Chapter 4 of this research, since there is a clear strategic difference given that the agents are acting in a less 'realistic' manner.

2.5 Game Theory and General Market Research

In a paper by Nicolas Jennings [26] the complexities of developing simulations to address real world problems are identified, primarily taking a software engineering approach to the development. Although a number of approaches are considered, one of the most critical aspects of the paper is his base definition for creating agents for these simulations, basing the definition on sections of the 1997 text "Agent-based software engineering" by Michael Wooldridge [63].

1. Clearly identifiable problem solving entities with well-defined boundaries and interfaces
2. Situated (embedded) in a particular environmentâĂŤthey receive inputs related to the state of their environment through sensors and they act on the environment through effectors
3. Designed to fulfill a specific purposeâĂŤthey have particular objectives (goals) to achieve

4. AutonomousâĂŤthey have control both over their internal state and over their own behaviour

5. Capable of exhibiting flexible problem solving behaviour in pursuit of their design objectivesâĂŤthey need to be both reactive (able to respond in a timely fashion to changes that occur in their environment) and reactive (able to act in anticipation of future goals)

This definition create a useful metric by which the development of the agents in a system, something that was further taken into consideration during the design of the agents in this work. The work does highlight two different pitfalls that are symptomatic with agent based systems:

1. Runtime Instability - The interactions are unpredictable and thus accurate timing can not be ensured for the operation.

2. Emergent Behaviour - The behaviour of individuals can be uncertain due to the complex interactions between different agents.

Both of these points were considered during the development of the agents, the expected impact can only be identified to a degree prior to the completion of much of the experimentation, however both of these points are best covered when evaluating the operation of the system as opposed to defining key decisions in the development.

A paper by Arifovic and Ledyard (2004)[2] identifies the use of learning models in games centred around public goods, this takes the idea of scaling up learning models that work on small scale games in order to see what happens on a larger scale. The paper points out a key aspect, which is the quick convergence on good solution spaces, as described by desiring the "quick discarding of 'bad' strategies" and the ability "to focus on good ones when you find them". The use of history as the driving factor for controlling these aspects, by keeping relevant solutions is a central feature of the evolutionary nature that underpins the best strategy (Individual Evolutionary Learning) and the findings are naturally helpful in the work this thesis presents.

The concept of exploitation vs exploration is an interesting study when looking at search spaces, especially complicated ones. Exploitation is termed in a paper by Auer et al.[3] as picking a strategy that seems to gain some success without looking into a large number of possibilities, whereas exploration tries a high number of available strategies in order to 'gather statistics'. The paper looks at an algorithm that aims to maximise the payoff by balancing out the exploitation and explorations, this is done by modifying the weighting of probabilities within the system. One of the major issues that arises is that due to a number of factors the comparisons cannot be directly made to real markets because there is insufficient information to perform an adequate validation.

The evolutionary approach to Game Theory is an important area of research, as it relates directly to key parts of the simulation designed to analyse an electricity market in this research. Sabourian and Juang (2008) [49] produced an insight into this subject, looking at two major questions, can we expect agents in this kind of game to react in a way to eventually find an equilibrium state and by extension, which of the equilibria that exist will they reach. The paper splits the topic into two major approaches, imitation and best response, where imitation aims to maximise profit from a strategy that repeats the actions of other successful agents, where as best response acts in such a way as to take advantage of the single best possible move available. It is this kind of response based actions that are focussed on in this research over the imitation strategy, for the expressed reasoning that (as defined in the paper), a response based system will tend towards the higher reward risky strategy, which can be overlooked by an imitation based system. With the expressed requirement to attempt to push the market as far as possible, it is with these 'risky moves' that more stable market states may be found that achieve this. Schipper (2009) [51] studies both imitators and responders and draws very much the same conclusion that Sabourian and Juang, which is that imitators achieve superior profit. Much of the work covered is based round a conceptual market as opposed to a more complex real market such as an electricity market, where the set of constraints that influence the market cause an asymmetry between companies, which would likely reduce the effectiveness of an imitation based approach, although without thorough testing this is speculative.

2.6 Modeling and Validation

In an extension to the work by Fagiolo cited as the metric for guiding the success of the system at it's task, Windrum, Fagiolo and Moneta (2007)[62] try to address the main problems face by those creating models and offer an number of solutions. This paper offers three different calibration approaches to validation without the requirement of strict empirical validation, two of which are relevant for use with this research:

Indirect Calibration: The user validates the system based on a set of stylised facts, they are interested in and wish to maintain, with the aim of restricting the analysis to those cases (or using limited parameters) where the initial hypothesis of these facts is upheld. This allows the user to look in more depth at the mechanisms in order to ascertain how and why the cases that work work and more specifically, why some cases fail, which in turn should lead to the redefinition of the styalised facts and a more valid system.

Wenker-Brenner: The Wenker-Brenner approach is an extended form of empirical validation, which aims to use limited relevant empirical data in order to initially define the working parameters, where the scope of the parameters should be based on the information available, increasing the value range where there is limited reliable data. The system proposes using "Bayesian inference procedures" in order to gauge the probability that any given tested parameter model is valid against limited empirical results. These probabilities are then used to redefine the parameters, intending to create a more accurate simulation.

These approaches offer a way to create more accurately reflected simulations given a lack of empirical data, althoug the authors do raise issues with each of the methods. With some of the initially considered data sets for the large scale simulations in this research, these approaches would have proven useful. However due to the decision to formulate much of the data model on the National grid, the reasoning for implementing such a validation structure becomes less important.

Despite the widespread success of agent based systems in economics, Richiardi (2003) [45] defines what he considers to be the three major pitfalls of these systems:

1. Interpretation of the simulation dynamics
2. Estimation of the simulation model
3. Generalisation of the results

These three pitfalls cover the broad subject of how accurate the simulated environment is in relation to it's real world counterpart. While each of the parts is important to consider, the third pitfall, generalisation of the results, is one that can be overlooked. While the focus on getting the initial simulation as accurate as possible is integral to the working of the system, the same careful analysis needs to be extended beyond the design into defining how much can be taken away from the work. This is especially relevant given the focus of this research.

Richiardi et al. (2006) [46] followed this by extending the base study and calling for a single protocol for creating agent based social simulations, citing the lack of publication penetration that many simulations seemed to have. Although the reasoning may not be as sound with a large number of relevant simulations being published, the desire for a standardised platform for creating social based simulations would greatly benefit those who research in the area.

As has been noted, the validation and verification of a model has been paramount, with this as a clear motivation for the continued development of simulations and model, Robert Sargent (2010) [50] offers an insight into the different methods available to achieve this. Figure 2.7, shows Sargent's view of the interaction between the real world and the simulated world (as defined by him), identifying the actions that he considers need either validation or verification.

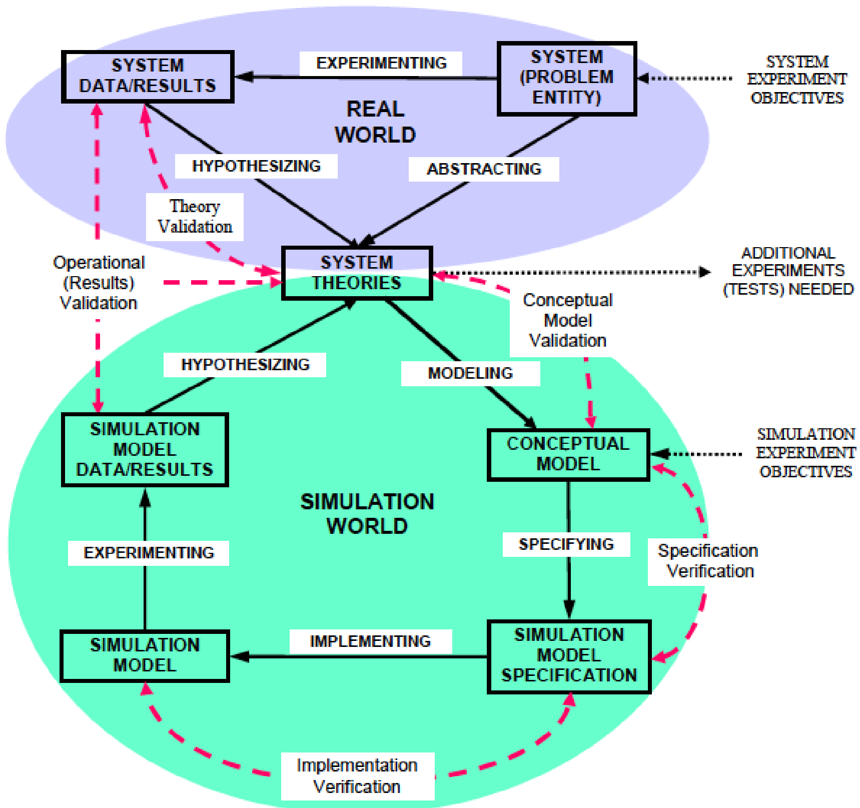


Figure 2.7: Real World and Simulation World Relationships with Verification and Validation (Sargent 2010 [50] Figure 3)

Sargent outlines the basics of fifteen different techniques for validating a model, a number of which are useful for validation in this research, such as 'Internal Validity', however some of these are either not relevant or achievable given the design and requirements of the simulation, for example 'the use of historical data'.

Despite this idealised scenario and detailed explanations for validating and verifying the model, Sargent is very clear about potential of spiraling costs needed to completely validate a model, also stating that "there is no set of specific tests that can easily be applied to determine the 'correctness' of a model" and that "Every simulation project presents a new and unique challenge to the model development team".

2.7 Summary

This chapter identifies the previous research that has been performed that is relevant to this research.

The previously performed research has shown that artificial agents using a variety of learning algorithms are capable of accurately replicating the operations in an electricity market. Where this research differs from much of the research covered is that the agents are operating on a simulation that are able to explore all of the possible search space.

The AMES system provides a detailed look at a sample electricity market with full coverage of the electrical engineering principles that can affect a transmission grid. This research is concerned to a more with the operation of the market as opposed to the transmission grid that it operates on. Additionally the EMCAS project covered shows clearly that large scale models of electricity market interactions are possible, and that detailed studies can be performed and the results can be used to influence policy.

The field of Agent Based Computational Economics is a field that has been explored in a number of different ways concerning many different aspects of the wider subject area. The research presented here is focussed on a single aspect of market design, which is the short run price efficiency of a market.

One of the main reasons stated for performing this research is to attempt to stretch different market designs, in this case pricing mechanisms, by creating an environment where those agents competing are actively doing so in a purely profit maximising manner. The concept under investigation here is that while evolutionary agents are highly adaptive in the environment that they operate, they are consistently able to exploit the rules under which they operate to give novel solutions to problems.

The work by Xiong et. al. presents a comparison of two different market designs, however this comparison did not use a constrained electricity market. This is one of the major differences that this research presents in the comparison of different market design, which would be expected to result in different behaviour by those competing in the market. By comparing market designs with the consideration of constraints, it is possible to get a more specific idea of how resilient and under what conditions the differnt markets are to the potential gaming of the system. While evolutionary based algorithms have been applied to the area of computational economics of electricity markets (such as Richter and Shebel's work), they have not been used in a comparative manner to explore the use of market power within these markets.

Where much of the literature offers learning based agents to test a market design with a level of rationale to the portfolio choices and actions, the evolutionary system proposed for this research is creating a simulation, where each agent is able to best explore all possibilities available to them. This use of an evolutionary agents for the creation of short run prices in a constrained electricity market allows for the potential of exploring the way that market power can be exploited that is not represented in the previous work presented here.

Chapter 3

Electricity Market Model

In order to create the best understanding of not only how a realistic electricity market works, but how it can be pushed to it's limits, a detailed simulation has been proposed to act as the operational framework in order to achieve this objective.

A proposed simulation for this research needs to cover all relevant aspects of a real market, including not only the expected trading regulations, but other aspects such as those of physical constraints (in the form of the power transmission network) and operational constraints (regulations), although the latter features more prominently in those who operate on the market (the Agents).

There are two main constraints that need to be addressed before the design of the simulation can be discussed, as they are crucial for the success of the simulation. The first is that the electricity delivery system must have a balance of supply and demand. The main reason for this is that an excess or a shortfall of supply can lead to an overload or underload of supply on the network, which can in cases lead to system blackouts. The National Grid in Great Britain has a small range on it's system load which allow it to be within it's safe operational bounds before it needs to be corrected. With regards to this research, much of the concern surrounding the exact load of the system is handled at the time of delivery where exact supply and demand is known, whereas a day ahead market, such as the one used in this paper, is based off of predicted demand, that doesn't operate at the time of delivery. While there isn't this perfect requirement in the proposed market structure to ensure that supply and demand equalise, due to this predicted nature of the data used and additional real-time balancing, the desire is still to balance a proposed level of supply and demand in the system.

The second aspect that needs to be addressed is that of the power network and electricity delivery system.

A number of studies in this field assume that the electricity is effectively generated in a limitless transport system, however the desire for completeness of simulations and the model used has generated the desire for representing a transport system. The importance of being able to identify a valid movement of electricity in the network is especially important when concerned with evaluating market rules with regards to realistic operation. The basis of the importance of the transmission system is that each power line that the electricity is transferred along has a standard maximum operating capacity, which in order to protect the line from damage should not be repeatedly exceeded. With regards to not wanting to damage the lines by repeated overloading, the simulation needs to have build in a measure to regulate exactly how much electricity can flow down a single line. Although the standard operating capacities on the lines can be broken within reason, it is desirable to minimise the amount of times this occurs, such that if there is a feasible way to rebalance the system without overloading any line then that is preferable. However in the case that a suitable alternative is not obtainable within a reasonable time frame, small overloads will be permitted.

The remainder of this chapter is concerned with the details of the design and implementation of the simulated power transmission system and electricity market. This is achieved first by looking at the AMES platform as an alternative to the developed system, followed by the design of the transmission system and rebalancing mechanism. The chapter follows by looking at validating the implementation of two different pricing rules that are used and the balancing mechanism.

3.1 Alternative Transmission Platform

One of the earliest considerations for this research was to implement a design using the open source AMES Model that has been developed by Tesfatsion et al [56]. The AMES model is a power flow test bed which emulates to a very high precision the the electrical engineering principles that are at the centre of an electricity transmission system's operation.

There are two main benefits to implementing the AMES test platform as the basis for this simulation. The major benefit of implementing the system is the precision of the results, since a high level of emphasis has been placed on emulating as closely as possible the electrical engineering aspects required for the power grid. This would instill a high level of confidence that the underlying aspects are less contestable, making the results achieved above it more reliable.

The other major advantage is that the system is that the AMES platform is open source, which meant that during development there was an available implementation that had been tested and had been verified as stable. This would save time and resources spent on developing a new platform. However in order to make the most effective use of the advantages the platform offers, a complete understanding of the operation and the code is needed.

It is this level of understanding that causes one of the main issues with developing on the AMES platform. In order to achieve the stated aim of this research, a number of modifications would have had to be made to the code to allow for the required interactions of the planned agents and market, which could have jeopardised the integrity and performance of the underlying system.

The other concern with the AMES platform was that at the time of development, the platform had not been tested on an network the size desired for the experimentation. The literature available on the project had identified the potential for developing on a larger system, however to that point the results had been based on a 5-Node network.

Although the AMES platform does have some significant advantages, the number of unknown factors that could affect the development and results of the simulation and the results were considered to be too high in this case. As such an alternate design was proposed using an approximation to the power flow model, which allows for a far more simplistic structure for development and integration, while maintaining enough of the complexity of a real transmission network to give confidence in the results.

3.2 Simulation Overview

The simulation used in this research is split into two main sections, the power transmission system and the day-ahead electricity market. The power transmission system is a representation of the physical attributes of the system, where the market governs the process by which the financial calculations for the simulation are handled. Figure 3.1 shows an overview of the design of the simulation, including the basic flow of information.

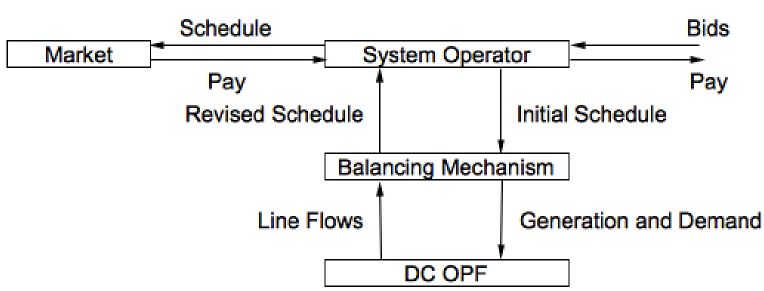


Figure 3.1: Overview of Simulation Interactions

The System Operator represented in figure 3.1 is designed as a central control for the various different aspects of the simulation. The primary function of the System Operator is to maintain the current 'best' state for the supply of electricity in the simulation. This is achieved by first creating an initial state, where all demand is filled as cheaply as possible from the bids supplied to it, which in the case of the research consists of those generated by the agents. At this stage no line constraints have been considered, in order to ascertain if the initially generated solution is passed to the balancing mechanism where it is tested in order to see if any line constraints are exceeded. This test is performed by calculating the flow along each line such that the generation schedule and nodal demand would result in, which is done using the Direct Current Optimal Power Flow (DC OPF) algorithm. The values calculated correspond to the amount of electricity that will flow down each line, this is checked against the operating capacity stored for each of the lines, where a valid state in this case is considered to be a load flow profile in which no line exceeds it's operating capacity.

Once validated by the balancing mechanism, the generation state is returned to the System Operator, which then submits the generation profile and bids to the market in order to calculate pay for each generator. If however during the balancing mechanism's validation process, the predicted load for any line exceeds the pre-defined maximum, then the state is considered invalid and the balancing mechanism will attempt to create a valid state by modifying the output of different generators in order to manipulate the flows along different lines. Once a new valid state has been found, then this new state is returned to the System Operator to calculate the pay levels for each generator.

3.3 Balancing Mechanism

One of the fundamental parts of the proposed simulation is the balancing mechanism, which is a function that is designed to ensure that a completely valid generation schedule (or in severe cases a minimally invalid schedule) is found, where a valid generation schedule is a set of generator outputs, such that supply equals demand and that the load on any given line does not exceed it's standard operating capacity.

A diagrammatic representation of the balancing process can be seen in Figure 3.2, following which each of the six stages represented in the flow chart will be covered in more detail.

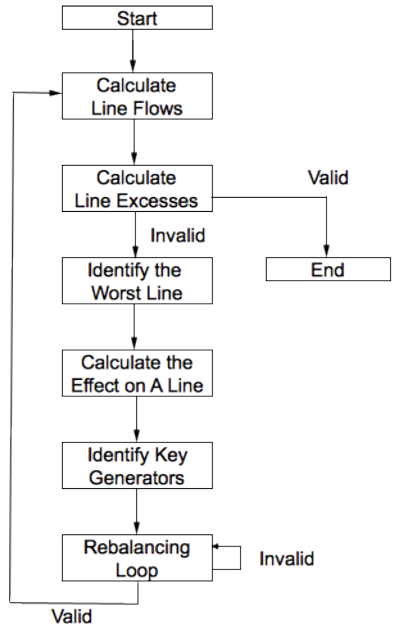


Figure 3.2: Balancing Mechanism Process

3.3.1 Calculating Line Flows

The initial stage of the balancing mechanism is to calculate the network injections (physical input of electricity onto the network) of the current generation schedule, referred to as a solution in regards to the balancing mechanism, which is either the initial solution from the System Operator or a revised schedule from a solution in the balancing mechanism. The network injections are performed by subtracting the total amount of electricity demanded at a node from the total generation at that node. These values are then converted into a vector, which represents the available supply (positive values) and remaining demand (negative values) in the network. This vector forms half of the Approximate DC OPF equation, where the other half of the equation is a transfer profile, which identifies how the electricity is effectively transferred, the basis of which is set out in Schweppe et at. (1988) [20]. The version displayed here is a matrix form presented in Green (2004) [21].

$$\underline{z} = \underline{y}(R^{-1}A(A^TR^{-1}A)^{-1}) \tag{3.1}$$

Equation 3.1 shows the approximate DC OPF algorithm in matrix form, Where matrix A is the admittance Matrix, a reference matrix of size m x n, where m is the number of lines and n is one less than the number of nodes. Matrix R is a diagonal matrix of size m x m, where m is also the number of lines, and the values held in the matrix are the resistances of each line defined in respect to each other. Vector $\underline{y}$ is the set of network injections as previously calculated and the output vector $\underline{z}$ is the calculated flow along each line.

A working of the algorithm in a simplistic case study can be seen in Appendix A.

In the development of this component of the balancing mechanism, the JAMA [38] open source matrix package was used for all applicable matrix operations.

3.3.2 Calculating Line Excesses

The line excesses are the differences between the standard operating capacity of the line and the actual or predicted load for the line. Equation 3.2 gives the simple form of calculating the line excesses.

$$\underline{a} = \mid \underline{z} \mid - \underline{c} \tag{3.2}$$

Where $\underline{z}$ is the set of load flows calculated according to equation 3.1, $\underline{c}$ is the set of standard operating capacities for each of the lines and $\underline{a}$ is the resultant excesses. Since the DC OPF algorithm gives each line's flow in terms of a directionality, where a positive value in $\underline{z}$ indicates a start-end directional flow and a negative value indicates an end-start flow, the load flow values must be taken as absolute values for this calculation.

A check is then performed on each of the values in a in order to find out if each line has a valid load level. A positive score for a line indicates that the predicted load for a line exceeds the maximum capacity of the line and will invalidate the solution and result in the requirement for (further) rebalancing, subject to the remaining number or rebalancing attempts available. If all values in a are less than or equal to zero, then the solution is validated and can be returned to the system operator.

In the case that the maximum number or rebalancing attempts has been exceeded, then the last solution tested is returned, in place of a completely valid solution.

3.3.3 Identifying the Worst Line

In the case that there is more than a single line that has a predicted load that exceeds it's standard operating capacity; then the system must identify which line it will prioritise in rebalancing the system.

There are two main approaches that can were considered for creating priority in rebalancing lines. The first method is to order the the lines by the absolute value that a predicted load exceeds the standard operating capacity, where the second method orders the lines by the percentage value that the load exceeds the capacity. An alternative to taking into consideration the actual imbalance of loads, is to order based on the line capacities, or on a predefined order, despite this method highlighting the major lines first, it has the potential to waste resources solving a minor line imbalance, albeit on a line with greater capacity, in preference to a line that needs

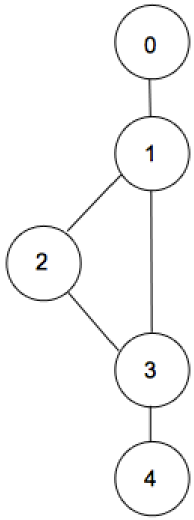
Of the two approaches based on the predicted loads, prioritising by absolute value was chosen in preference to the percentage method. The reasoning for this is similar to the reasoning of not predetermining the order to rebalance, in that there could be a minor line that is overloaded by a significant percentage of itâĂŹs capacity, but has a lower absolute level of load than one of the major lines. As such, the aim in taking the largest imbalance first, is that a number of the smaller imbalances are corrected as a result of the adjustments made to the generation schedule. Although not guaranteed in all cases, the expectation is that this method will result in fewer iterations required to rebalance the generation schedule.

In the simulation's implementation, the values of vector $\underline{a}$ in equation 3.2 gives the differences in load against the capacity and the simulation selects the highest vale from amongst these for the rebalancing process.

3.3.4 Calculating the 'Effect' on a Line

One of the key attributes in rebalancing the loads on the system, is to know how the change in output of a given generator will affect the load on the target line. This process is performed to help later identify the key generators that will cause the required impact on the load profile such that the load does not exceed the capacity on the given line.

To calculate the effect on a given line, is a process to determine the impact that a single MW of generation has on the target line. This is done by simulating a single MW of generation at each node and calculating how much of the generated MW will flow down the line. To get a complete view the MW of generation is simulated to be required at each end of the line independently, this is so as to identify both the potential positive and negative impact on the line. Figure 3.3 shows a simple network and the relative effect that a single MW of generation has on a given line.



	Target Node	
Node	1	3
0	0	$\frac{2}{3}$
1	0	$\frac{2}{3}$
2	$-\frac{1}{3}$	$\frac{1}{3}$
3	$-\frac{2}{3}$	0
4	$-\frac{2}{3}$	0

Figure 3.3: Diagram of the Effect of a Single MW of Generation on a line

In the example shown in figure 3.3, the imbalance being corrected is on the line between nodes 1 and 3, with the directionality of the flow from 1 to 3. The table shows how a single MW injected into the network at each node will affect the flow on the line.

3.3.5 Identifying the Key Generators

With a defined set of 'effects' based on a change in generation at each node in the network, the next step is to identify the financial impact that a change in output for any given generator will have on the target line. This is done by taking each of the bids supplied by the generators and scaling the price that a MW is supplied at in relation to the effect on the line, such that for each bid, there is a monetary value that can be attributed to increasing or decreasing a single MW of flow along the target line.

The bids are sorted into two arrays, based on the effect they have on the line, the first array contains all of the generation that is currently available, that will reduce the load along the line (in relation to the current direction of flow). Currently available generation is defined here as any generation that has not been utilised in the current generation schedule, either from an unused generator or additional generation from a generator that is scheduled, but is not scheduled to produce at capacity. The second array consists of all currently scheduled generation, that can be removed from the generation schedule, such that the net effect will be a reduction of the load on the line (in relation to the current direction of flow).

The two arrays are sorted by their financial impact per MW adjusted. The array that contains the available generation is sorted, such that it minimises the cost per MW fixed, where the scheduled generation array is sorted so as to maximise the savings per MW adjusted.

3.3.6 Rebalancing Loop

With a complete set of bids that impact the line and the extent to which they impact it, the loads can be adjusted to reduce the load on the target line. The rebalancing loop consists of multiple iterations of increasing the generation selected from bids in the available generation array and reducing the generation from the bids in the currently scheduled array.

The process works by taking the cheapest impact MW from the available generation to replace the most expensive impact MW on the surplus side and repeating until the load on the line no longer exceeds the defined capacity. Once this process has been completed for the current line, the generation schedule is updated to reflect these changes and is returned to the first step of the balancing mechanism to attempt to validate the new schedule.

3.4 Market Validation

It was noted in Chapter 1 that in creating a simulation there is a great importance in validating the model so as to better draw reliable conclusions from the experimentation presented later in this chapter and for the large scale study in Chapter 7.

As was noted in Chapter 2 when discussing validation and verification, it was noted by Sargent that defining the method and success of any such verification or validation is a challenge that is presented to the development team of the model. In Chapter 1, one of the main attributes of this research is that the agents are developed in such a way that they are aiming to explore weaknesses in the market design, the main point of validation that needs to be considered is the correct application of the market rules such that the evolutionary agents are not exploiting issues with the programming.

To validate the model, two different tests are performed identifying critical aspects of the simulation. The first aspect that needs to be validated is the operation of the two pricing mechanisms, where the main issue is ensuring that the deterministic aspects of the balancing mechanism are correct. Whereas the second aspect is the validation of the line constraint calculations, ensuring that when bids are submitted they are handled correctly by the market operation.

3.4.1 Validation of Market Mechanisms

The initial validation being performed is concerning the operation of the payment mechanism, this is achieved by considering a simple case where we can calculate the pay for each agent and compare it to the simulated result.

By modelling the interactions of the market in a pseudo 2-node network, it is possible to clearly identify if the model is performing the correct calculations that are expected. To perform this test a number of post balancing mechanism states for 5 bids split across two nodes are constructed where the pay for each of the generators can be calculated in each case. For two alternative 2-node scenario, 4 different dispatch schedules need to be considered, a constrained and an unconstrained version for each of the market designs.

Bid	P(£)	Q (MWh)
A1	10	100
B1	20	100
C1	30	100
D2	40	100
E2	50	100

Table 3.1: Market State A Bid Offers

Bid	P(£)	Q (MWh)
A1	10	100
B1	20	100
C1	40	100
D2	30	100
E2	50	100

Table 3.2: Market State B Bid Offers

Tables 3.1 and 3.2 shows the bids offered to the market in the two cases for this validation, where bids A, B and C are offered from Node 1 and bids D and E are offered from Node 2. The two situations considered are an unconstrained case (a demand of 300MW) and a constrained case (a demand of 400MW).

Buy Back Unconstrained

The unconstrained Buy Back scenario defines a situation, where no rebalancing was needed in order to create a valid load flow. This means that all market participants scheduled to produce should be paid at the uniform market price.

For a quantity of 300MWh, the uniform price should be £30/MWh in both states, where A1 and B2 should be paid a total of £3000 each and then in State A C1 will be paid £3000, but in State B D2 will receive the payment instead of C1.

Nodal Unconstrained

Under Nodal unconstrained conditions, the market should create a scenario, where the price paid at each node for generation is equal and set at the price of the most expensive generation scheduled. In either state the most expensive generation scheduled is the For a quantity of 300MWh, the nodal price at both nodes should be £30/MWh in both states, where A1 and B2 should be paid a total of v 3000 each and then in State A C1 will be paid £3000, but in State B D2 will receive the payment instead of C1.

Buy Back Constrained

The Buy Back constrained scenario is designed to test at a simple level that should a schedule require rebalancing that the payments made to each individual are correct based on the market rules.

In this scenario the demand of 400MWh would in both cases initially be scheduled by A1, B1, C1 and D2. However if a constraint is considered that requires the reduction of generator output at Node 1 from bid C1 of 100MWh and an increase in output at node 2 from bid E2 of 100MWh. This should see that A1, B1 and D2 are paid at the uniform price level of £40/MWh, C1 should be paid at the uniform price minus the bid price and E2 will be paid at its bid price of £50/MWh. In State A, the price C1 will be paid should be £10/MWH and in State B should be paid £0/MWh as the uniform price is equal to the price bid by C1.

Nodal Constrained

The Nodal constrained scenario is designed to test at a simple level that should a schedule require rebalancing that the payments made to each individual are correct based on the market rules.

In this scenario the demand of 400MWh would in both cases initially be scheduled by A1, B1, C1 and D2. However if a constraint is considered that requires the reduction of generator output at Node 1 from bid C1 of 100MWh and an increase in output at node 2 from bid E2 of 100MWh. The constraint should see two nodal prices being calculated that relate to the respective bids for the generation. In both States A and B, the nodal prices should be £20/MWh for Node 1 and £50/MWh for Node 2.

An extension to this case can be considered where there is a reduction of only 50MWh from C1 (and increase of 50MWh from E2), will cause no change in nodal price at node 2, however at node 1 the nodal prices will be £30/MWh in State A and £40/MWh in State B.

Results

The results presented here show the outcome of the payment and balancing mechanisms within the simulation. In both states, the results come out to those predicted in the scenarios as described above. The results presented here show the total payments made to each of the generators rather than the price per MWh produced as it more useful in clarifying the basic operation of the market within the simulation.

Case	A1	B1	C1	D2	E2
Buy Back (Unconstrained)	3000	3000	3000	0	0
Buy Back (Constrained)	4000	4000	1000	4000	5000
Nodal (Unconstrained)	3000	3000	3000	0	0
Nodal (Constrained)	2000	2000	0	5000	5000

Table 3.3: Market State A Payments

Case	A1	B1	C1	D2	E2
Buy Back (Unconstrained)	3000	3000	0	3000	0
Buy Back (Constrained)	4000	4000	0	4000	5000
Nodal (Unconstrained)	3000	3000	0	3000	0
Nodal (Constrained)	2000	2000	0	5000	5000

Table 3.4: Market State B Payments

As noted in Chapter 1 the pricing mechanisms act as analogies to the long run contracting process, so the outcome of this validation, is not to state that these pricing mechanisms work exactly as the market documentation states, but to identify that when the experiments are run there is confidence that the mechanisms are operating in a predictable manner. From the results presented, both pricing mechanisms appear to operate correctly under constrained and unconstrained conditions.

3.4.2 Validation of Load Flow Equations

The second consideration that needs to be made is that the line flow calculations are acting correctly and restricting the generation of the agents where necessary. While the previous validation method appears to show to some degree that the rebalancing method appears to be operating correctly, the focus of this section is in ensuring that generation is constrained correctly when the load is being transfered between intermediatry nodes.

In order to test for the validity of the line constraint calculations, 3 different small scale scenarios have been developed that represent cases that could be potentially experienced by a market.

Each of these test cases uses a simple 5 node network, each with their own characteristic generation and demand schedules that create the desired scenario.

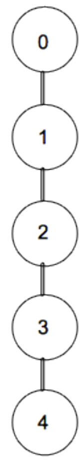


Figure 3.4: A Simplistic 5 Node Network Design

Line ID	Start Node	End Node	Capacity(MW)
0	0	1	500
1	1	2	500
2	2	3	500
3	3	4	500

Table 3.5: 5 Node Test Case Line Data

Never Constrained

The never constrained case is a specific case that under marginal cost conditions there should be no binding constraints even at the highest demand level. The demand and generation is split evenly amongst the generators and the only determining factor in deciding generation is the price.

The expected outcome from this should show that no lines are congested under any case with marginal cost bids. The lowest cost generators should be dispatched in full up until all demand has been filled.

Node	Generation Capacity (MW)	Cost per Unit (Âč)	Proportion of Demand
0	320	5	0.2
1	320	6	0.2
2	320	9	0.2
3	320	11	0.2
4	320	13	0.2

Table 3.6: Never Constrained Test Case Generator Data

Highly Constrained

The highly constrained case is designed to ensure that under all demand levels above the initial 30% demand level the line between nodes 0 and 1 will be constrained under marginal cost conditions.

The expected outcome in this scenario is that at the 30 level the lines will not be constrained, however at the higher demand levels the output of the generator at node 0 will be restricted to the nodal demand plus the 500MW line constraint. The 60 and 70 demand levels will also cause the constraint between nodes 1 and 2 to become binding, and will require dispatch from the generator at node 2 in order to fulfil the required demand, while the output from generator at node 1 is restricted due to the large excess of supply at node 0.

Node	Generation Capacity (MW)	Cost per Unit (Âč)	Proportion of Demand
0	650	5	0.1
1	355	6	0.3
2	200	9	0.2
3	200	11	0.2
4	200	13	0.2

Table 3.7: Highly Constrained Test Case Generator Data

High Demand Must Run

The high demand must run case creates a scenario, where under marginal cost conditions no lines are constrained, however in the 50 demand cases and above, the generator at node 0 must run. Under marginal cost conditions, this effect is not-relevant as there is no attempt made at exploiting the market.

The expectation in this case is that no lines should have a binding constraint and so the generators with the lowest cost should be dispatched to meet the demand.

Node	Generation Capacity (MW)	Cost per Unit (Âč)	Proportion of Demand
0	850	5	0.4
1	350	6	0.2
2	200	9	0.2
3	100	11	0.1
4	100	13	0.1

Table 3.8: High Demand Must Run Test Case Generator Data

Results

The results presented here show the generation of each of the generators, while the Never Constrained and High Demand Must Run cases are interesting as case studies and are revisited in the next chapter. The main results come from the Highly Constrained case, which demonstrates the rebalancing method operating to ensure that no generator produces more electricity than they can exported given the line constraints.

	System Demand				
Generator	30	40	50	60	70
0	320	320	320	320	320
1	160	320	320	320	320
2	0	0	160	320	320
3	0	0	0	0	160
4	0	0	0	0	0

Table 3.9: Never Constrained Test Case Generation with Demand as a Percentage of Total System Generation

The never Constrained case shows a simple scenario, in which generators are scheduled in merit order up to capacity, at which point the next generator in the merit order is selected to produce. Given that there are no constraints that can be breached there is no revised schedule, as the initial schedule does not breach any constraints.

	System Demand				
Generator	30	40	50	60	70
0	480	564	580	546	612
1	0	116	220	288	336
2	0	0	0	76	172
3	0	0	0	0	0
4	0	0	0	0	0

Table 3.10: Highly Constrained Test Case Generation with Demand as a Percentage of Total System Generation

The results in the Highly Constrained case show that while a generator may have spare capacity available, if they are not able to transmit electricity because the lines are constrained by other generation, then the system creates a more optimal schedule.

In each of the 60 and 70 percent demand cases the generator at Node 0 produces enough electricity to fill demand at their own node and flood the lines going south. This means that while the generator at Node 1 is able to produce electricity, it cannot produce more than the demand of the node it is based at. The remainder of the demand is then produced at the next cheapest node, in this case Node 2.

	System Demand				
Generator	30	40	50	60	70
0	480	640	800	850	850
1	0	0	0	110	270
2	0	0	0	0	0
3	0	0	0	0	0
4	0	0	0	0	0

Table 3.11: High Demand Must Run Test Case Generation with Demand as a Percentage of Total System Generation

The high demand must run case is a less interesting verification scenario when operating at marginal price, because there is no gaming of the markets for profit. In this case the Large generator generates up to capacity and then the smaller generators fill the remaining capacity.

The results shown identify that in a simplistic case, the rebalancing mechanism is able to identify if a schedule is valid and rebalance it in an efficcient manner if required. Much like the validation of the pricing mechanisms, this serves as a means by which to measure the operation of the simulated balancing mechanism and that a real world rebalancing mechanism may operated differently according to market procedures.

3.5 Summary

This chapter creates a method of simulating a day ahead wholesale electricity market with two different pricing mechanisms.

The simulation creates the initially cheapest schedule available and attempts to validate it using the DC OPF algorithm. Invalid schedules are rebalanced by reducing the generation on the most expensive generators that impact the given line and increase generation at the cheapest available generators that will help reduce the load on a selected line.

The payments for valid schedules are calculated by the two pricing mechanisms. The buy back mechanism calculates an initial uniform price for generation and calculates payments for rebalance scheduling based on bid prices. Nodal pricing calculates a price at each node on a network and generators are paid based on the price at their node.

At the close of this chapter, two simple tests are performed to identify if the aspects of the simulation that form the market are operating as expected. The methods verify that both the pricing mechanisms and the rebalancing mechanism operate in a manner that give results consistent with the expected outcomes in a number of different scenarios.

Chapter 4

Agent Design

One of the major components of the simulation are the bids that are used to formulate the generation schedule, these bids define how much electricity a generator is willing to supply at different prices. Although a simplistic system could be defined to generate bids for each of the generators, this research is focused on the strategic games that can be played in the market and by the individuals that make these decisions, as such a more intricate method for defining how the bids are created is desired.

This chapter identifies the process taken behind designing the agent based system for operation with the simulation, first looking at the reason for using agents and what they are expected to do in this system, followed by a number of different designs considered for the agents, with an explanation as to what aspects made the implemented design preferable over the alternatives. The chapter then outlines the components of each of the agents, followed by a discussion of the assumptions and limitations made in the design of the agents. The chapter closes by identifying how the agents and simulation interact to perform the experiments described in chapters 5 and 7.

4.1 Rationale For Artificial Agents

With a real electricity market, the decision making process on the bids supplied is a job given to one or more people at a generating company or at a single generator. An agent, in the sense of this research and many other similar projects, is defined as a simulated representation of either the single person or collective people whose job it is to make the decision on the course of action that will maximise their objective welfare. Which in this case means that they are creating bids for generators that they control such that they maximise their profits.

The bids that are created have to be created in such a way, that they are carefully reasoned to reflect the interests of the generator owners. As such in the real market these decisions are taken to create bids that maximise profit and potentially minimise risk. It is with this line of requirement that a way of simulating not just the creation of a bid, but a process to make the best possible bid. A.I. based systems have a large and varied tool-kit, that makes them ideal for a number of different approaches in creating bids for market based simulations.

As previously stated, this system aims to replace each of the generators' operators with an artificial representation, it needs to be considered that this is not intended to be done in a way to directly replicate their behaviour. When looking at real market scenarios, the main focus tends to be towards the general operation of the market and is often conducted in a manner directed towards understanding how exactly the market will operate under normal conditions, which requires an approach that is characteristic of how an individual would act and react to create the realism of the market environment. However, this research aims to use the versatility of an agent based system to explore different strategies, that although their aim is to act and react with the market, they will not have the same burdens that the real operators of the generators have that potentially limit the risks taken, even when a potentially much greater payoff is available.

4.2 Alternative Designs

While developing the AI to govern the bid creation system, a number of different approaches were considered. These approaches are all centred around an agent acting to create a single bid for themselves, the following identifies the different ways in which these bids can be created. The three approaches considered are individual strategies, collective strategies and search agents.

The individual strategies consist of each agent generating a set of different possible bids for use in all cases for the market, which should cover enough of the search space to account for a variety of different scenarios. For any scenario all the different possible bids would be tested in the market, with the one with the best predicted result being selected for use. The selected bid would then be tested again with minor modifications being made to attempted to further improve the results achieved in the market, with the best of these being submitted to the market as the agent's bid. The set of initial bids to choose from would consist of a selection of specific cases (such as marginal cost and price cap values) as well as a set of bids created by testing low medium and high demand scenarios, where several iterations of testing the different strategies are used to create the set of bids for the agent to use.

The collective strategies approach is similar to the individual strategies approach, but instead of each individual agent generating it's own set of strategies, a single pool of different relative bids is created. The bids provided in this case contain less specific information for each generator, such as "bid 50MW at £25", and contain a more generalised form, such as "bid 25% of maximum capacity at marginal cost + 15%". The collective pool would be generated by testing a variety of low, medium and high demand scenarios, taking a sample of different generators making modifications across a number of iterations to give the final set of bids offered in the collective pool. Also much like the individual strategies method, after each agent has selected it's bid from the collective pool, through the same manner of trying each one to see it's relative payoff, they can make modifications to the bid in an attempt to create a better fitting strategy for the current market state.

An alternate version of the collective strategies would be to categorise each of the generators into several small groups by generator size or company and create a pool of strategies that each of these can select from. This could potentially create more relevant strategies for each of the generators than the collective pool, and reduce the number of semi-redundant strategies that would exist at an individual level.

The final method is the search based approach, rather than having pre-defined strategies for agents, the agent instead develops the bid at the time that it is required and tailors it to the current market state. For this approach two different search algorithms were considered, the first was a simple search algorithm that uses a single solution, in the case of this system a single bid, and checks neighbouring solutions in the current search space in order to find a better solution. This process is repeated a fixed number of times, allowing for the process to be restarted if no better neighbouring solutions can be found, with the best result seen throughout the process being selected as the final bid.

The alternative search algorithm considered was an evolutionary algorithm, that uses the dynamics of a population of different solutions in order to find the best result. The dynamics involved in this process involve the population of solutions interacting to create new solutions by trading critical aspects of their solutions amongst themselves to create offspring that share characteristics of the two solutions used in generating. These solutions are then modified to see if a small change is able to help improve the newly generated solution and make it better than any of the existing solutions, if it is an improvement then the best performing solutions replace the worst performing solutions currently being used.

With a total of four different approaches considered that were viable for use with the proposed simulation, a single method from these four was going to be used, the following outlines the choice of agent design and the reasoning behind it's selection.

The primary point for choosing which method to implement was, "how optimal is the bid made?". The optimality of a bid comes down to the overall process that the bid generation is going to be the outcome of a multi round game between all of the agents, where each market participant is aiming to move the market state into a most desirable position for themselves in the form of profits earned. By identifying these desirable positions, which will be the optimal position at any given stage of the game for the market participants, as such it will give the observer the opportunity to see if gaming within the market is enough to achieve abnormal levels of profit

By looking at the different methods highlighted, the two approaches that select from a pool of strategies, either individually or collectively, are less likely to produce an optimal result against the search based algorithms in a general case. Given a sufficiently large pool of strategies, both cases would be able to create highly optimised bids, however the time taken to create and search these pools would also increase. Both of these approaches would create an effective way of simulating a real market environment since they would allow for a viable set of different options that a human could reasonably estimate the effectiveness of in deciding on a bid to offer. However for this research, the algorithms that are designed for searching for the optimal result are preferred over the strategy pool approach.

In order to decide which of the two search algorithms is best suited to the requirements of the proposed simulation, the search space of the market for each agent needs to be considered. The main complication that exists, is that every transmission grid layout, set of market rules, trading arrangements and regulations will result in the formation of a different game and for each market state in a given game, there will be a different search space that an agent needs to traverse in order to find the globally optimal bid. In order to decide which of the search algorithms was best suited, a main use case needed to be considered, which was centred around a market with a large number of agents with a transmission grid and demand of proportionate size.

Although not reasonably testable prior to implementation, the search space that was hypothetically expected would be similar to the one shown in figure 4.1.

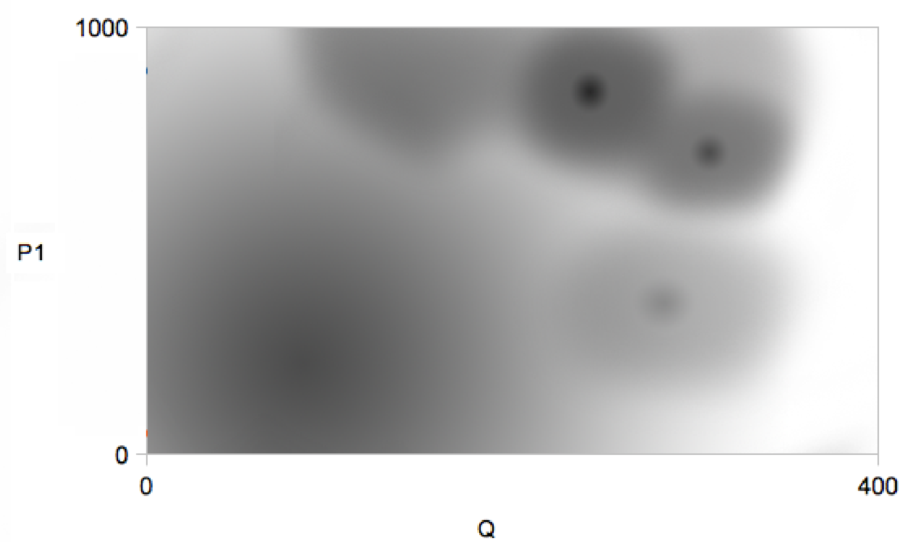


Figure 4.1: Possible Search Space

Figure 4.1 shows a number of different optima within a search space for a given market state, denoted by the darker areas as regions that offer a higher fitness score, this includes a prominent local optimum centred close to the marginal cost value. However the expectation is there are numerous other optima in the outlying cases. If the global optimum bid is frequently the prominent local optimum then the simple search algorithm is a more suitable approach. However if the outlying optima contain values superior to the large optimum, then they would be preferable and are more easily explored by an evolutionary based system.

With regards to this research, the interest is in the potential that the outlying cases have to influence the market, and the best method to explore these cases is the evolutionary algorithm, it is for this reason that an evolutionary algorithm was selected for the agent implementation. Although it should be noted that given sufficient resources the simple search algorithm would also be able to fully explore the search space in order to test the outlying cases, however during development the requirements for this were unknown.

4.3 Final Agent Design

The method for generating and analysing strategies is similar to the methods used by Richter and Shebel, where the strategies are developed using a Genetic Algorithm and the fitness function used for evaluation is based off of a market price prediction using those values.

In using an evolutionary search algorithm as the foundation of the agents, there are a number of important design decisions that need to be made regarding the operation of these agents. The diagram in Figure 4.2 shows the system flow for the bid generation for an agent.

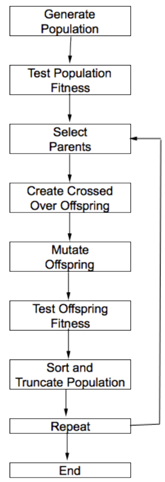


Figure 4.2: Bid Generation Procedure

This method breaks down the process into an iterative sequence that is repeated for a finite number of times, where the finite number is a predefined maximum number of repetitions or a point where the population of solutions has converged onto a single successful operational point.

In order to understand how this process works, the four key algorithms: parent selection, crossover, mutation and the fitness function must be defined. In order to understand the four key algorithms much of the process, the structure and generation of the population must first be defined.

4.3.1 Population

The population as referred to in evolutionary computing is a working collection of different potential solutions to the problem that the algorithm is trying to solve. In the case of the agents within the proposed simulation framework, a solution is a two step bid that could be supplied to the market in order to represent the willingness of the generator to supply it's electricity at one of two prices. Therefore the population in this case is a set of these bids, any of which could be supplied to the system operator.

Within the operation of the agents, the population is a constantly maintained as the set of the best solutions evaluated for the market state so far. A major part of this process involves the addition of of new solutions generated by the evolutionary algorithm to the population post evaluation, before the results are sorted based on their fitness and the population truncated to a defined maximum size.

In the case of these agents their fitness is defined as the total profitability of all related generators to the parent generation company. In the case that only a single generator is owned by a generation company, then it is their own profitability that is considered to be their fitness function.

The initial population that is used for each agent is a series of randomly generated two step bids that are created based on the physical limits of the generator that it represents, in addition to the rules of the market that the agent is a participant in. Although these restriction don't need to be adhered to in order to allow for operation of the simulation, in most cases, however it aids in ensuring that a valid schedule is always available to the system operator and that the strategies being used by the generators are at the very least valid.

An initial bid is formed of three randomly generated numbers, one each for the two different price levels that define the two steps of the bid and a single value for the quantity that that denotes how much of the total generation capacity will be available at the lower of the two bid prices.

$$0 \leq P_1 \leq P_2 \leq P_{cap} \tag{4.1}$$

$$0 \leq Q \leq G_{cap} \tag{4.2}$$

The two prices can have a value in the range of 0 to a maximum price cap and the quantity can range from 0 to the maximum output capacity of the generator.

4.3.2 Fitness Testing

The way any individual is tested, either for the initial population or one of the offspring, is to submit it as on offer to a simulated market with the other currently used bids for each of the agents. the simulated market will give an expected payment for each of the generators given the currently submitted bids.

The predicted pay that is generated as a result of the simulated market is passed to an algorithm that calculates the profit for the current generator as well as any other other generators that share a parent company. The sum total of the profits of each of the generators is the fitness score for that agent.

The total company profit was selected as the fitness metric as it best represents the way that a generation company would operate. This is due to the idea that the sum total of the profits of all generators owned by a single company would be preferable to the profits of each individual generator. the aim of this metric is to impact the way the agents operate, such that the effect is to create a different search space that the agents are traversing, that may under identical market states have alternative outcomes to a more conventional search of an agent's individual search space. This aspect of the agent design is one that will be investigated as a part of this research, allowing for a look at how changing an agent's fitness function in order to boost the welfare of the collective impacts on the market state.

4.3.3 Selection

The process of generating a new solution from the population of current solutions, first needs to define the parents who will supply the initial genetic material to form the basis of the new offspring. In the case of this research, the genetic material referred to it is a bid.

The selection process used is a system called tournament selection. Under this selection scheme, each member of the current population, and possible parent, is assigned a weight, which refers to the probability that a given solution will be selected as a parent. In tournament selection, these weights are assigned according to the individual's current ranking within the population, such that the solutions with the highest fitness are the most likely to be selected.

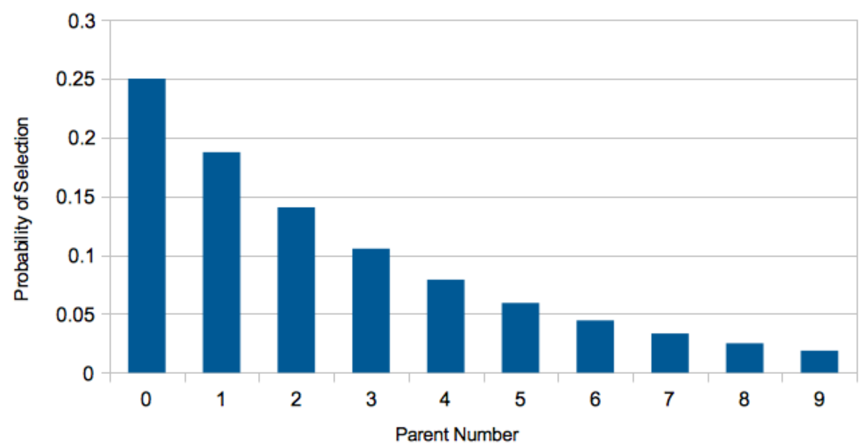


Figure 4.3: Basic Tournament Selection Ranking

Figure 4.3 outlines a sample of tournament selection using the form $p((1-p)^n)$ as the basis for calculating the probability, where n is the position of the solution in the ordered population and p is a base probability of selection, which in this case is 0.25.

Two parents are selected for each pair of offspring that are to be created, where each member of the population can only be selected once. After selection an individual in the population is removed from the selection pool and the weights adjusted to maintain the sum total of all weights equal to 1.

4.3.4 Crossover

For each of the two parent pairs that are created during the selection process, they will create two offspring. The process of creating offspring consists of two parts, the first of which is called crossover. Crossover with respect to this research, revolves around swapping aspects of the solution between the two parents to create two 'new' solutions.

In the case of the agents presented here, the two parents can have between 0 and 2 of the attributes (P1, P2 and Q) swapped, since swapping all three attributes would have the same result as not swapping any, and would lead to a bias in the crossover towards not swapping any attributes. Within the implementation, the two parents are cloned prior to the crossover and the process is performed on the clones maintaining the integrity of the original solutions.

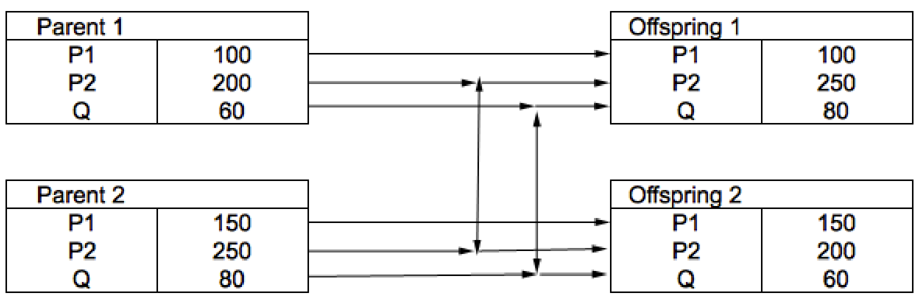


Figure 4.4: Sample Crossover

The diagram in figure 4.4 shows a two attribute crossover with sample parents based on the outlined agent design. As has been previously noted P1 must be less than or equal to P2, which might not be maintained as a result of the crossover; in this case, the values for P1 and P2 for that member of the offspring are swapped, so as to maintain the integrity of the solution as defined by the population.

4.3.5 Mutation

Having generated the basis of the two new offspring, the final step in creating the new solutions is to slightly modify their characteristics so as to potentially explore new areas of the search space or improve slightly on the exploration of the current region of search space. This is done by mutating between none of and all three of the attributes.

If an attribute is selected to be mutated, then the current value is taken and has a modifier applied to it to give a new value. The modifier is normally distributed around 0 and scaled in accordance with a pre-defined parameter, which gives the effective likelihood of the mutations being relatively large or small with respect to the system.

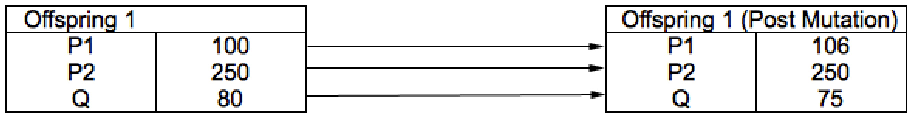


Figure 4.5: Sample Mutation

Figure 4.5 shows the possible mutation of a price variable for a sample offspring. The mutation is also bound by the same rules as stated previously, so if a value of P1 is mutated above P2 or P2 below P1 they will be swapped at the end of the mutation, in the case that they still breach the inequality. The other condition of the constraint is that they can not offer a price above the price cap or below 0, and likewise for the quantity, that can not go below 0 or above the maximum allowed generation, in either of these cases, the value is truncated to either 0 or the maximum allowed value.

4.3.6 Limitations

The main limitation that can be seen here is the use of perfect information in each agent's decision process, meaning that an agent receives an exact version of the current market state including all the competitors bids. The main consideration with this was that although the accuracy of the other generators' bids could be masked by applying some margin of error to the bids passed to an agent, this would require the agents to repeat the fitness process a number of times to reduce the margin of error in their decision making, which would lengthen the time taken to run the simulation process considerably.

4.4 Complete System Overview

Having identified the key component of the electricity market model and the agents, it is important to identify how these different components interact when performing the experiments.

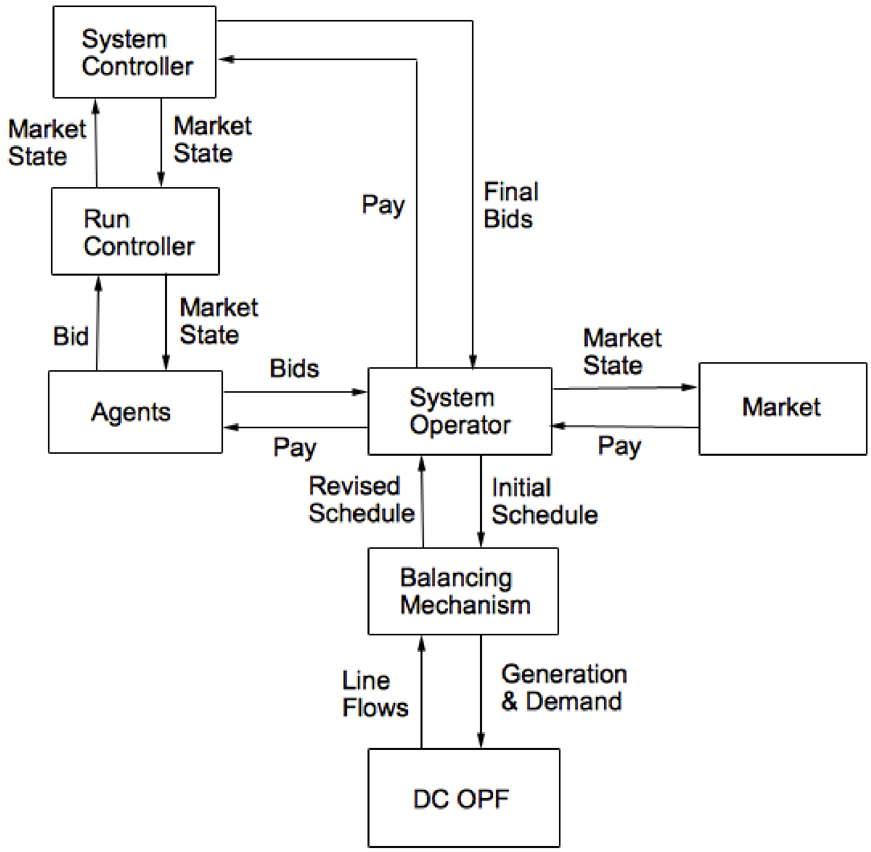


Figure 4.6: Overview of Data Flow in the Simulated Environment

Figure 4.8 shows the data flow within the simulated environment, where the data interactions between the Agents and the System Operator have been noted earlier in this chapter, however there are two new components in Simulation Controller and Run Controller that need to be covered in order to bring the entire simulation together.

4.4.1 Simulation Controller

The System Controller is the container from which the simulated game is run. This controller maintains two major roles, the creation of the initial market state and the operations that need to be performed after each call of the Run Operator.

The initialisation process involves creating a set of bids for each of the generators that creates a market state that is used as the initial starting point of the simulated game. The bids created are always a valid bit that a competitive agent would be able to supply it to the market and as such are constrained by equations 4.1 and 4.2.

This initial state acts much like a normal market state, with the only difference being that no agent has performed a move.

Following a single call of the Run Controller, a final evaluation of the market needs to be made with the new market state. This process is much the same as the evaluation of a bid made by an agent, involving a System Operator call with the market state, however the payments, generation, and profits are calculated and stored for each of the generators for each of the agents as opposed to calculating the total company scores for optimisation purposes. Following the end of turn calculations, the market state that was used is then passed to the run controller for the start of the next turn.

Once a predefined number of calls to the Run Controller have been made and the results calculated for the final run, the system outputs the collated results from each of the final market states.

4.4.2 Run Controller

The Run Controller is the container that contains the processing for a single cycle of a game, where a single cycle in this case is defined as a turn of the game in which every agent makes a move within the game. The Run Controller has two main functions, the first is to create a randomised order for each of the agents to take their turns and the second is to maintain the current market state of the game.

The randomisation of the play order amongst agents is aimed at removing bias from those agents that are able to operate later in a turn. If the game always reached a Nash-Equilibrium then this would not be a requirement, however it will later be seen in Chapter 6 that when the game is played by the intelligent agents shown in this chapter, the game cycles between a number of different market-states. Having identified this requirement, it can be argued that since the Simulation Controller calculates the market state at the end of a single cycle, the benefits for those agents who would be able to repeatedly offer bids late in a turn would bias the results in their favour. To reduce this bias for individual agents, the position in the turn order is randomised at the beginning of each cycle.

The results for the experiments performed in this research are taken as the average result across each of the cycles for a game, this is given the fact that we frequently do not see a single equilibrium state reached and taking only the final result could potentially give a result that represents any number of intermediary states. This means that across all runs the likelihood that any agent can be seen to be profiting from consistently acting later is much lower than a non-randomised order.

In the Run Controller an agent is called to calculate their move, characterised by the bids that they make as a result of the optimisation process. In order to do this an agent needs to take the most up-to-date state that exists within the market, where the most up-to-date state contains all of the most recent actions of preceding agents. In the case of the first agent acting in a run, they have the state that is passed by the Simulation Controller, which in the case of the very first cycle is the initial state generated by the Simulation Controller. Once an agent has decided on their most optimal action, the agent returns that action in the form of a bid, which is then used to update the current market state by replacing the previously stored bid with the new one. This updated Market State is then made available for the next agent that is called.

Once every agent has made a move, the turn is complete and the market state that was last updated from the final agent's action is then returned to the Simulation Controller.

4.5 Summary

This chapter outlines the artificial agents that are used to compete in a simulated wholesale electricity market, identifying potential alternative design and justification for the final selection.

The agents use an evolutionary process for creating a bid that is to be offered in a market. Each agent creates a set of possible bids called a population, from this a number of generations of offspring are created in an attempt to find the most optimal bid possible for the current market condition. Every bid that is created is tested using the simulated market given the current market state in order to give the solution it's fitness.

Chapter 5

Small Scale Experimentation

In order to create an accurate simulation of a real market, in this case an electricity market, a certain level of testing needs to be performed on the system in order to ascertain if the simulation is operating correctly. Although most of the individual component can be tested independently to identify if there are any operational errors, however testing the operation of the entire system to ensure it is correct is slightly more difficult.

The way the agents are designed is such that they should be able to identify any flaw in the the market or the programming in order to maximise their fitness. To ensure that the simulation works as accurately in terms of market replication as can be expected a small scale model has been designed and implemented for the purpose of testing, such that a reasonable level of confidence can be placed on the operation, that any exploitable flaws are in the market and not the coding.

In addition to testing the simulation, there are other reasons for wanting to perform experiments on a reduced size model. The first of these reasons is to be able to give us an insight into the behaviour of the agents and how this relates to the proposed hypothesis. It is because of the limited size of the model, that the actions of the agents can be studied closely and aspects of their interactions in the simulation can be better understood than on a large scale. Although there is a limit to what can be extracted as behaviour that will be relevant when the simulation operates with a large scale model, since many of the interactions will be symptomatic of the model. This however comes back to the key questions of "What does the agent do?", a look at the more specific actions taken and is more representative of the data used, whereas the other important question "Why would the agent do that?", is more relevant as it gives the characteristics of the decision process that the agent effectively takes and is more likely to be reflected in the outcomes of the large scale models.

5.1 Set-Up

Having defined the need for a small scale experiment, the design of a small scale model must reflect the requirements for the desired outcomes of understanding the basic market dynamics and agent behaviour. As such there are two main aspects that need to be decided upon, transmission grid layout and generation capabilities.

For a simple set-up there are a number of different network layouts that could be used, given that the model wants to be simple enough to understand the dynamics of the market and the agents and yet complicated enough to not consider it too trivial to draw anything meaningful from. The decision was taken to create a 5-node model, that consists of a transmission grid with five different generators, one at each of the nodes, with electricity also demanded at each of the nodes. The AMES project uses an intricate 5-node network that would work appropriately in running the basic simulations. Although the AMES network works well for experimentation, it was felt that the network layout could potentially mask some of the base level interactions that the experiment was designed to identify. For this reason, the most simplistic 5-node network was designed, a linear configuration, where every node is linked in series to the next, but not joined into a loop. This was done in part to ensure that the line constraints for every line could be monitored easily during testing of the simulation.

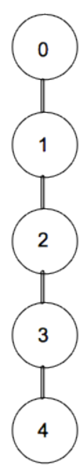


Figure 5.1: Small Scale Network Design

Node	Generation Capacity (MW)	Cost per Unit (Âč)	Proportion of Demand
0	275	5	0.1
1	275	6	0.15
2	550	9	0.175
3	250	11	0.275
4	250	13	0.3

Table 5.1: Small Scale Case Study Generator Data

Line ID	Start Node	End Node	Capacity(MW)
0	0	1	500
1	1	2	500
2	2	3	500
3	3	4	500

Table 5.2: Small Scale Case Study Line Data

The distribution of the generation and demand were designed such that there would be a surplus of supply in the north and a deficit in the south; this would require the movement of electricity from North to South; This would require the movement of electricity from North to South. The costs and scale of generation, effectively create a boundary between nodes 2 and 3, with the aim, that during peak hours the cheap electricity available in the north is not sufficient to cover all the demand in the south due to the operational capacity on the line between nodes 2 and 3. In addition to this, the generators south of the boundary between nodes 2 and 3 are incapable of fulfilling their demand with the combined generation available at both nodes 3 and 4. This effect could be achieved with a 2 or 3 node network, the additional nodes allow for the potential of extra complexity in the agents.

5.2 Defining the Experiment

There are two experiments that will be run on the small scale model, both of which are similar to the experiments that are also run on the larger scale later in this thesis.

The first experiment is designed specifically to look at the difference in results achieved when using the Buy Back Market as opposed to the alternative Nodal Market design. The reason for doing this is to gain an initial insight into how the system operates using both of these different markets, with the aim of this being to create a more detailed revision of the initial hypothesis.

To second set of experiments will be run looking at how the interactions of the agents are able to influence the market, where it is not only the market design, but these interatctions being tested. This will be performed by running the simulation with a base case, where each generator bids marginal cost, to give the underlying value of the market for that time step. Then this will be compared to a case where every generator acts independently and a case where the agents 0 and 1, and 2 and 3, act together in an attempt to replicate the operation of a larger GenCo, where agent 4 still acts independently.

For each agent there are only three different variables that are being optimised. With only a small number of parameters being evolved, the requirement to have a long evolutionary process is not necessary. One of the main considerations made with the parameter settings is the run-time of the simulation, where the evolutionary parameters are set such that for a given agent the strategy converges on an optimum strategy.

Both experiments will take the average of 5 runs, where each of the runs is performed for a number of different demand levels across the system. The demand is decided as a percentage of the total generation capacity of the model, where the lowest value tested will be a 30% demand level and will be incremented by 10% until a 70% demand level is reached.

Table 5.3

Parameter	Value
Run Cycles	100
Generations	100
Population	40
Offspring	20
p (Selection)	0.25
p (Crossover)	0.33
p (Mutation)	0.33
Price Cap	1000

Table 5.3: Small Scale Experiment Parameters

5.3 Results and Evaluation

The results presented look initially at the overall payouts of the system operator under different configurations and as increasing note is made of the strategy, where a brief mention of how three different GenCos (Companies 1, 2 and 3) profits are affected when co-operation is allowed as opposed to when each individual is only interested in maximising their own profit.

The results aimed at comparing the nodal to the buy back market, consist of identifying the outcome of several runs, Figures 5.2, 5.3 and 5.4 show the average payment made by the System Operator to the generators across 5 runs.

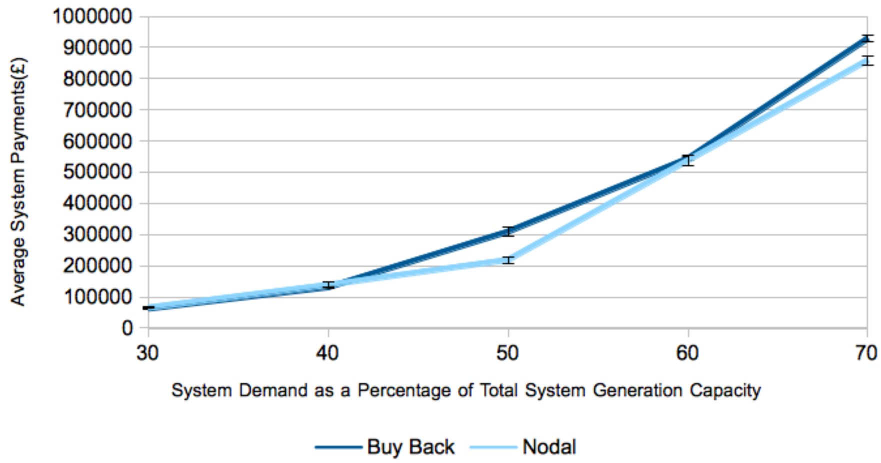


Figure 5.2: Average System Payments on a simulated 5-Node Network for Agents Co-Operating With the aim of maximising their Generator Companies Total Profits

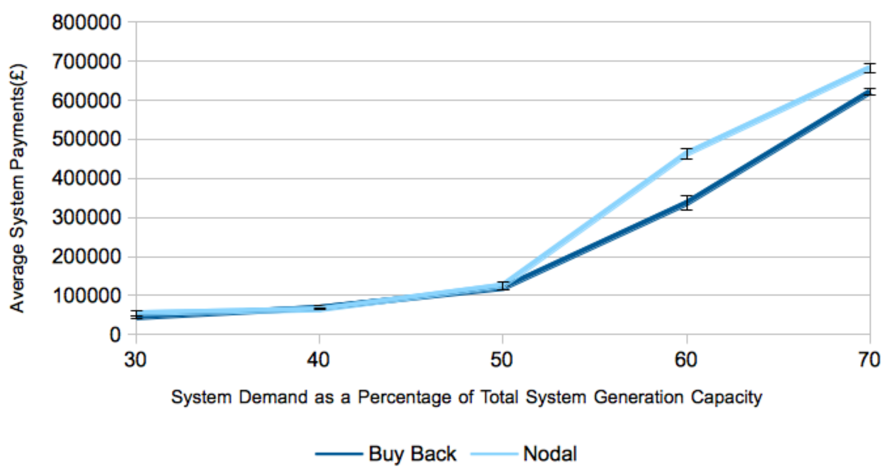


Figure 5.3: Average System Payments on a simulated 5-Node Network for Agents Acting to Maximise their Individual profits, not the Generation Company's Profits

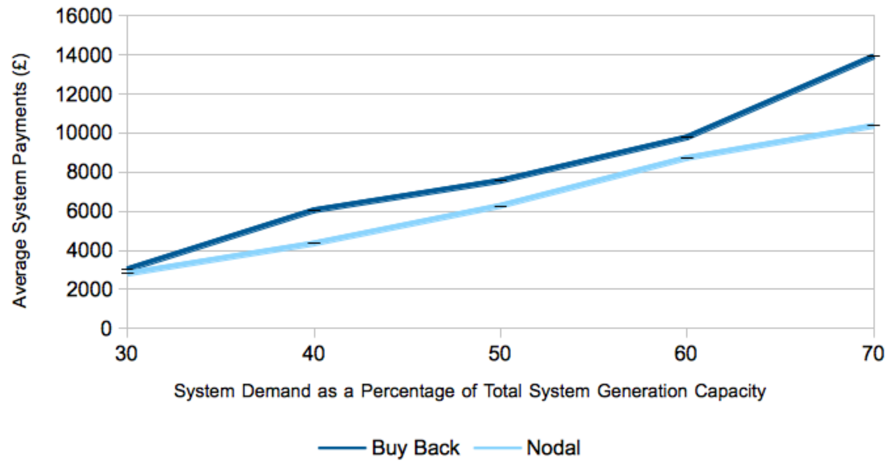


Figure 5.4: Average System Payments on a simulated 5-Node Network for Agents Bidding Marginal Cost

The lines in figures 5.2 - 5.4 show the trends of the different configurations, for theare three key operational pairings that explain the dynamics of the market; These are the Co-Operative, Individual and Marginal Cost pairings, since the Nodal and Buy Back configurations are directly comparable in these cases.

The value for the co-operative pair, shows the most interesting result, since the Nodal market offers on average a similar level of system payments as the Buy Back except for the 50% demand level, at which point the market creates a significantly different gap ($t(8)=6.98$ $p = 0.0001$). The trend in the graph shows a more consistent growth for the Buy Back market, as opposed to the Nodal Market, which shows a more rapid icrease in price after the 50% level.

In the Individual case, there is no significant difference in the average system payments made by the System Operator up to the 50% level. At the 60% level the Nodal Pricing Mechanism creates payments that are significantly above those of Buy Back Market ($t(8)=-5.74$ $p = 0.0004$), this gap is smaller at the 70%, but still maintains a significantly difference($t(8)=-5.9$ $p = 0.00036$).

This change in the market behaviour can be categorised as the point at which the generators on the high demand side of the constraint are required to generate electricity to fill the system demand. This requirement to generate on the supply side pushes the price at which the generation is offered up higher, where the generators that are working in collaboration with each other appear to increase their bids disproportionately to the increase seen before.

Figures 5.5 - 5.7 shows the average price that is paid per MW produced in the simulation.

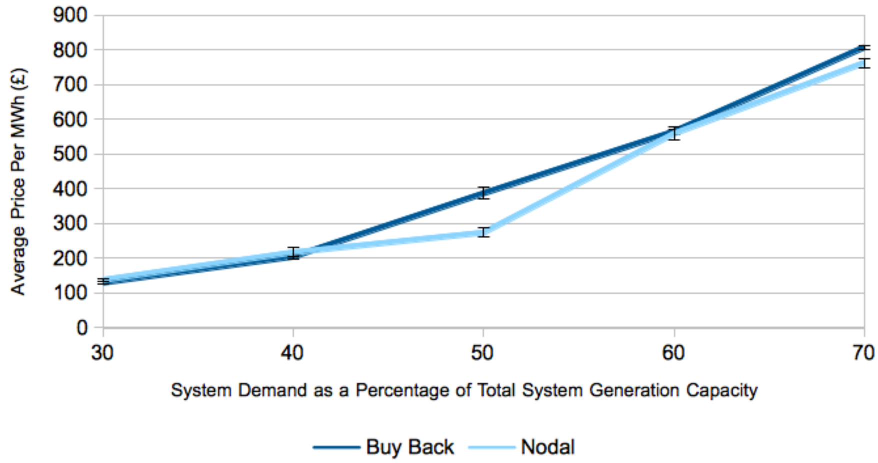


Figure 5.5: Average Price Paid per MW on a simulated 5-Node Network for Agents Co-Operating Within a Company

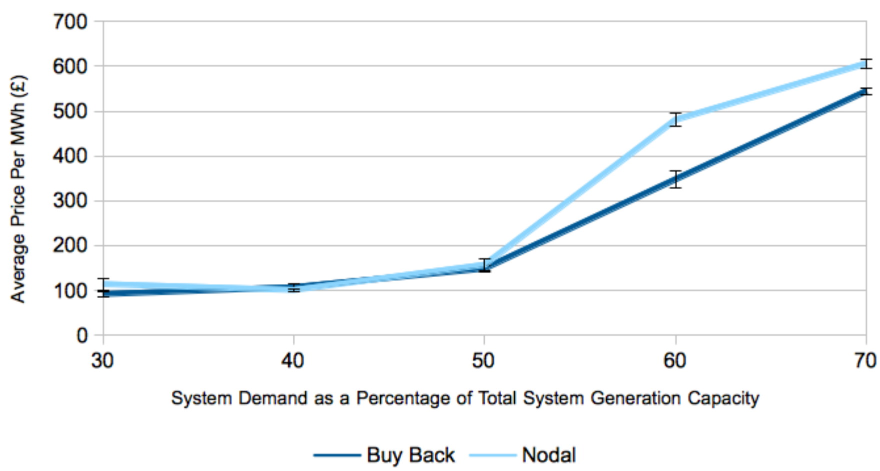


Figure 5.6: Average Price Paid per MW on a simulated 5-Node Network for Agents Acting Individualy

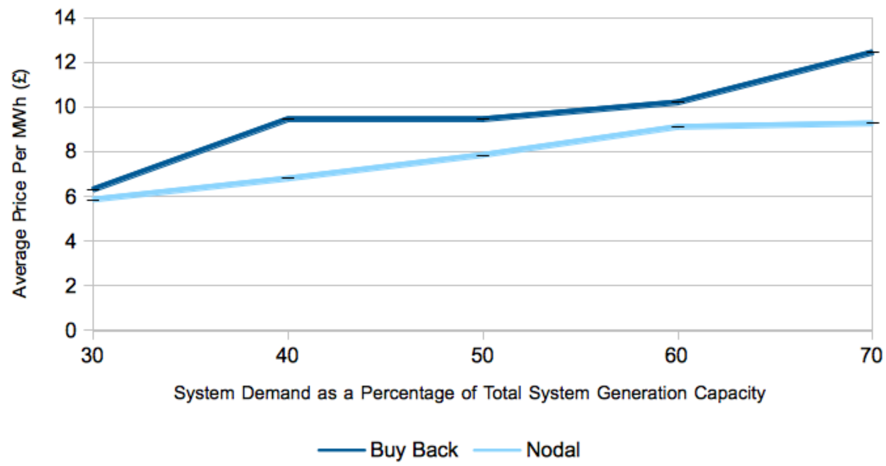


Figure 5.7: Average Price Paid per MW on a simulated 5-Node Network for Agents Bidding Marginal Cost

The general trend in the average price per MW shows that in the corporate case mirrors the results seen with the Average System Payments. At the 70% level, the two different pricing mechanisms both create an average price at more than Âč750 per MWh.

In the Individual case, the average price per MWh shows little growth up to the 50% level for both pricing mechanisms with rapid growth in the price after this level. This seems to indicate, that the price holds a stable consistent price for both mechanisms while the system is not constrained, but under a constrained environment the agents are able to game the market creating these high prices.

The marginal cost shows a much lower growth, as the price per MWh is only affected by the demand and will only increase due to network constraints

This can be seen in Figure 5.8, displaying the percentage increase in the system payments for both the Buy Back and Nodal Markets when allowing direct co-operation over individual profit maximisation.

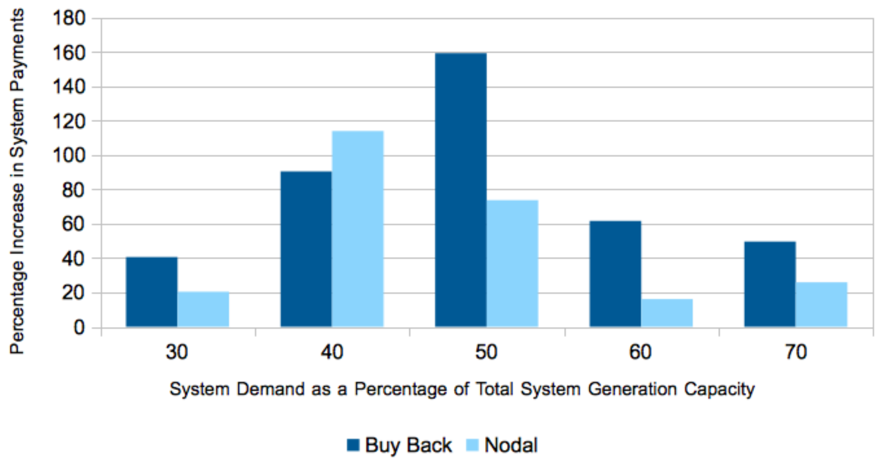


Figure 5.8: Percentage Difference in System Payments Between Co-Operative and Individual Agent Behaviour

The percentage increase in system payments when co-operation as a company, is larger in the Buy Back Market than the Nodal market at all demand exept for the 40% level. It is the change in behaviour available to the agents that is able to influence this, where those competing in a buy back market are seemingly able to influence the price to a greater degree, this is primarily due to the effect that a change in a bid might have on the initial global price of a buy back market against the rise in a nodal price in a nodal market.

In terms of the change in profits of the three companies, the percentage difference are shown in Figure 5.9 for the Buy Back and 5.10 for the Nodal:

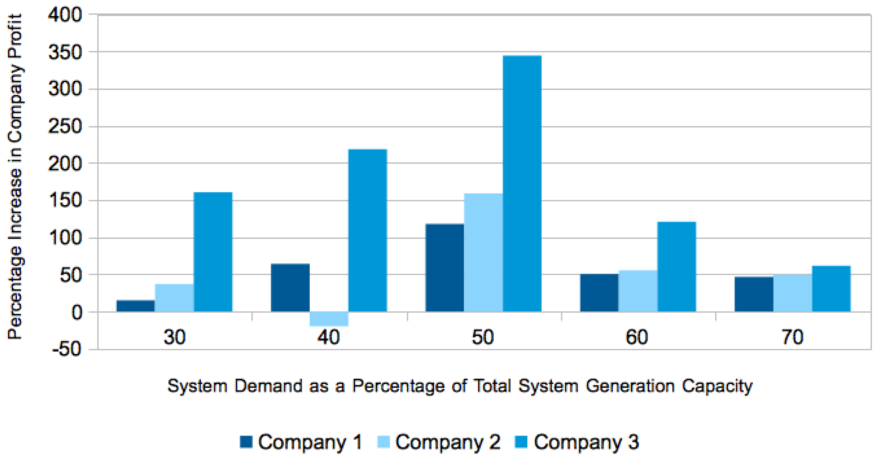


Figure 5.9: Percentage Increase in Profits per Company Co-Operative Versus Individual Strategy using the Buy Back Pricing Mechanism

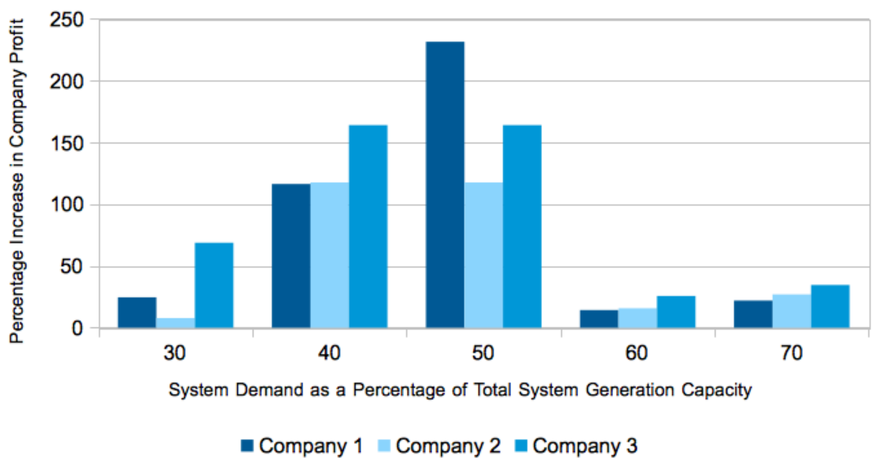


Figure 5.10: Percentage Increase in Profits per Company Co-Operative Versus Individual Strategy using the Nodal Pricing Mechanism

With the exception of a single reduction in profits for Company 2 at the 40% demand level using the Buy Back market, all of the other cases produce a positive increase in the average profit levels of the companies. Overall this is an expected result, since the co-operation of the generators reduces the level of competition, meaning that where their competitive actions when bidding individually might take away from the profit that the other generator they are paired with, the co-operative generators are aware of how a profit maximising bid on their part might actually reduce the genco's profits. The exception in this scenario is Company

3, which consists of only the generator at Node 4, which is not paired and even with no additional direct support, the indirect market dynamics of the reduced competition are able to increase their average profit, in some cases performing better than either of the two other companies.

5.4 Validation of Hypothesis

Having introduced a small scale case study, it was discovered that under the corporate case, the buy back market on average achieved a higher average price per MWh than the Nodal Market, however only at two price points was this a significant difference. However this same trend was not seen when there was direct competition between the agents, where the nodal market was able to on average achieve a higher price per MWh than the buy back Market. The hypothesis stated at the start of this work identifies that Nodal markets are better able to exploit market power in competitive electricity markets, where the more competitive the electricity market the lower the price that the buy back market design will be able to achieve and in more monopolistic designs, the results should show a significant gap between the price per MWh of the two different market designs.

In order to assert that this is a valid conclusion and not a specific result of this case study the effect needs to be replicated under different conditions. This will be done by revisiting the three alternative load flow test scenarios discussed in this chapter, looking at both the Corporate and Individual cases to identify if the case that a more competitive market favours the efficiency of a buy back market is a valid assertion.

5.4.1 Load Flow Validation Cases

By revisiting the load flow validation cases we can see that there are components that can be used to help define if this is a realistic result. In case 1 where there is no binding constraint at marginal cost levels the outcome should remain at a level where the market does not favour the buy back mechanism as the compe. In case 2 there is at a number of constraints that will become binding, which should result in an increase in the average price paid per MWh of electricity at these levels for the buy back market under the less competitive corporate case.

Potentially the most interesting scenario is case 3, where there is no binding constraints, but a must run generator. The must run generator should cause the average price per MWh to increase towards the price cap for both of the pricing mechanisms (where generator 0 is bidding at the price cap), however it is the effect that this change in viable bidding behaviour without the requirement of constraints that is of interest.

While the prediction stated above defines that there should be no statistical difference in the price per MWh of electricity supplied when there is no binding line constraint this scenario offers a case that there is an alternative constraint which will reduce the competition in the market and allow the buy back market to create a higher price.

Never Constrained

In the never constrained case, we can see in figure 5.11 is that against the prediction, the results of the corporate based market is that the buy back market creates a significantly higher price per MWh than the Nodal market.

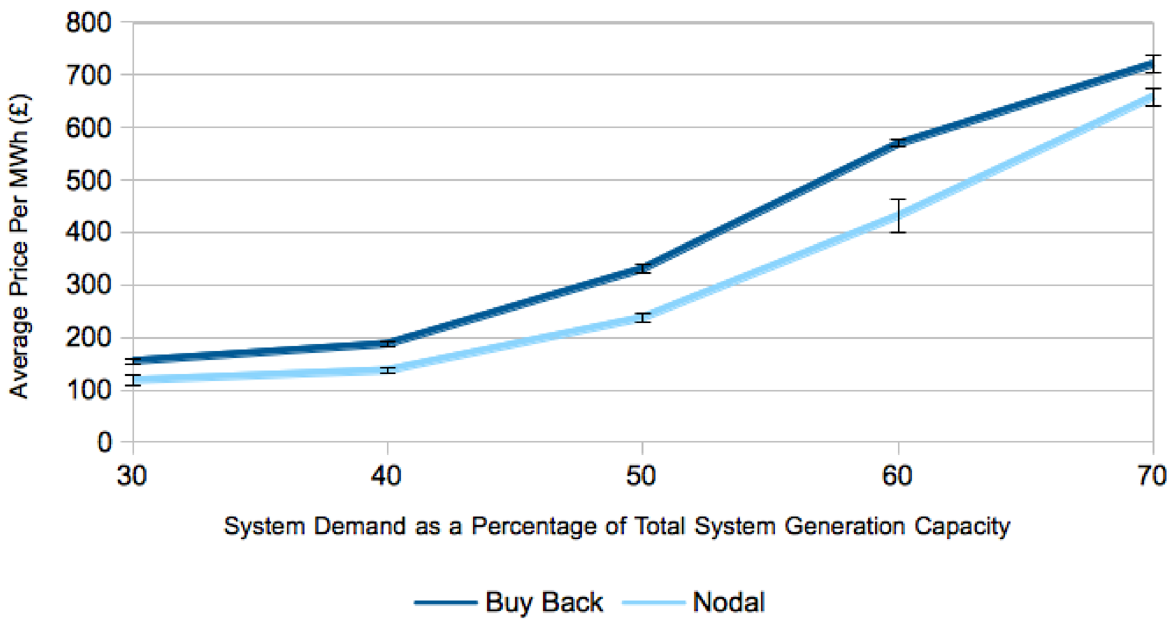


Figure 5.11: Average Price Paid per MW on a simulated 5-Node Network for Agents Co-Operating Within a Company for the Never Constrained Test Case

The possible reason for these results is that without the presence of a required binding constraint, the companies are effectively withholding part of their generating resources by offering very high prices. In the case where both companies 1 and 2 perform this, they are able to greater influence the initial global price of the buy back market than they are in the Nodal market.

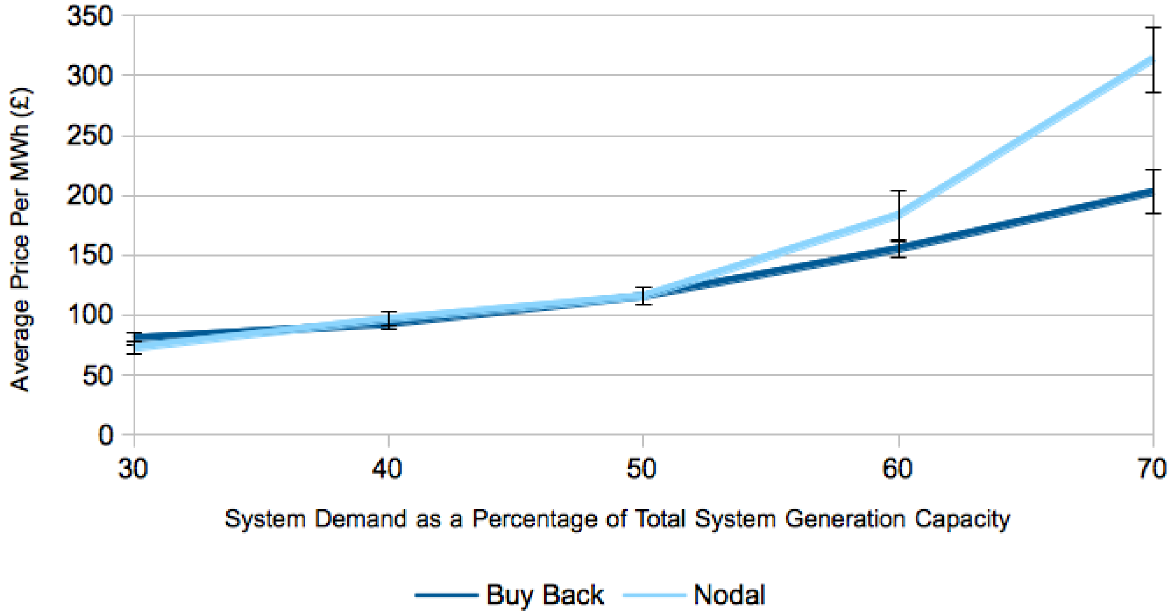


Figure 5.12: Average Price Paid per MW on a simulated 5-Node Network for Agents Acting Individually for the Never Constrained Test Case

The results for the individual case shown in figure 5.12, show that both mechanisms show no significant difference at the low demand levels(40% $t(8)=-1.26$ $p = 0.243$), however at the high demand levels the generators in the Nodal market are able to start influencing the price in such a way that the results are significantly above those of the buy back market(70% $t(8)=-1.26$ $p < 0.0001$). If the example of withholding demand is taken to be the cause of the high prices when there is less economic pressure from line constraints.

Highly Constrained

Figure 5.13 shows the average price per MWh for the two market designs under high levels of line constraints. On the low demand cases, the Nodal market creates a higher average price per MWh than the buy back market, however at the higher demand level this trend is reversed and the buy back market averages a higher price per MWh. With the Nodal market able to create individual nodal prices, these prices for the constrained nodes will often be higher as they can effectively create their own price, and for the lower demand reach a level that causes the average price to rise above that of the buy back market. However at the higher demand levels, where the generators have less spare capacity, they can force the price higher than the average of the nodal prices.

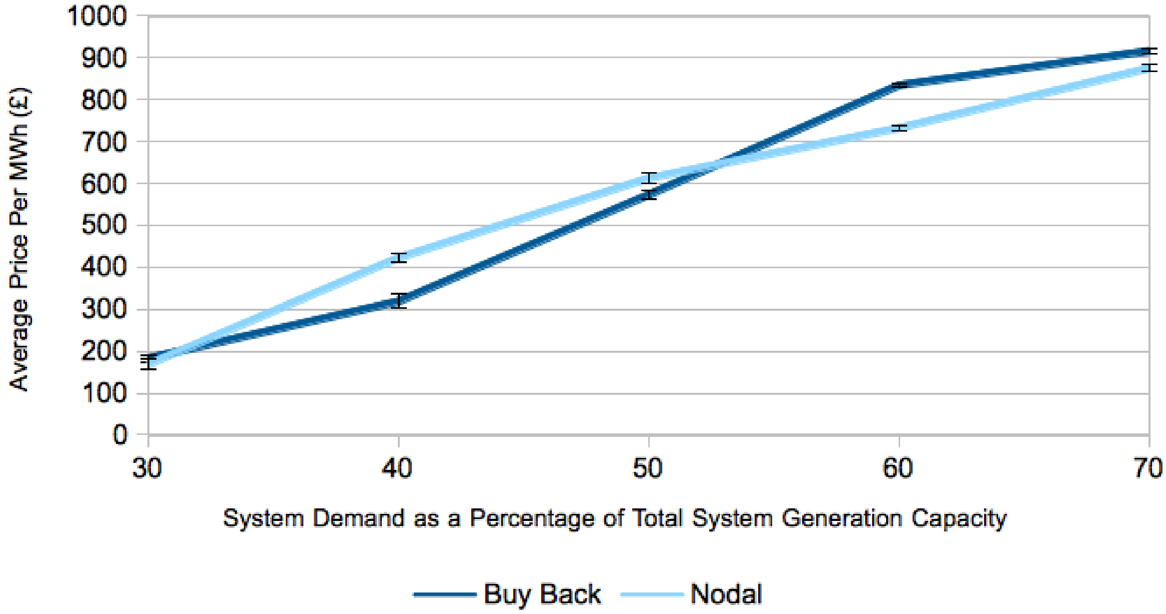


Figure 5.13: Average Price Paid per MW on a simulated 5-Node Network for Agents Co-Operating Within a Company for the Highly Constrained Test Case

In the Individual operation case shown in figure 5.14, the nodal market design is able to achieve a significantly higher price per MWh than the buy back market for the 40-60% demand cases (50% $t(8)=-7.17$ $p < 0.0001$). Taking the increase in competition as the differentiating factor, the generators are still acting competitively in the market at the higher demand levels where a must run price can be enforced in the corporate market.

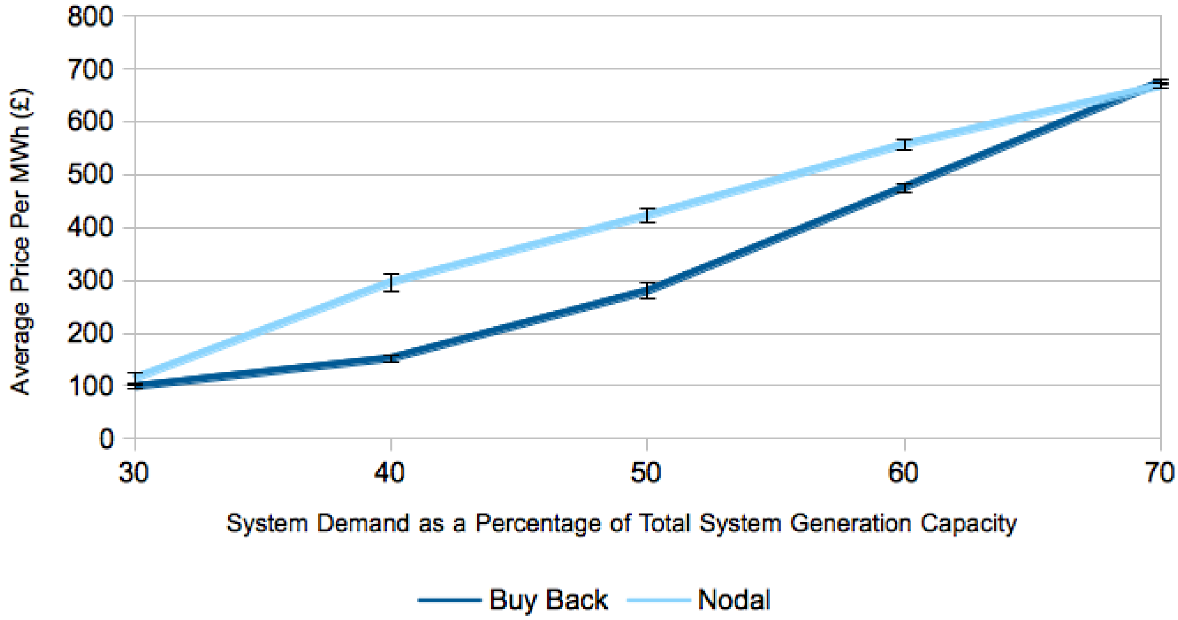


Figure 5.14: Average Price Paid per MW on a simulated 5-Node Network for Agents Acting Individually for the Highly Constrained Test Case

The most interesting aspect of both cases is that the results begin to converge at the highest demand levels. With the more prevalent binding constraints, the prices were able to be forced more consistently to the same level.

High Demand Must Run

In a scenario that creates a must run generator at higher demand levels, the results in figure 5.15 clearly show that there is a significantly higher price per MW in all cases for the buy back market against the Nodal market (50% $t(8)=6.98$ $p < 0.0001$). The buy back market creates an average price of Âč956.84/MWh, which is approaching the price cap of Âč1000/MWh, which in many cases means that the generator was offer

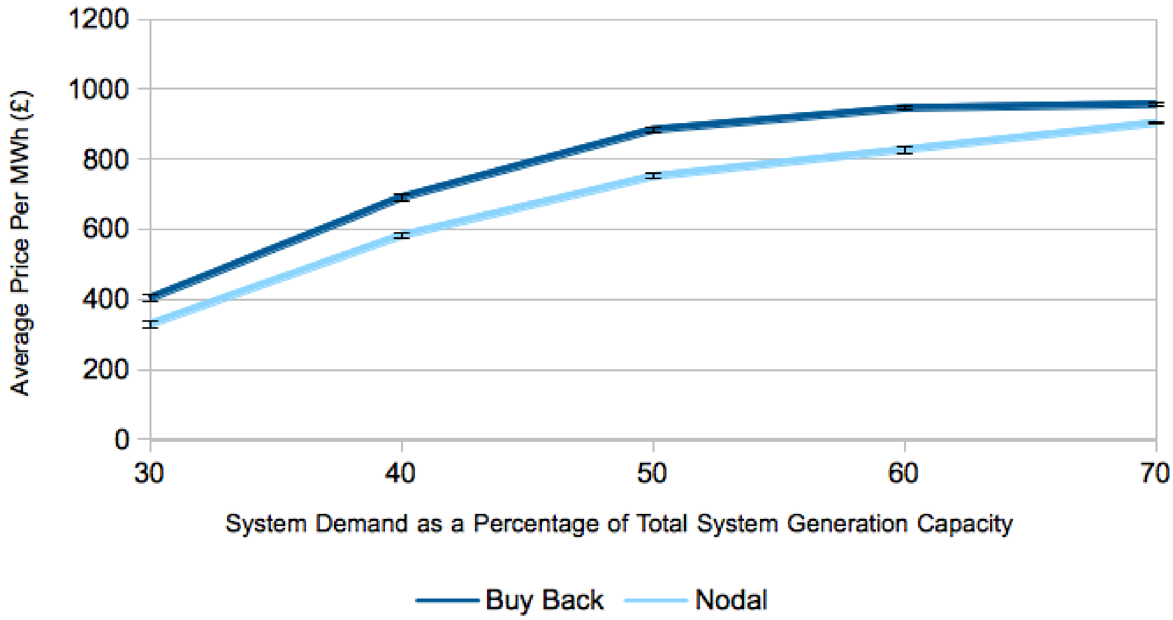


Figure 5.15: Average Price Paid per MW on a simulated 5-Node Network for Agents Co-Operating Within a Company for the High Demand Must Run Test Case

In the Individual case, shown in figure 5.16, both market designs show a similar rise in the average price per MWh, but unlike in the other cases where the increased competition has caused a lower price for the buy back market, the price in this case is higher. Similar to the Corporate case, the single must run generator is able to bid at a higher price because there is a guarentee of production and that the uniform price is fixed at a high level. In contrast the greater competition amongst the remaining generators leads to a lower average price.

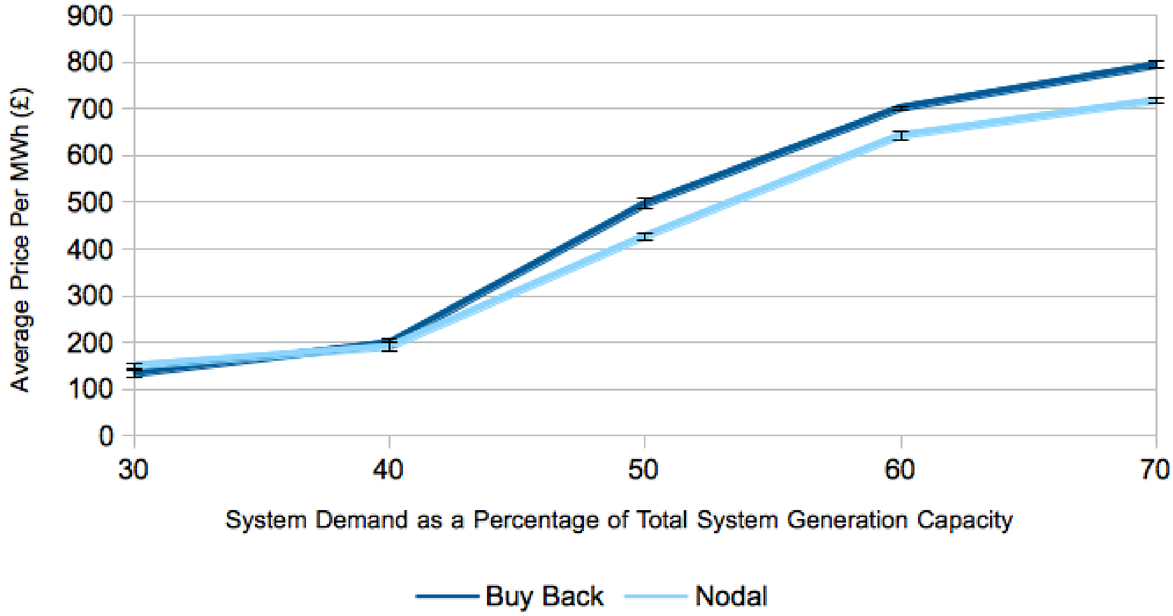


Figure 5.16: Average Price Paid per MW on a simulated 5-Node Network for Agents Acting Individually for the High Demand Must Run Test Case

5.4.2 Line Capacities

The main conclusion seen to this point is that the more competitive Individual case results have followed more closely with the predictions and the less competitive Corporate case results have not followed those predictions.

In addition to the four test cases, the initial validation case was revisited so as to identify if changing the capacities on each of the lines is capable of differentiating between the two market designs. To do this the four lines are each set to have new capacities, with the aim of trying to identify if this can create a better understanding of why the results to this point have not shown the trends expected from the previous results.

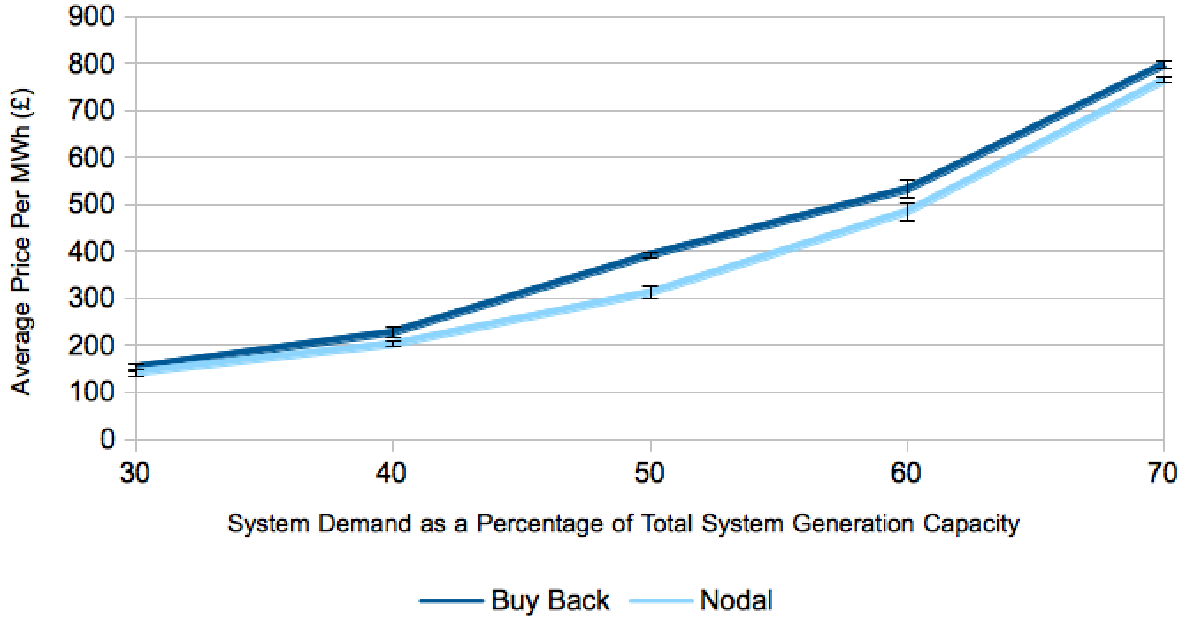


Figure 5.17: Average Price Paid per MW on a simulated 5-Node Network for Agents Co-Operating Within a Company for With Line Capacities of 600MW

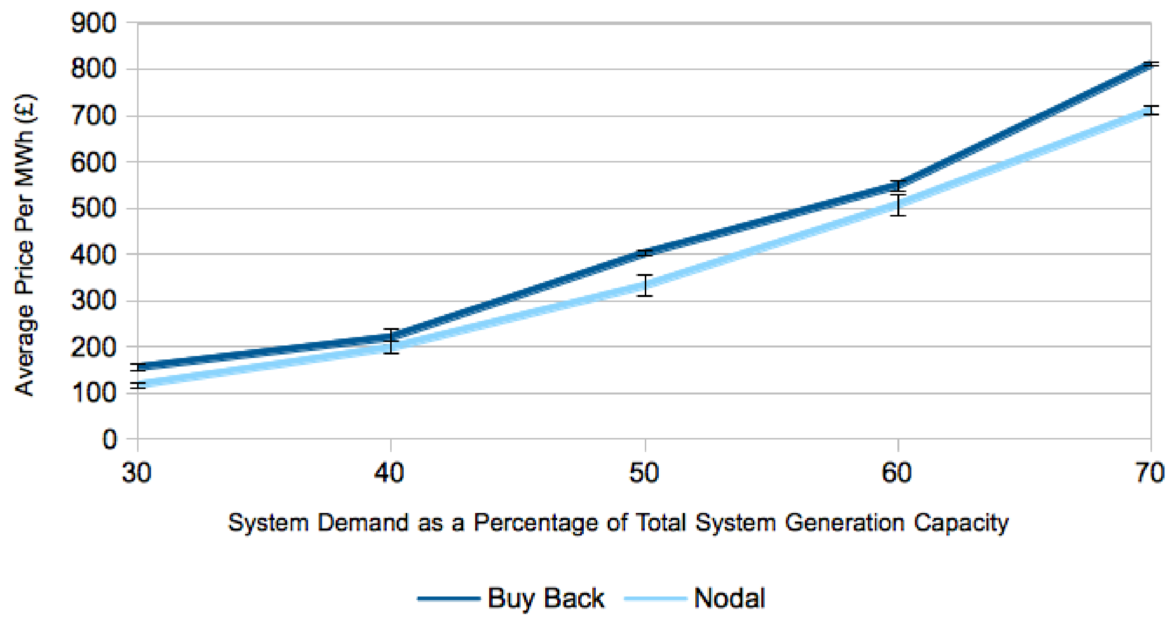


Figure 5.18: Average Price Paid per MW on a simulated 5-Node Network for Agents Co-Operating Within a Company for With Line Capacities of 700MW

Figure 5.17 and Figure 5.18, show the results in the corporate case for increasing the capacities on each of the lines from the initial level of 500MW to 600MW and 700MW respectively. In both cases there is a difference in the average price per MWh of between 20 and 50 Âč/MWh, with the exception of the 70% demand level with the line capacities set at 600MW, where the difference is Âč100/MWh. At these higher levels and the initial 500 MW level, the prices at each demand level tend to be similar to those seen in the other demand cases, where the price at the 70% demand level is consistently averaging Âč800/MWh, this is with the exception of the 50% demand level in the initial constraint. This seems to indicate that the actions performed by the generators are acting independently of the line constraints in forming their bids.

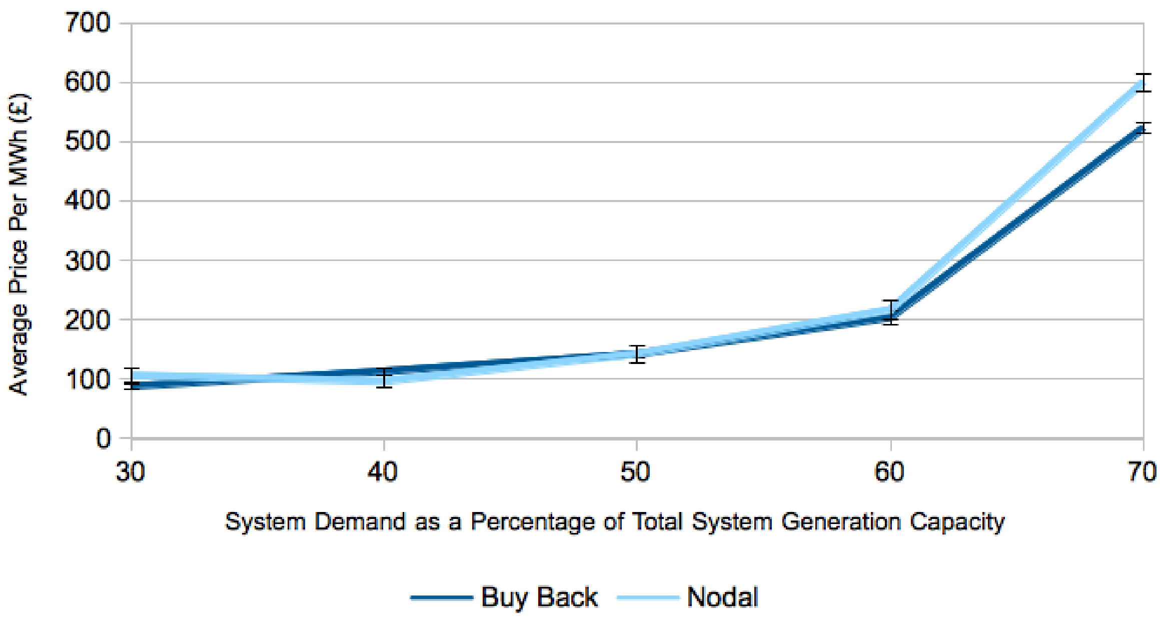


Figure 5.19: Average Price Paid per MW on a simulated 5-Node Network for Agents Acting Individually with Line Capacities of 600MW

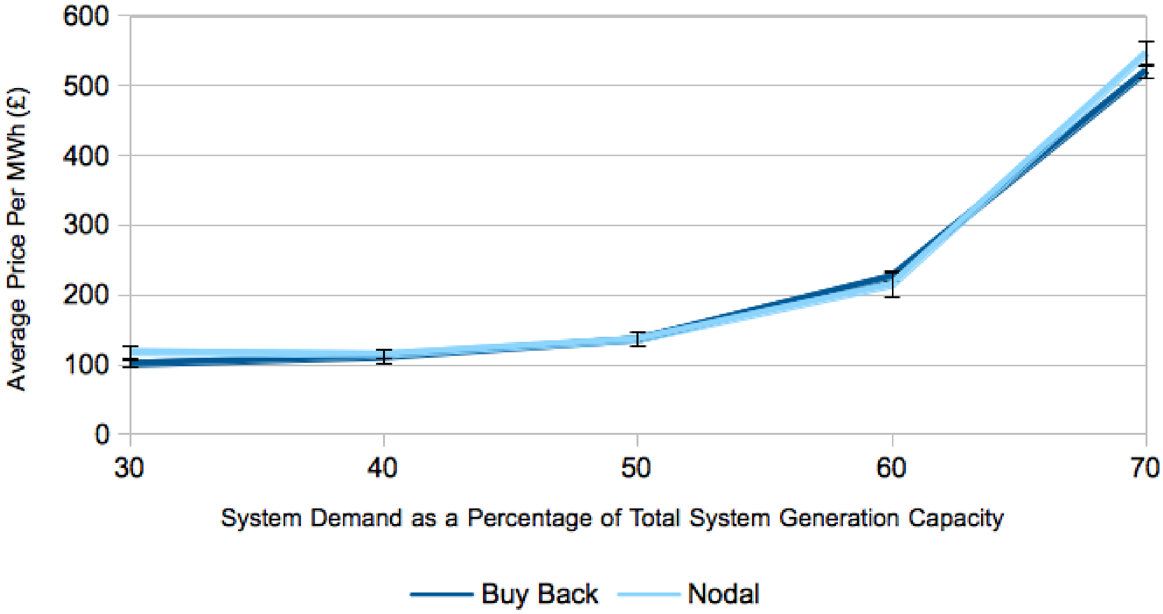


Figure 5.20: Average Price Paid per MW on a simulated 5-Node Network for Agents Acting Individually with Line Capacities of 700MW

Figures 5.19 and 5.20 show the same increase in line capacities but in the case of each generator acting Individually. The results show that when the lines are not constrained, then the two market designs perform fairly evenly, however once the constraints become binding the Nodal market is able to consistently average a higher price than the buy back market.

The intuition would be that if in the corporate case the agents are able to act independently of the line constraints then the results for reducing the line capacities would reflect those of increasing them to show a consistent pattern across all of the results. In the individual case, the expectation of the results would be that reducing the line capacities will cause the constraints to bind earlier and cause an earlier divergence of the prices offered by the two different market designs.

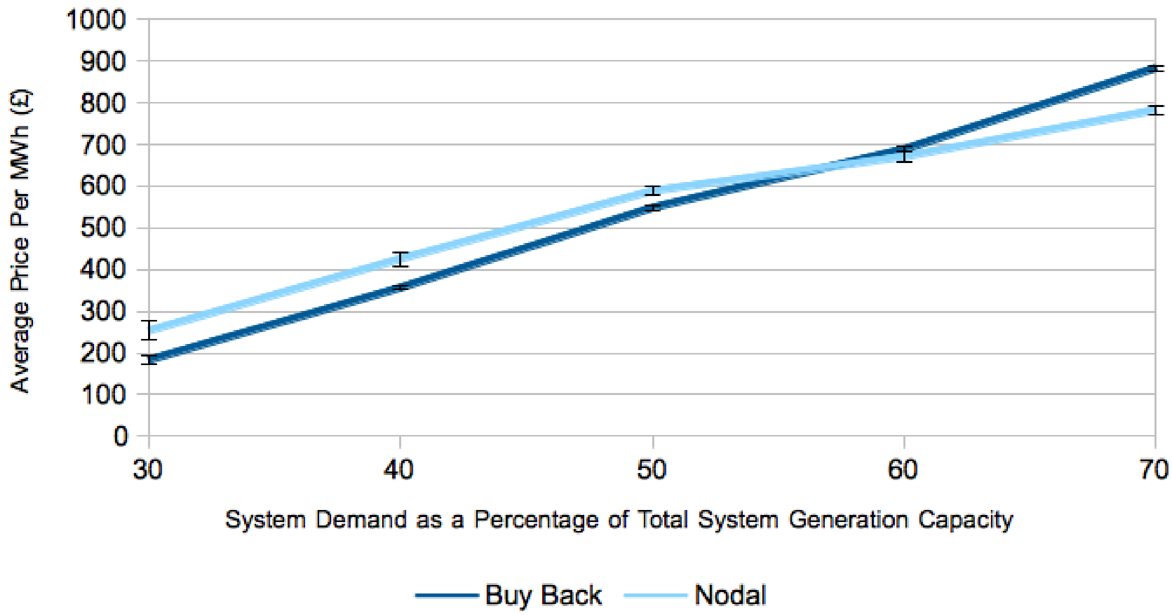


Figure 5.21: Average Price Paid per MW on a simulated 5-Node Network for Agents Co-Operating Within a Company with Line Capacities of 300MW

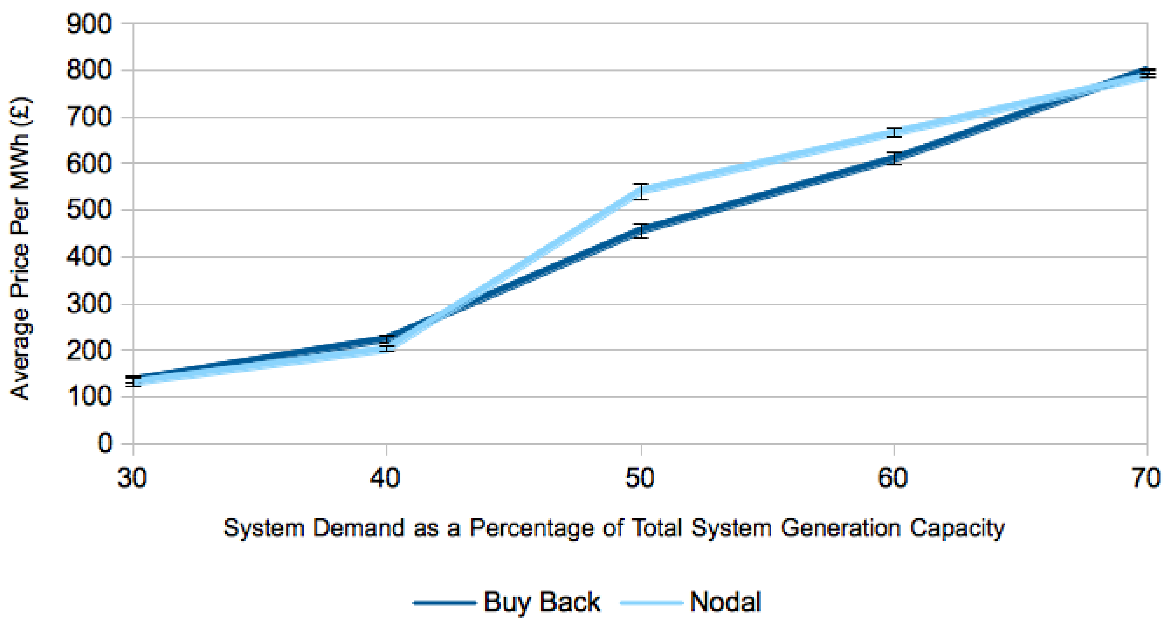


Figure 5.22: Average Price Paid per MW on a simulated 5-Node Network for Agents Co-Operating Within a Company with Line Capacities of 400MW

Figures 5.21 show that with low line capacities the results tend towards those seen with the must run generator case, where the Nodal market is able to create a higher price at lower demand levels, but once the must run generators are able to affect the price, then the buy back market averages a higher price. However, in Figures 5.22 this is not seen as the Nodal market reaches a higher price than the buy back market up to the 60% level, however the opposite is then seen at the 70% level.

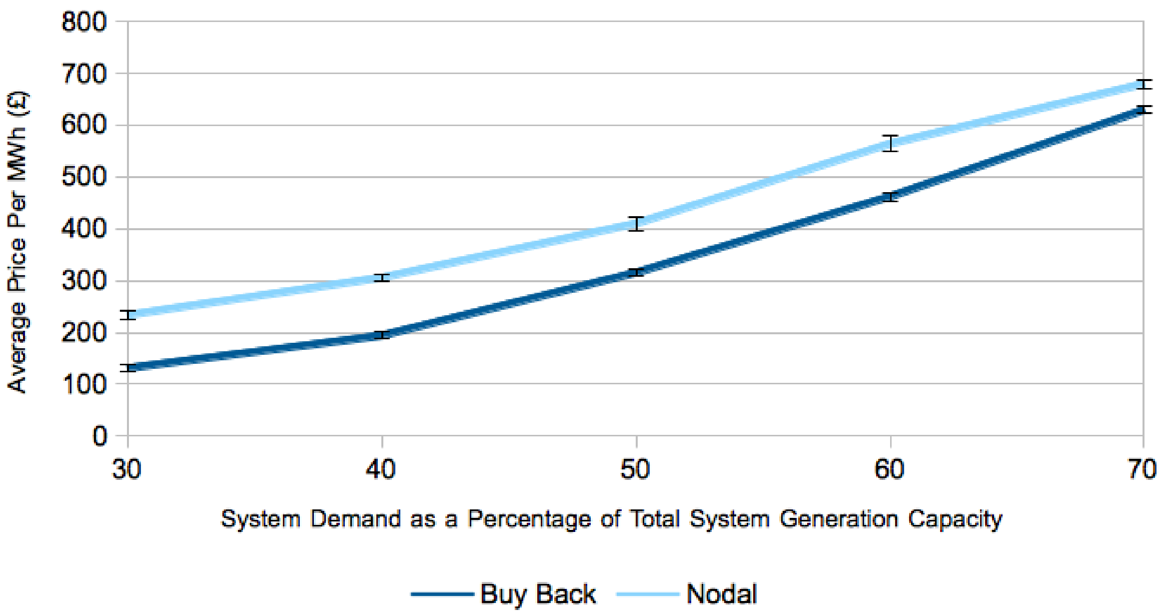


Figure 5.23: Average Price Paid per MW on a simulated 5-Node Network for Agents Acting Individually with Line Capacities of 300MW

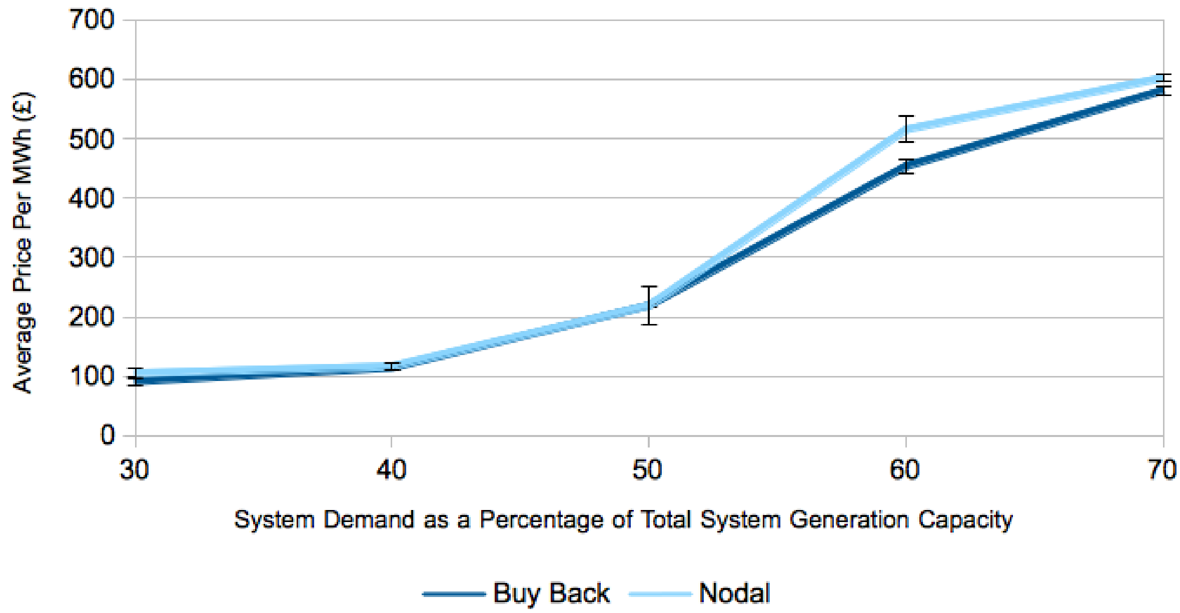


Figure 5.24: Average Price Paid per MW on a simulated 5-Node Network for Agents Acting Individually with Line Capacities of 400MW

Figures 5.23 and 5.24 show the results in the individual case, where the difference between the two market designs is more predictable, where in the 400MW Line Constraint case the results are similar to those in the initial 500MW case. In the 300MW case however, there is a significant gap at all price levels (50% $t(8)=-8.78$ $p < 0.0001$), which indicates that there is some ability for agents to game the Nodal market with lower line capacities that isn't possible for agents in a buy back market.

5.4.3 Alternative Networks Designs

To identify if the results observed on the simple network are consistent with a more complex transmission grid design two new grid layouts have been developed to test if the assertion that the competition between the agents is more critical than the network layout and the constraints in determining the price. The alternative network designs presented here are designed to represent the meshed nature that comprise realistic networks, which may help identify if the initial network was representative or if the over simplification causes unrealistic market power to be created from a forced congestion.

The two alternative networks use the same generation and demand data as the initial case study, in order to determine if the network design itself is a determining factor in the market. The network design presented in this case is a network that has a ring network connecting four of the five nodes, with the cheapest node connected to the top two nodes in the ring. Figure 5.25 shows the network configuration of the network and the transmission capacities on each line are shown in table 5.4.

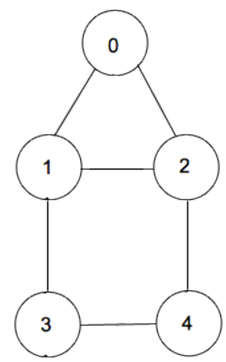


Figure 5.25: Alternative Network Configuration A Network Design

Line ID	Start Node	End Node	Capacity(MW)
0	0	1	250
1	0	2	250
2	1	2	250
3	1	3	400
4	2	4	400
5	3	4	250

Table 5.4: Alternative Network Configuration A Line Data

The two major lines between nodes 1 and 3, and 2 and 4 are present to ensure that the demand can be filled at the higher demand nodes by electricity from the cheaper nodes, so as not to create a de-facto must run generator as present in some of the other cases presented in these results.

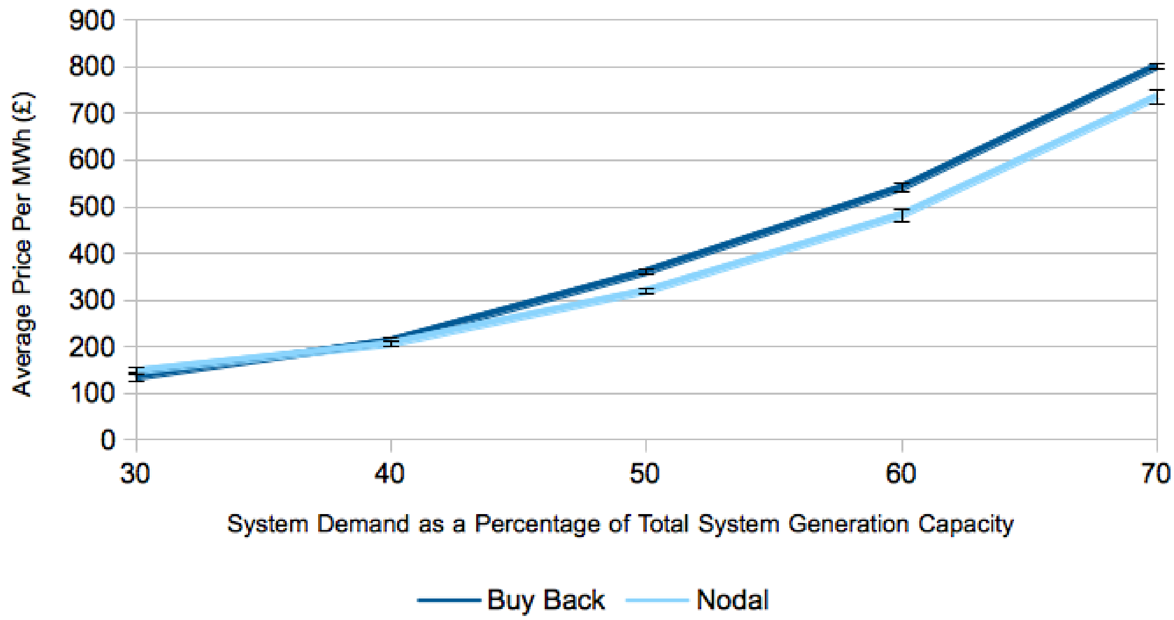


Figure 5.26: Average Price Paid per MW on a simulated 5-Node Network for Agents Co-Operating Within a Company with Alternative Network Configuration A

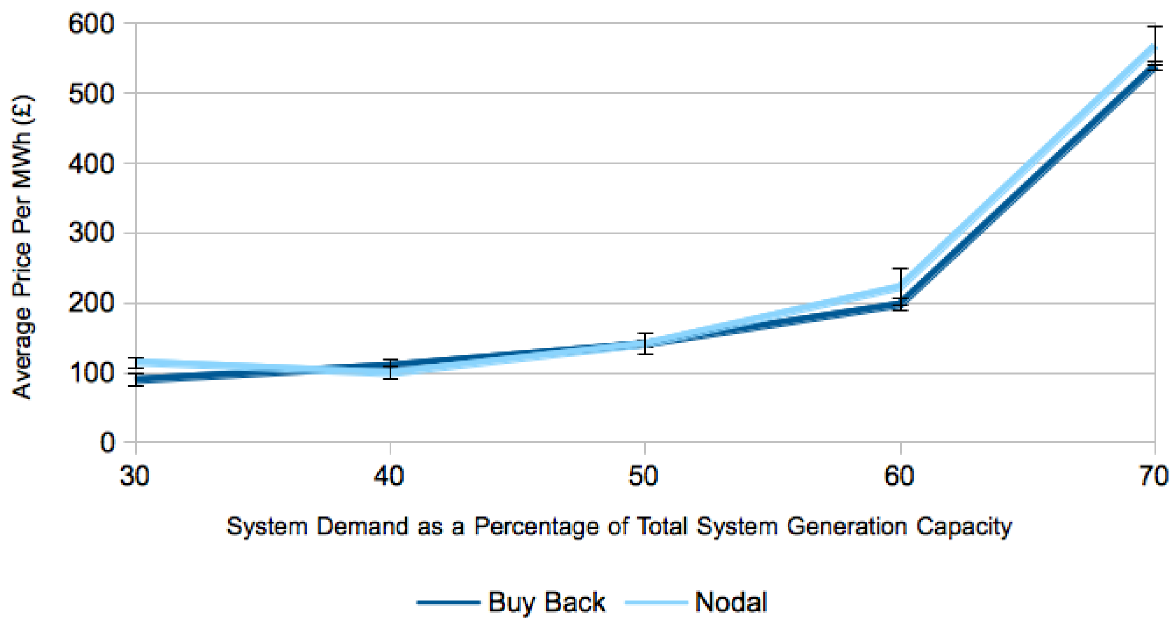


Figure 5.27: Average Price Paid per MW on a simulated 5-Node Network for Agents Acting Individually with Alternative Network Configuration A

The results shown in both the Corporate (figure 5.26) and the Individual (figure 5.27) cases both seem to follow the trend of the high capacity line scenario. The price in the Corporate scenario in the buy back market sees a rises to around Âč800/MWh with a 70% demand level, which is consistent with the high line capacity scenario. Additionally the two market designs share similar results to each other, which is consistent with the results seen in the results for the 700MW Line Capacity scenario.

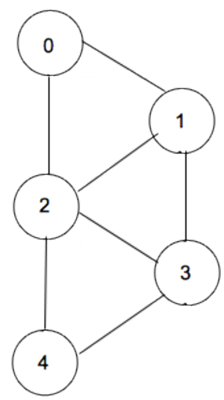


Figure 5.28: Alternative Network Configuration B Network Design

Line ID	Start Node	End Node	Capacity(MW)
0	0	1	250
1	0	2	250
2	1	2	250
3	1	3	250
4	2	3	250
5	2	4	250
6	3	4	250

Table 5.5: Alternative Network Configuration B Line Data

The design in the second alternative is similar to that of the previous design, but reduces the maximum line constraint between nodes 1 and 3, and 2 and 4, but adds a line between nodes 2 and 3 to compensate for the reduction in dispatch. Of particular note is that Node 2 is the most connected node on the network and also has the largest amount of generating capability, which may influence the market operation as they are in a strong location. The network configuration and line transmission capacities for this example are shown in figure 5.28 and table 5.5.

From the previous network design, the results seemed to indicate that the results presented are similar to results seen in the 700MW Line Capacity scenario. Figure 5.29 show the results of the Corporate case, where the two pricing mechanisms again follow the same trend seen in both the high capacity and the other alternative network design scenarios. The two mechanisms create prices in a similar

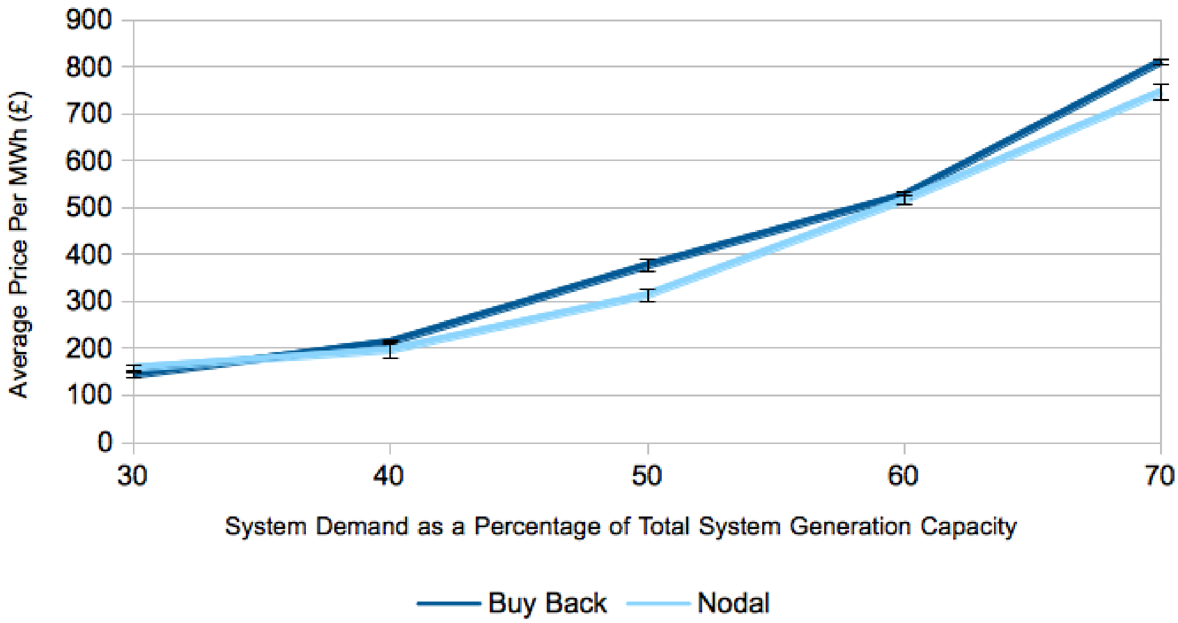


Figure 5.29: Average Price Paid per MW on a simulated 5-Node Network for Agents Co-Operating Within a Company with Alternative Network Configuration B

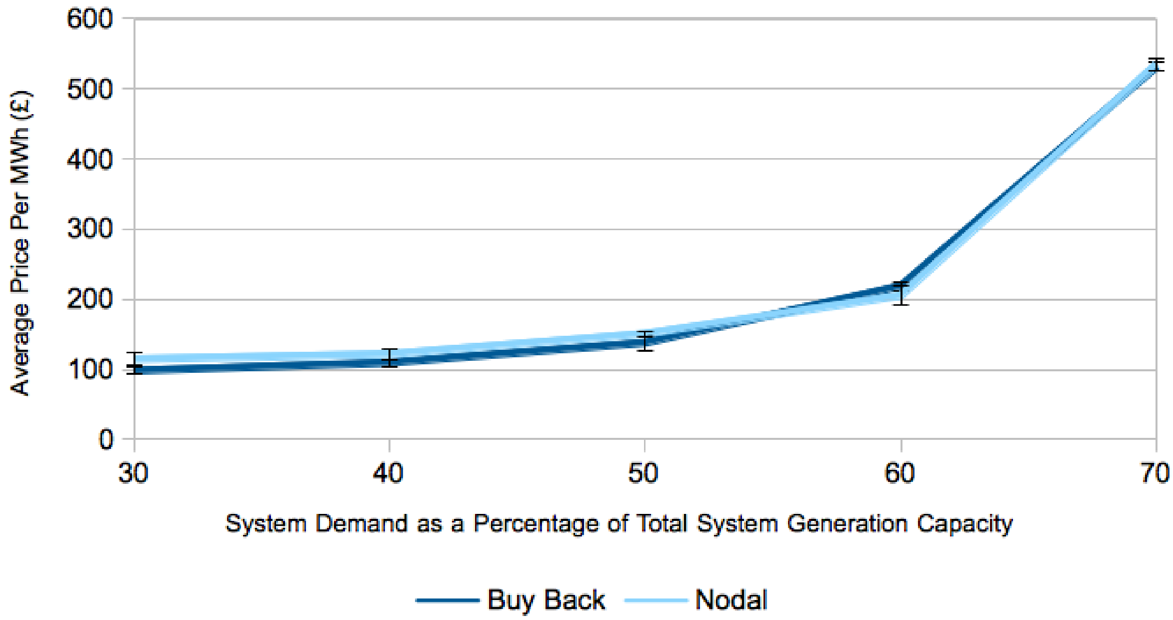


Figure 5.30: Average Price Paid per MW on a simulated 5-Node Network for Agents Acting Individually with Alternative Network Configuration B

In figure 5.30, the results of the two mechanisms show no statistical difference at any demand level, this is in contrast to the two similar scenarios seen in the Corporate case, such that both those designs only have statistically similar results for the 40, 50 and 60% levels despite showing the same trends.

5.4.4 Higher Competition

If the generalisation of the results seen so far is that in the corporate cases the buy back market agents are able to influence the price in a manner that allows it to create higher prices in general than the Nodal market, but when acting with increased competition they aren't able to exploit the same market vulnerabilities, then increasing the competition further should further decrease the market power of each individual and there should be a noticeable difference in the results. To test this a new scenario has been created using the initial test grid design of 5 nodes connected in a line, with the same demand and total generating capacities at each node. The difference in this scenario is that there are now two generators at each node, where the generators have approximately half the generation capacity each and equal costs. Figure HCGen shows the new network design.

Node	Generation Capacity (MW)	Cost per Unit (Âč)
0A	150	5
0Bv	125	5
1A	150	6
1B	125	6
2A	275	9
2B	275	9
3A	125	11
3B	125	11
4A	125	13
4B	125	13

Table 5.6: Increased Competition Case Study Generator Data

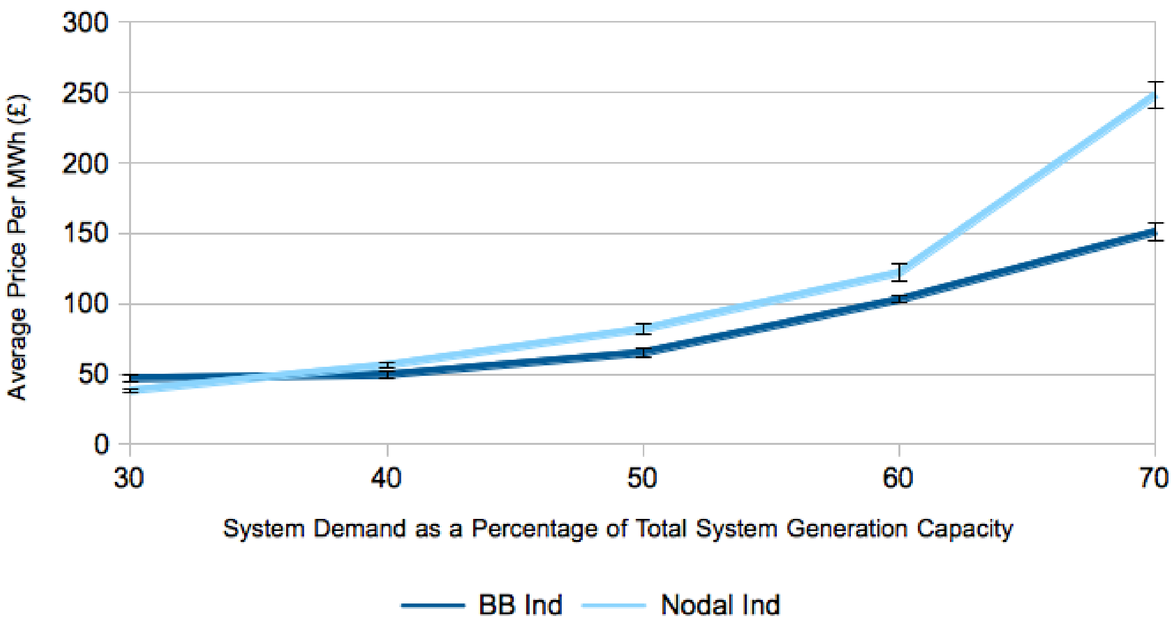


Figure 5.31: Average Price Paid per MW on a simulated 5-Node Network for Agents Acting Individually with 10 Different Agents

The results shown in figure 5.31, show that much like the original test scenario, when acting individually, there is little difference between the two pricing mechanisms at low demand levels. However once the constraints become binding in the market, the Nodal Market is able to exploit some market power, which the Buy Back agents are not able to in a slarge a manner causing a rise in price.

The most interesting aspect, is that the increased competition has reduced the average price paid per MW drops to a much lower level than seen previously. In the corporate case using the same market the price per MWh at the 30% demand level is larger than the price per MWh at the 60% demand level seen in this case for the buy back pricing mechanisms. Although the Nodal market price does reach a lower level than previously seen, the pricing mechanism can still exploit some market power in order to bring the price up significantly higher than the levels in the buy back market (70% $t(8)=-11.85$ $p < 0.0001$).

5.5 Discussion

The key finding from these small scale results seems to be that the amount of competition that is present in a market is a key factor is defining the amount an electricity market can be gamed by agents in both markets. The difference appears to exist, that while the nodal market is still able to maintain a relatively high price, the buy back market is unable to maintain such a high price. The hypothesis indicates that the amount of influence that an individual generator has in controlling the price of a market would be much lower under a buy back market than a nodal market. As such the results suggest that this is the case, given the high prices seen by the agents in a buy back market with three competing companies against the much lower price seen when there are ten competing companies.

One of the questions raised earlier in this chapter, that was defined as one of the key reasons for wanting to run detailed small scale experiments is "Why would the agent do that?", and this is especially relevant given that the bids made by all of the agents under a competitive scenario are in general all vastly above the marginal cost and yet are not all bidding at the price cap, although in some scenarios there are bids accepted at the price cap.

This behaviour is possibly the most interesting factor of these experiments, as it shows that the agents are able to clearly identify a place in the market, where they manage to perform suitably well given their competitors behaviour, this is especially true in the lower demand cases where the expected outcome would be close to marginal cost because of the level of competition

The possible reasoning for this, is that despite not actively implementing a risk verses reward scenario, the agents have implicitly found a market location that balances out the risk of putting in a high offer versus the payments obtainable.

As such in many cases placing a significantly lower bid than the ones offered in the simulation will on average increase their output, but the lower price will yield less profit, and much higher bids will cause the average generation to drop to near zero levels causing profit again to be much lower. These kinds of bids potentially leave the generators at the risk of higher levels of fluctuations in terms of profits, due to the fact that they are offering electricity at a price that does not force anyone out of the market.

5.6 Summary

This chapter presents a 5-Node network that is used to test the operation of the simulation and the agents. Where a series of experiments have been performed comparing different levels of competition between agents across the two diffrent market designs using a variety of different market configurations.

The results presented here indicate that with lower levels of competition, agents operating in a buy back market are able to create prices that are at least as high if not higher than those in a nodal market. However as the level of competition increases the ability for agents in a buy back market to be able to create higher prices seems to fall much greater than those in a nodal environment.

When competition amongst the agents is increased, the influence that each buy back generator has on the market is not sufficient to push the price of electricity higher than the nodal market participants at any price level.

Chapter 6

Large Scale Model

During the design process of the simulation and the agents, it was always considered that there would be a requirement to make observations with a larger model. In the context of this research a the requirement of a large model is such that the size and complexity allows for a reasonable comparison to be drawn to a realistic scenario. This chapter aims to identify and explain the requirements and steps taken in designing a suitable large model.

The chapter proceeds to outline the requirements of the model, followed by the considerations made for designing the data set, followed by a look at the finalised model that is to be used, with a note of the assumptions made in design and known limitations.

6.1 Requirements

While designing the model, a number of initial conditions were set out, that were required in order to ensure that any experimentation performed using the simulation had some realistic market pertinence.

6.1.1 Use of Appropriate Data

During the testing and for initial observations, the use of a five node network with arbitrary data was adequate to ensure the correct operation of both the simulation and agents, and to gain some insight into the operation of the markets. However in order to fully explore the impact that different market rules have on a market, the data used had to be more detailed.

The reasoning behind this requirement is that although more simplified data allows for a clearer picture of the possible processes and applications of the agent behaviour to the market, it would be incapable of showing if those aspects were replicable in a realistic system, even if only from a hypothetical standpoint. Although it is by using a more complex data set that we can tell if the hypothetical behaviours of the agents can be seen in these markets, it is by the same admission that the use of realistic data could cause any specific behaviour to become lost due to the over-complication of the model.

In balance, it is better in this specific market-related case to see the realities of the market results and try to infer the behaviour that caused it than to identify the behaviour and try to imply the resultant realistic market state. More information can be collected or generated, within the simulation, concerning the process by which the agents make their decisions in order to reduce any possible gap in reasoning that might occur surrounding the bids that they make.

While the complexity of the real network layouts would make the computational feasibility of the simulation too high to be effectively simulated. For this reason, a large scale model ideally wants to represent aspects of the real market, for this research we are interested in representing a stylised transmission grid.

6.1.2 Minimal Operation Time

One of the key aspects of this work is to ensure that any results found are as accurate as possible in order to ensure that the conclusions drawn can be considered valid within a level of reasonable doubt. In order to ensure that this is the case a number of different runs of the simulation need to be performed and the time taken to run each simulation needs to be taken into account.

If the resources available for this work were limitless, then it would be feasible to use a full and comprehensive data set as the basis of the model. However in reality, this is not possible. Also considering the other requirement, to use a appropriately detailed data set, it is of importance that the model needs to be balanced with this requirement to minimise the operating time for any given action. As such part of the discussion into designing the model is the size of the computational process. There are two aspects within the simulation that will affect how long the process takes to run, the first as stated above is the size and complexity of the data set used in the model and the other is the configuration of the maximum length of computational processes, such as the maximum number of cycles an agent is allowed to attempt and converge on a bid.

6.2 Design Considerations

During the development of the model, there were two main factors that had to be defined in order to complete the model. The first was the network layout, this is the number of nodes and how they are connected. The other factor is the data source for deciding generator capacity, demand, line capacities and company data.

6.2.1 Representation of a Larger Electricity Network

Initially there was no firm requirement for the model to represent a realistic electricity network. There were two different approaches that could be taken in selecting a basis for the model, a real world market or an IEEE standard grid design.

The IEEE Models are designed for computational problems, there have been a number of grid layouts designed for various sizes of problems. The major problem that exists with the IEEE Models is not in the details of the grid data, but in creating an effective market that runs on top of the grid, with two overlapping issues, the source and validity of the market data.

Although it is possible to collect generation data concerning a wide range of real world generation capacity, this could not be done in such a way as to ensure that there is no arbitrary assignment of supply and demand. It is this arbitrary nature of data being assigned to nodes that could cause the observations made to be more trivialised.

The primary advantage in using a styalised realistic market in the development of a model and simulation is the availability of the data. This help to solve the problem of arbitrary data assignment, since everything being represented has a real basis there would be no ambiguity in the decision making process. This is of greatest importance when considering generator ownership within the system, the dynamics of the market are such that a change in generator ownership would likely change the behaviour of the agents that control them.

6.2.2 Potential Real Grid Designs

In selecting a real market to base the styalised data mode on, there was a number of different grid layouts that were considered, considering not only the size of the market, complexity of the potential market interactions but also the availability of relevant information in order to accurately design and build the model. There were three different grids initially investigated, which were chosen because of the access to relevant information concerning not only the grid, but the other aspects of the market. The grids considered were The Great

Britain's National Grid, Nordpool and Yao et al's[65] Belgian Market Model.

Both Great Britain's National Grid and Nordpool markets covers a large geographical area with a variety of different generating capacity, which made them both suitable candidates for this study. However it is the geopolitical boundaries and interactions that make this a potentially difficult case study to work with. It is especially notable that although the simulation is capable of handling some regulations concerning price and generation, the political complexities of multinational generations and trade could cause too much complexity to see value in the results computed by the simulation. Unlike the Nordpool network, where the boundaries have the ability to directly and independently influence the market, the Great Britain's national boundaries have little impact on the electricity market.

While the basis for implementing a grid based on markets where the information is more openly accessible, an alternative consideration was taken based on the work carried out by North et al [41] for the EMCAS simulation tool, which was focussed around using a stylised version of the Belgian Market and transmission grid, having a basis presented in a work by Yao et al. The main concern with using this stylised market is that although based on a real system, the data set given in terms of generation and demand does not allow for as in-depth a study as can be created from either of the others.

Having considered the different designs, a final decision was taken to use a grid layout based on the UK. Although each of the different markets have their own merits for study, it is because there is a large scope for clear and justified understanding amongst a highly competitive market that the UK was chosen.

With the simulation being built on the design of the Great Britain's electricity trading arrangements (BETTA), it is therefore a reasonable decision to develop a model based on the GB grid and market. It would be reasonable to want to test these arrangements in different markets to see it's effectiveness.

Two different data sets were used in creating this model, the first is a data model of the Great British transmission system under development at Strathclyde by Bell et al. and the second is the data published by the National Grid in their Seven Year Statement.

6.2.3 Strathclyde Data Set

The data set that was initially considered was a working data set being developed at Strathclyde [55] [43] , which was aiming to replicate Great Britain on a computationally reasonable scale. The data set consisted of 29-Nodes and 34 generators that give an overall view of the UK market in terms of representative scale.

However there are two identifiable problems that occurred when considering this data set for the purposes of this research, the first is that there is a lack of clear demand data. More specifically there is a lack of nodal demand data available that means that and demand data has to be generated. Although demand data could be generated based on the relative size and scale of the UK, the process can't be guaranteed to be correct.

Additionally the generation data was not designed to be reflective of the intricaciescies of the market process, while some care had been taken to identify the kinds of generation available at each of the nodes, they were considered by type and so the relevant supplier information was lost. Much like the demand some estimate can be made to roughly identify who owns each generator in order to create the required portfolios, in order to complete the model

6.2.4 National Grid Data

The National Grid posts a regular report called the Seven Year Statement [24]. This report covers the current trends in the electricity industry for the Uk, as well as forecasting the next seven years in the industry. Within the report there is information regarding the supply and demand of electricity inside the UK that is highly relevant in designing a model for the UK electricity market.

One of the major aspects of having access to the data supplied by the National Grid in their seven year statement, is that there is a complete set of generators listed for the UK. This data is provides a set of all of the generators, their capacity, location and the company that owns them. The National Grid data set could be used in its complete form or if necessary simplified to a fit in with an alternative grid design.

Most of the major companies have their generation labeled under their umbrella companies there are number of generators that although owned by a major company, they are reported under a subsidiary company or previous owner. To ensure that the generator ownership data used is as correct as possible each of the major seven companied had it's portfolio verified by their own company reporting.

Another of the key features of the National Grid Seven Year statement is that there is complete peak demand data available for every node on the grid. Although there is often more than a single supply at a given node, the data is such that the summation of each of these values gives the total peak demand for any given node. Much like the generation data this is useful in being able to formulate an accurate picture of not only the total demand at maximum for the network, a scenario that is at the heart of this research, but more importantly the distribution of this demand by region, which is important in giving one of the major dynamics of a constrained electricity market

Although the data set is fully comprehensive it does have one major problem in it's usability for the complete simulation, which is that it is too large to be computed within the simulation. The main issue would not be in completing single runs of the simulation using this data, but in performing enough runs on the data in order to explore in detail the market designs such that adequate conclusions can be drawn to the proposed experimentation. The biggest issue with the time is due to the complex nature of balancing the grid subject to the grid constraints, despite there being scenarios where there is no requirement for rebalancing the cases where the system is pushed to it's limits are expected to require rebalancing.

6.3 Model Data Set

The following section outlines the model that has been developed and identifies the data that the various components are based upon.

Having considered the various data sources the following decisions were made in order to create a comprehensive model based on Great Britain's National Grid, while ensuring that the expected computational time would be reasonable enough to allow a multitude of experiments to be run on the simulation with these model.

6.3.1 Network Layout

The 29 Node Model developed by Bell et al. [55] [43] is substantial enough in size to be able to reflect an approximation to the geographical layout of the Great Britain's National Grid. Not only is the size of the grid a computationally manageable size, but any results obtained from the simulation can be clearly represented without a considerable amount of reduction, something that would not be possible with the full National Grid data.

The organisation of the real Great Britain Transmission Grid is such that there are many small nodes, these reflect the high voltage electricity entry and exit points across the country. Since one of the considerations is that the National Grid data is too large to be reliably computable, these nodes have been condensed down to fit in with the 29 Node Strathclyde grid layout. In using the grid layout, there is a set of lines and capacities that are associated with them. The following Diagram outlines the nodes and line connections, the capacities for each of the lines are given in the complete data model given in Appendix B.

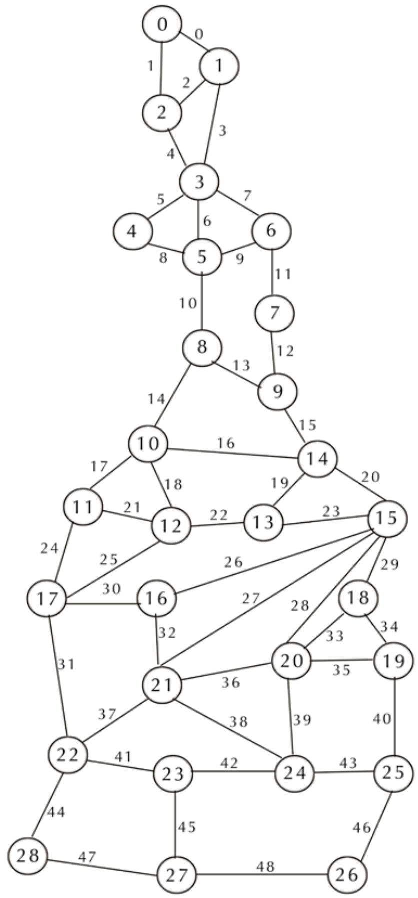


Figure 6.1: Grid Layout for 29-Nodel Model

The diagram is laid out in a manner so as to reflect the intended realistic grid, as such the nodes at the top of the diagram represent the nodes in Scotland and the nodes at the bottom represent the southern costal region of England. Of particular note in the layout is that node 24 represents London, which is expected to be a node of particular interest during much of the experimentation.

The generation in this system is designed such that not only is the output per generator as accurate to the National Grid data as possible, but also that the locations of the generation is also as accurate as possible. However with a reduction in the number of nodes, there has to be some assumptions made regarding the assignment of a node, this was done by taking the overview of the grid and sectioning it by the 29 nodes, and assigning them according to the map. In certain cases where there were generators on the predicted boundaries or better connected to other nodes in a different section, they were assigned to the node that would best reflect a central location for them.

6.3.2 Generation and Demand

The following section gives a brief overview of each of the major companies that are represented in this model, full details of the generation and location for each of the generators in the model are presented in Appendix B.

There are seven companies that are considered as 'major companies' in this data model, which accounts for approximately 80% of the total generating capacity of the market.

Company A

Company A controls 7 different generators with a total output of 7994 MWh, the majority of the capacity is located in the northern regions of the grid, with the remainder of the capacity located in the south-east. Company A has a portfolio of 5 different generator types, which allows for some resilience in cases where there is volatility in the variable prices of different technologies.

Company B

Company B controls 13 different generators with a total output of 10961 MWh, the capacity for this company is spread across the transmission grid, with more capacity located in the middle and the south than in the north. This spread of generation allows for some resilience against congested lines, since the generation allows for generation either side of a constraint.

Company C

Company C controls 11 different generators with a total output of 10438 MWh, the capacity of this company is spread amongst the middle and south of the transmission network. Most notably this company has 3 generators located at node 24, which is the point of highest demand on the network, and 5 generators at nodes with lines connected to node 24. This portfolio might perform best in scenarios where the lines surrounding node 24 are constrained or where possible constraining the lines into the node themselves to push up the local cost as they control approximately a third of the generation at node 24.

Company D

Company D controls 13 different generators with a total output of 12778 MWh, with the capacity spread in the east and south of the transmission network. This company controls the largest capacity of the companies in this model. The company has a portfolio containing 6 different kinds of technologies, where the company does not own two generators of the same kind at any given node. Additionally there is only a single node where the company owns two generators with capacity over 1000 MWh.

Company E

Company E controls 7 different generators with a total output of 3994 MWh, the capacity of the company is located primarily in the middle of the network. This company has a portfolio consisting entirely of one kind of technology, this gives it less resilience against potential price fluctuations on the fuels for this technology. In addition to the main portfolio of Type 4 generators, Company E has a 20% share of the six must run Type 6 generators, which gives them some stable income against a relatively inflexible portfolio.

Company F

Company F controls 7 different generators with a total output of 6612 MWh, the capacity of the company is located primarily at the west and south west nodes on the transmission grid, with one large Type 4 generator located at node 14. Of particular note Company F controls 2 different Type 8 generators that are the cheapest to run, but are not must run generators and as such are able to compete within the market.

Company G

Company G controls 3 different generators with a total output of 4806 MWh, the company controls 2 generators at node 15 and one at node 20. However in addition to the three generators Company G owns, their portfolio comprises of an 80% share in the six must run generators co-owned with Company E. While this limits the number of generators that they are able to compete in the market with, each of the three competitive generators have a capacity greater than 800MW, however the extent that they are able to game with these generators may be limited given that the largest amount of generation for any given node is at node 15.

Others

The remaining 25 generators are not owned by any of the other 7 companies and are acting independently of each of the other generators. The generators in this category account for 20.7% of the total available generation in the market.

In order to completely represent a market, there needs to be a cost associated with each generator. The costs of production used in this research may not reflect those in the real market, however they are suitable for understanding the market dynamics within a complex environment. The costs of generation are presented in table 6.1.

Generator Type	Cost per MW (£)
Type 0	115
Type 1	125
Type 2	105
Type 3	88
Type 4	124
Type 5	125
Type 6	64
Type 7	25
Type 8	90
Type 9	160
Type 10	136
Type 11	64

Table 6.1: Cost per Unit for Different Generator Types

The data used for setting the demand is taken as the nodal winter peak values as defined by the National Grid Seven Year Statement, these values to give the maximum expected demand and then two alternative cases were created for Summer Baseline and Average Day in order to better explore the market dynamics. Although individual nodes in the National Grid may have a wide variation of demand between summer and winter, and some will not vary much at all, the expectation is that in condensing the data down to a relatively small number of nodes these variations will be evened out and a single scale factor can be applied to each nodal demand to create the new demand forecasts.

The demand for the system uses the same system as the locating of the generation, where the nodal references given in the National Grid data apply the same to both generation and demand. This ensures that the demand and generation are consistent in their accuracy and that although assumptions have been made in the process of deciding which node each generator is assigned to, there is no relative loss in accuracy between supply and demand.

Node ID	Node Peak Demand (MW)	Total Generation at Node (MW)
0	341	1527
1	717	1108
2	62	364
3	431	0
4	202	844
5	2234	4248
6	2244	3631
7	193	1416
8	222	0
9	1749	420
10	317	2987
11	781	0
12	2557	4902
13	3421	7832
14	1596	1934
15	1533	10545
16	2504	0
17	2435	2964
18	2399	1700
19	1291	1942
20	2262	3674
21	7100	4632
22	2436	5733
23	3958	2884
24	9738	3657
25	1323	6958
26	1307	1501
27	2446	2289
28	1852	2306

Table 6.2: Peak Nodal Demand

Table 6.2 gives a single set of peak demand figures that are defined for each of the nodes. In order to use these figures in other demand cases, they are scaled evenly based on the predicted demand level. although this does not completely identify the distribution of growth in demand across the country, the relative scale of the model incorporates this variety as a function of reducing multiple real nodes into a single simulated node.

6.4 Assumption and Limitations

While creating this model, a number of operational assumptions have been made in order to ensure a correct and realistic, it is important that these issues have been considered and there is reasoning behind why they are limiting and the impact they will have on the experiments.

The nuclear capacity of a market has a few important criteria that cause some limitations in operation. Based on the start-up and cool-off times of a nuclear generator, the output is rarely ever changed and as such they are considered to be required to run at all times. Within this research, Type 6 generators are given the analogy of being a nuclear generator, with low costs. While this assumption is not too limiting in itself, it is the potential market implications that are of greater consequence. If they are required to run, then an agent will naturally bid the maximum they are able to bid before a regulator takes action to endure they aren't abusing their market position. In the simulation, this has to be taken into account, so the nuclear generators offer a bid of 0, this is to ensure that not only are they always the first generators selected, but in the rebalancing mechanism, there is no inherent financial reason to reduce their output; Although there might be reason to reduce the output, due to the effect attribute in the rebalancing calculations being positive, the cost multiplier will be zero, thus negating any effect.

One of the biggest difficulties was selecting the nodal boundaries, although an attempt was made to ensure that the nodal boundaries lined up in such a way as to not only fit the 29-Node Grid layout that was used, but to ensure some reality to the major lines within the National Grid's actual layout. As such some generation and some demand could have been placed at several different nodes, but this was always going to be part of the challenge in condensing the data down to a useable level, without losing the integrity of the market.

6.5 Summary

This chapter presents a new data model of an electricity market that is designed as a large scale model that is built using an analogous representation of the geographic layout for the National Grid in Great Britain, with a number of generators representing large energy companies allong with a number of individual generators.

Chapter 7

Experimentation

This chapter presents an outline of the three experiments that have been conducted to test the hypothesis "A nodal pricing mechanism is more susceptible to the influence of market gaming than a buy back mechanism in a constrained electricity market" and the experimental parameters of the simulation. This chapter also presents the results of each of these experiments as well as a discussion of how the results corrolate with those seen on the small scale.

In order to appropriately test not only the hypothesis that "A nodal pricing mechanism is more susceptible to the influence of market gaming than a buy back mechanism in a constrained electricity market", but also various aspects of the operation and dynamics of the large scale model that could have some bearing on the relevance and impact of the results obtained in the comparison of the pricing mechanisms.

In order to approach this task of understanding the hypothesis, three experiments have been proposed, each focussed on a different attribute of the simulation. The first is the direct comparison of the Nodal and Buy Back markets, which aims to cover the major points of the research's hypothesis. The second experiment is looking at the behaviour of the agents in respect to how they behave when interested in either only themselves or the parent company. The final experiment aims to look at a more rational scenario in the market to see if the results are still relevant, where the case is made that not every generator is in a position to attempt to play games in the market, but instead only some generators actively play the game while others bid at a level just above marginal cost.

After identifying the simulation's operational parameters that each of the experiments will be performed by, the remainder of this chapter will go into specific detail regarding each of the experiments, outlining the reasoning behind performing the experiment, as well as what is expected as a result.

7.1 Experimental Configuration

Each of the experimental configurations will consist of a 15 round game, where each agent has a population size of 40 and generates 20 offspring per generation, from 10 pairs of parents. Should an agent not be able to converge on a single solution, the process is concluded after 100 cycles, where the best solution found to that point is selected as the bid. This is similar to the small scale, since the size of the search space is the same despite being potentially more difficult to explore given the increased number of agents.

The major consideration in not running the game for more than the described 15 rounds is primarily due to the fact that the increased time taken to obtain the results does not appear to obtain any increased value in the results obtained. Where one of the initial expectation for this research, was that the agents would be able to locate a single equilibrium point in the game and enough time would be allocated to ensure that this equilibrium was found. However under testing on the small scale, after 200 rounds there was no single equilibrium point obtained and that the market cycled between a number of states. As such to reduce the already large processing time, required given the magnitude of the model implemented, the number of rounds the game is played has been reduced

Having seen that the market price on the small scale cycles between at least two values, repetition of the experiments is necessary to reduce the apparent variance that can be seen in the average prices. Owing to the run time required to optimise the behaviour of all the agents, a minimum of five runs allows for some generalisations to be made about the results.

The maximum number of allowable attempted rebalances is 40, this is to allow for an attempt to be made to rebalance each line should it be required, or more intricate rebalancing to be performed. At the same time it is not excessive in the amount of processing time it is willing to dedicate to attempting to create a new schedule for an overly complicated market state.

Parameter	Value
Run Cycles	15
Generations	100
Population	40
Offspring	20
p (Selection)	0.25
p (Crossover)	0.33
p (Mutation)	0.33
Price Cap	1000

Table 7.1: Large Scale Experiment Parameters

7.1.1 Nodal vs Buy Back

In order to answer the primary question at the centre of this research, a study of the operation of the Nodal and Buy Back markets needs to be undertaken. The experiment consists of looking across the average of a number of different runs of the simulation at different levels of system demand using both of the pricing mechanisms independently.

The results of the simulation can then be compared at each level to see which market mechanism averages the lowest total system payments, which from the point of view of the system operator would be the more successful pricing mechanism.

It is important to look beyond just the results obtained in the market to look at aspects such as fluctuations and reliability of the results obtained in order to definitively explain if one pricing mechanism design is significantly better than the other.

The small scale results presented in Chapter 5, showed that within this simulation, when competition was low, then the Buy Back market reached on average a higher level of system payments than a Nodal based system using the same model, however under a greater competition, the nodal system began to average higher payments than the buy back market. Given the small scale results, it is expected that the nodal market should reach on average a higher level of market payments than the buy back market based on the increased level of competition.

7.1.2 All Generators vs Selected Generators

As has been mentioned previously, not all generators are in a position where they would realistically consider themselves able to complete in the market such as to drive and influence the price. The reason for this is the generator owners might not be willing to take unnecessary risks with their production schedule so as to attempt to earn at times limited extra profit.

While the previous experiments have dealt with more idealised scenarios where every agent is capable of attempting to play the market. This experiment aims to look at a case where only a limited number of agents attempt to influence the price, as a reflection of a more realistic scenario. As such only a select number of agents will be attempting to game the market, where all the other agents will bid at a level of their marginal cost plus 15%.

Of the 92 generators there are 67 are controlled by the major companies, 6 of which are the joint owned Must Run (Type 6) Plants, these as stated have to run, and offer a minimal price to do so. A further 16 generators owned by the major seven companies have a capacity of less than 400MW, although some of these generators may not be entirely insignificant, their contribution to the market dynamic is minimal and in order to minimise the run time, they will not be using the intelligent bidding mechanism.

The proposed selection of generators accounts for only 49% of the generators, but these generators hold 66% of the total generating capacity of the model. However, due to the 'must run' requirement of the nuclear generators, this equates to 73% of the generation available to those that could bid strategically.

All non-nuclear generators that aren't using an intelligent agent are bidding a marginal cost value, of absolute cost with a mark up of 15%. This is to reflect the nature of small entities within the market, although they would ideally like to make as much profit as possible; They can only achieve that by running, however running at a loss would not be considered acceptable.

A side effect of these fixed plans is that there are a number of power stations that could potentially have an impact on the market dynamic, however over the course of the experimentation it could be of interest to allow a smaller or independent generator to be able to use the intelligent bidding system.

The predicted results for this should see a significant reduction in the total system payments made, since the generators that are attempting to influence the market will be competing against agents that are using a more stable bidding pattern, the bids that they make must reflect this. While a reduction in system payments is expected from the Selected Generators case, the extra stability that comes from fixing the value of some bids might increase the number of opportunities that the profit seeking generators have to influence the market.

Of specific interest in this case is the change in output of those competing in the market between the two cases as well as the change in the amount of money those generators average for each MW. An expected outcome would see a fall in generation for the actively competing generators, but a rise in the average price they are paid per MWh produced.

7.1.3 Individual vs Corporate

One of the key points noted on the small scale was how the agents acted differently in a market where there was more competition, while the large scale model has been designed with the generator ownership in mind, it is important in understanding more about the agents and their interactions with the market to look at a scenario, where each agent is out for themselves.

In order to achieve this, the agents that were part of the seven large generation companies will act although they belong to a company consisting only of themselves, much like the independent generators. The results they achieve will be compared to those of their corporate counterparts to not only see how the market is impacted, but what the effect is on the generation companies.

The expected result of this, based on the effects seen on the small scale is that the average system payments should fall. In the case of the small scale this was on a level of approximately 10% between the two cases, so given the number of extra generators competing, this gap would be expected to be wider in most if not all cases.

7.2 Results

For each of the experiments identified in the previous chapter, the configurations were run 5 times, and the results presented in this section are the average of those 5 runs. This chapter presents the key results for the experiments and explains what the results show and how they relate to the relevant hypotheses.

The remainder of this chapter is divided into three sections, each one dedicated to one of the experiments, starting with the Nodal vs Buy Back followed by the Individual vs Corporate and finally All vs Selected Generators.

7.2.1 Nodal vs Buy Back

The experiment defined in the previous chapter, called for the Nodal and Buy Back pricing mechanisms to be tested against each other on the large scale. This experiment is aimed at studying how the market acts at different demand levels under normal operating conditions.

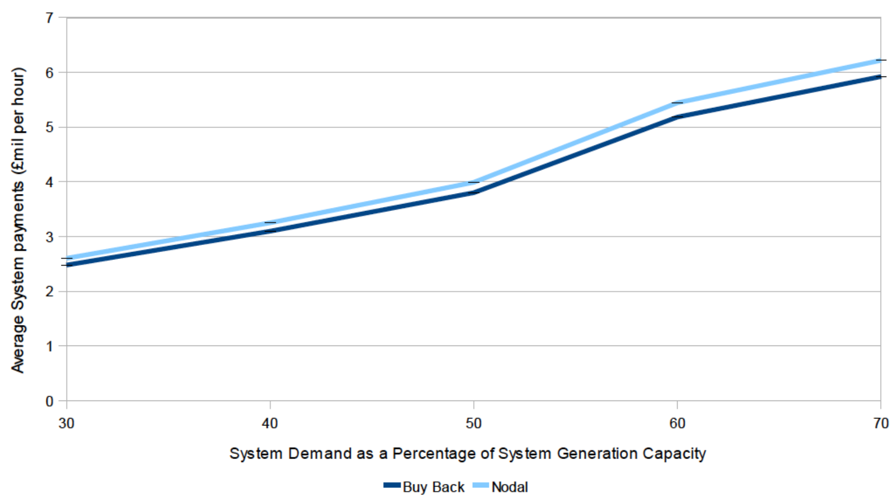


Figure 7.1: Average System Payments for a Buy Back and Nodal Markets on a 29 Node Network with Agents Bidding Marginal Cost

Figure 7.1 shows the outcome of the simulation for both of the pricing mechanisms, where all generators bid marginal cost for all of their capacity. The results show that the Buy Back market achieves a lower average level of market payments than the Nodal market. A lower level of Buy Back market payments was not seen on the small scale in chapter 5 under Marginal Cost conditions for any demand level.

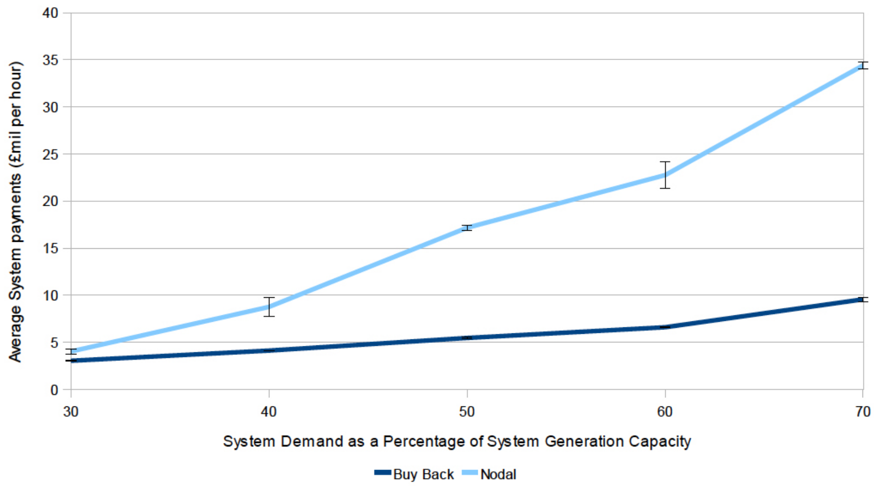


Figure 7.2: Average System Payments for Buy Back and Nodal Markets on a 29 Node Network

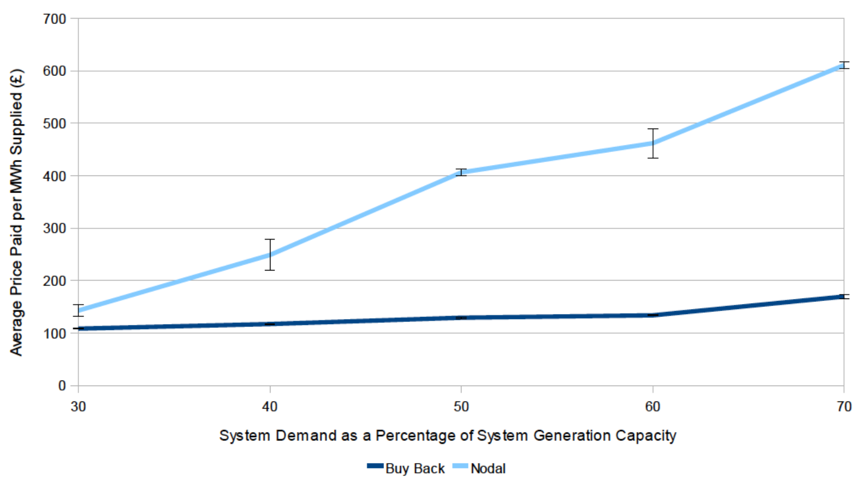


Figure 7.3: Average Price Paid per MW for a Buy Back and Nodal Markets on a 29 Node Network

The results displayed in figure 7.2 show a clear trend that the total system payments obtained in the nodal market and significantly higher at all time steps than in the buy back market. This trend can also clearly be seen when applied to the average price per MWh, and the percentage changes between each of the states shown in figure 7.3 displays that the system payments in both cases seem to have a fairly consistent growth level until the final 10% rise in demand where both payments have an above average increase.

While the hypothesis appear to be accurate, in that the system payments for the nodal system are higher than the buy back market, it is that the scale of the eventual gap between the system payment made in both cases is greater than expected. While the hypothesis stated that the difference was expected to be "significant", a move to 173% on the large scale is beyond expectation.

In comparison to the small scale results of the nodal vs buy back pricing mechanism, it is clear that there is a definitive case that the results are not reflected when scaled up to a larger model. At no stage does the nodal system offer a lower cost schedule than the buy back mechanism. Even considering the predicted error in each of these cases, the two sets of results are sufficiently spaced even at the lowest level tested, such that there is no reasonable case that the scenario in which the nodal market performs better than the buy back market.

Although the small and large scale models are not perfectly comparable in terms of the exact values, the trend that occurs with the results is and it shows clearly that where the Nodal mechanism is allowing the agents to inflate their prices, under the buy back mechanism they are not able to do this.

An explanation for the inability for the agents of the buy back market to push the price per MWh higher comes from the level of competition in the market and can be best explained by comparing it to the specific case of the Buy Back mechanism when relating it to a set of base cases. By comparing the results of the market when allowing competition and a scenario where all the agents bid uniformly at marginal cost or at marginal cost plus either 5 or 15 percent, gives an interesting insight into how the agents operate under this mechanism on the large scale. Figure 7.4 shows a comparison of the results in this scenario:

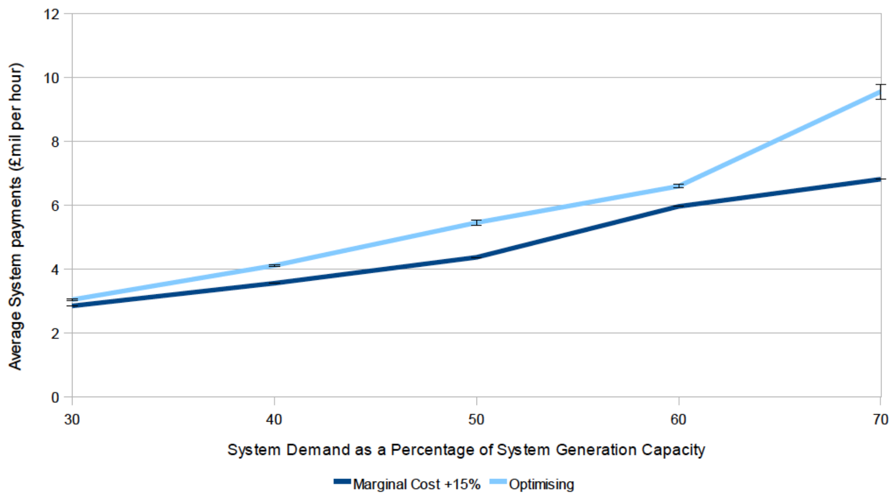


Figure 7.4: Average System Payments for a Buy Back Market between competing agents and those bidding Marginal Cost on a 29 Node Network

For this scenario, the results identify that the agents are only able to push past the marginal cost plus 15% level in the cases of high demand. The reason for this is the same as the reason that the small scale results under competition achieved lower levels of profit, in that there is less stability in any agent offering a higher price, as such the effective stable level that agents found within the system was on a level only just above the marginal cost plus 15% strategy. As such the same effective conclusion can be drawn such that:

In many cases placing a significantly lower bid than the ones offered in the simulation will on average increase their output, but the lower price will yield less profit, and much higher bids will cause the average generation to drop to near zero levels causing profit again to be much lower.

In this case the lower levels of profit could be 0 or negative if the bids are sufficiently low, which for a profit maximising agent are not desired outcomes and there are enough generators that the probability of being selected when offering a higher price is extremely low as there are a lot more generators that are capable of fulfilling the same role, something that was not as well represented on the small scale.

However unlike the small scale conclusion, where no-one was being forced out of the market due to the higher prices being offered, the price levels presented here are sufficiently low enough to cause many of the more expensive generators to have been priced out of the market, as such minimising the risk to the cheaper generators of not being selected.

In the case of the nodal system, the big question is "Why can it push the price so high?", to answer this question the key factor of what is causing this price to be so high needs to first be addressed. In order to do this, the range of prices that are accepted in the nodal market need to be observed. Figure 7.5, shows the average prices that is achieved by agents for different nodes at the highest demand level:

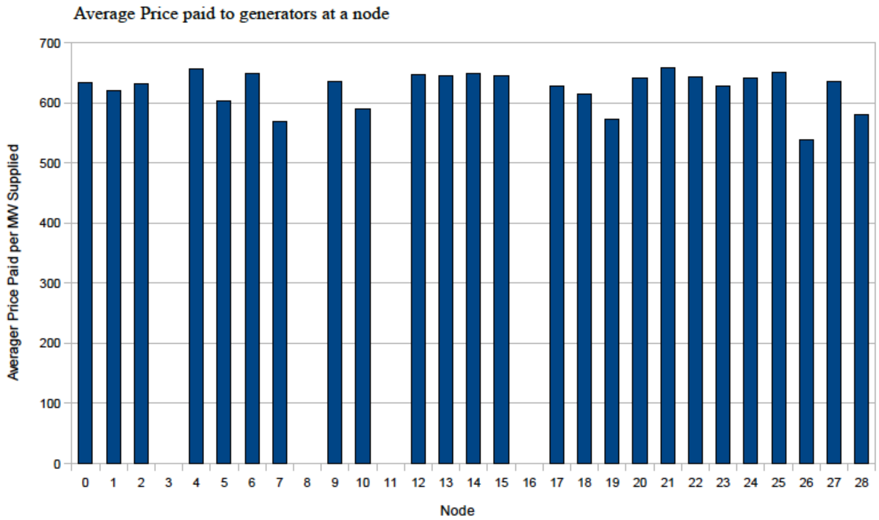


Figure 7.5: Average Price per MW Paid to Generators based on Location in a Nodal market

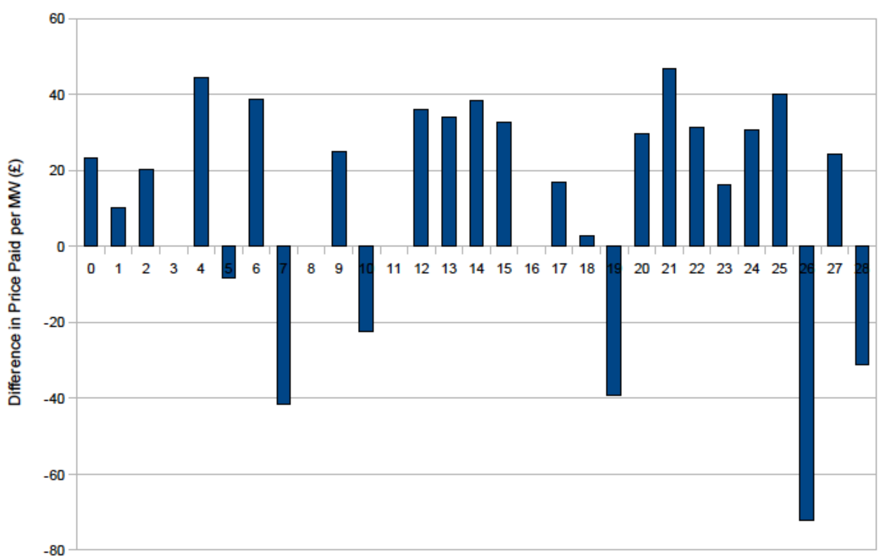


Figure 7.6: Average Percentage difference in Price per MW Paid to Generators based on Location in a Nodal market over the Global average

There is some variance in the prices paid to the generators based on the node they are at, where the 0 values are nodes which have no generation. The resultant price paid on average only deviates away from the average by up to £80 per MWh at some nodes, with the majority of nodes achieving a higher prices than the mean. Each of the nodes that report a below average nodal price have a must run generator (Type 6) located at that node. With the nuclear generators bidding zero, the other generators at the node have to bid more competitively than those at other nodes to be selected for the schedule.

The results show that it is not simply the generators at a minority of nodes pushing the price up, but a high price bid by the majority of generators across the system. In the majority of cases, those that achieve a system price vastly lower than the average, the lowest price paid to a generator was £349 per MWh and the highest price paid was the pre-defined price cap of £1000 per MWh.

Despite using the same agent process, the two pricing mechanisms cause the agents to act in completely different ways, with the agents using a market with the buy back mechanism, they are forced to bid low to protect their generation and seem willing to accept the price that the market offers them, however those using the nodal pricing mechanism are less willing to accept a lower price and instead push for a higher price.

7.2.2 All Generators vs Selected Generators

The second experiment is concerned with taking into account the reality of market participation, in that not every generator is willing to attempt to play strategically on the market in an attempt to try and obtain high levels of profit. The smaller generators owned by the major generators and all of the indepdent generators, termed cost-based generators, are concerned only with ensuring that they have their generation scheduled and that it is at a marginally profitable price. The agents acting using the evoultionary procedure outline in Chapter 4 are termed stratgic generators in this section.

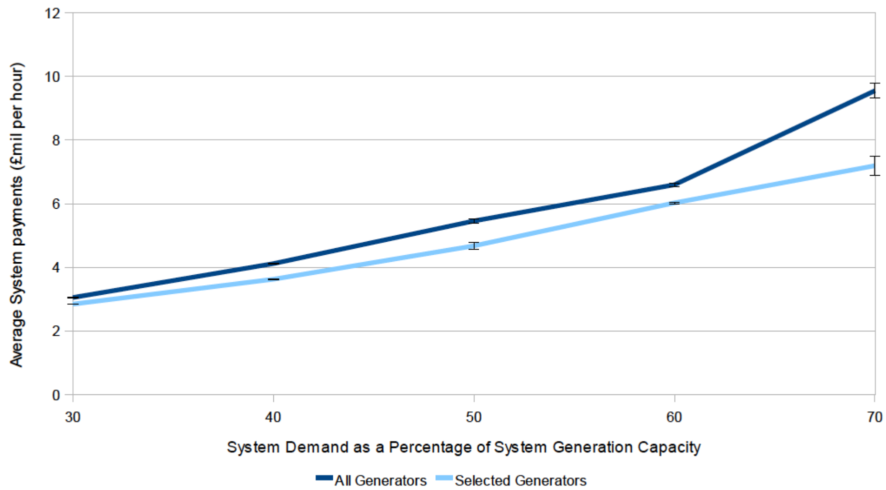


Figure 7.7: Average System Payments for a Buy Back Market on a 29 Node Network with All Generators Actively Competing and Selected Generators Actively Competing

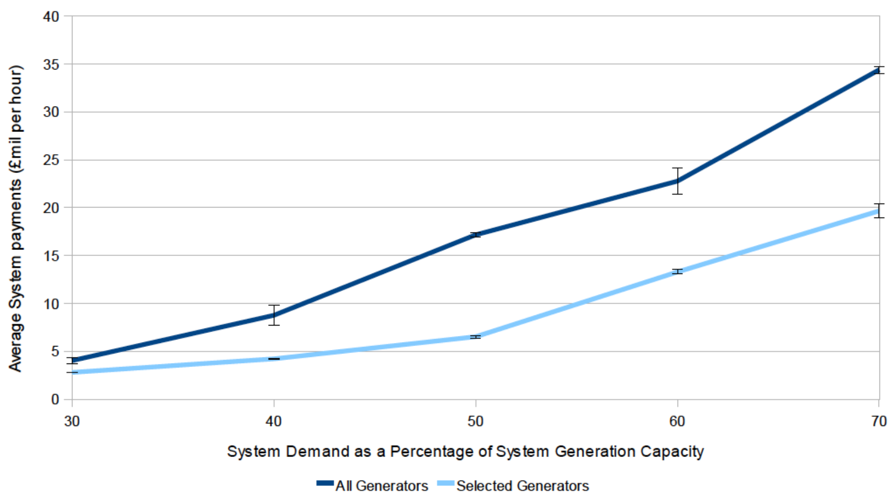


Figure 7.8: Average System Payments for a Nodal Market on a 29 Node Network with All Generators Actively Competing and Selected Generators Actively Competing

Both cases in figures 7.7 and 7.8 show that when all the agents are allowed to compete that the system payments made will be significantly higher than if only some of the agents are allowed to compete. However at no point does the buy back market achieve a higher level of system payments or generator profits than the nodal market.

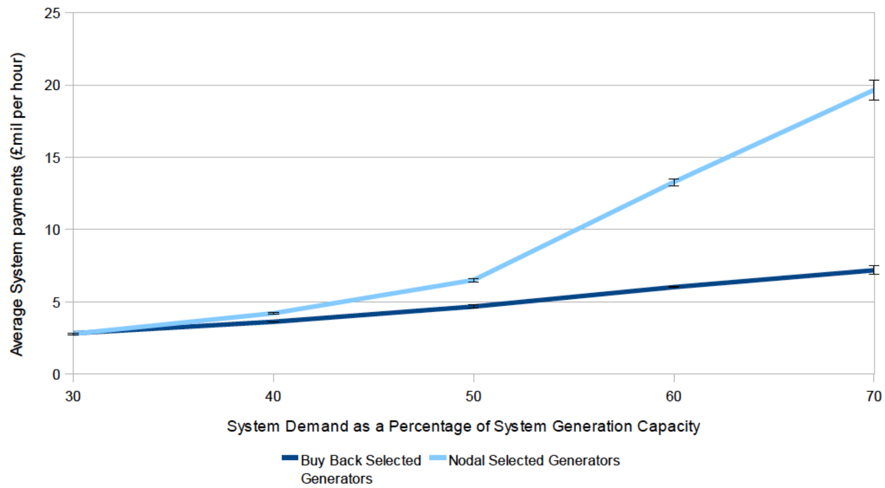


Figure 7.9: Average System Payments for a Buy Back and Nodal Market on a 29 Node Network with Selected Generators Actively Competing

The results seem to indicate that for every action that an agent takes in this market framework, there is an increased risk, since there are not as many competitive generators, the risk associated in trying to push the price higher is greater. As such the approximate level at which the agents find stability is much lower than in the case of the fully competitive results.

The main question is not concerning the actual results obtained, since they act in line with convention and expectation, but what is causing this disparity. By analysing the two groups, the competitive and non-competitive agents, it is possible to tell where the influence on the system is. Taking a single case at the 70% level, the trends can clearly be seen. Figures 7.10 and 7.11 show the percentage of generation share by the competitive generators and their non-competitive counterparts.

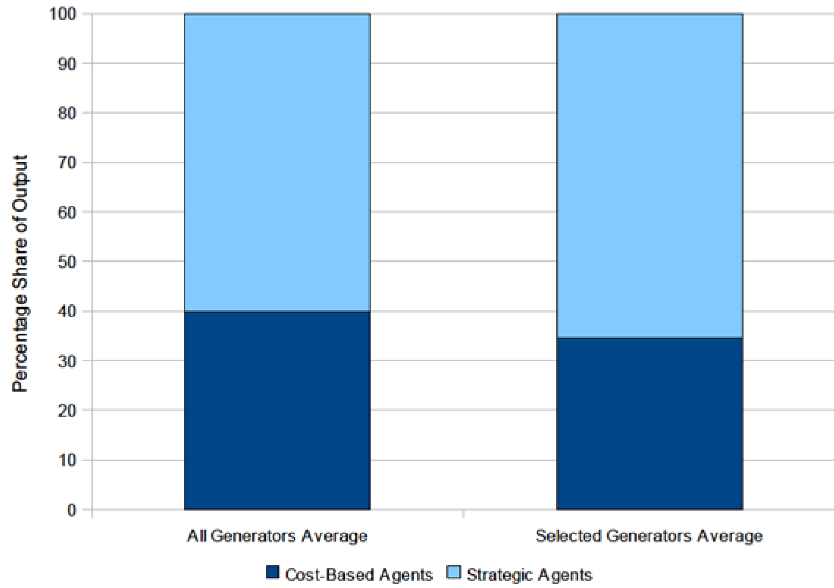


Figure 7.10: Distribution of Output between Competitive and Non-Competitive Agents - Buy Back Case

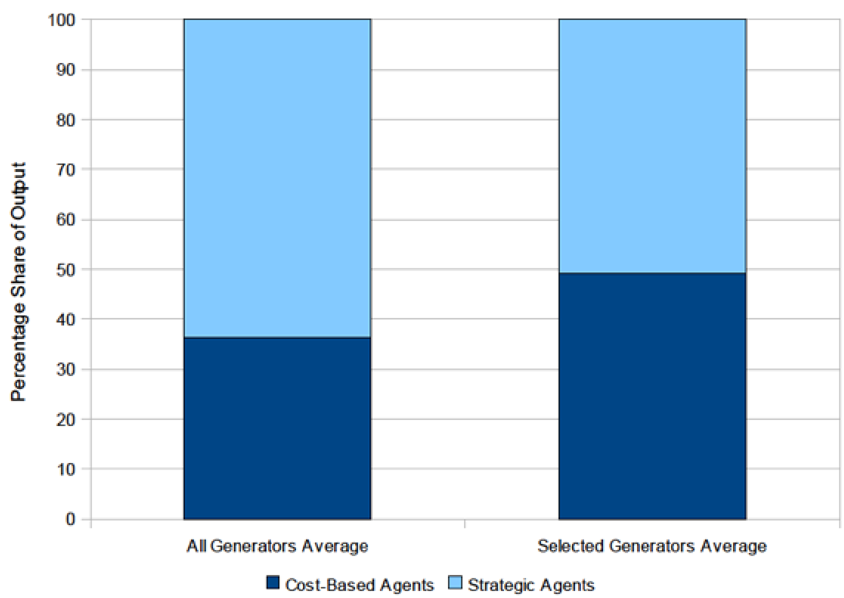


Figure 7.11: Distribution of Output between Competitive and Non-Competitive Agents - Nodal Case

The change in distribution can be most clearly seen in the case of the nodal market, where there is a relatively even split between the two groups in the case where they all compete, however this drops by 15% for the competitive agents when the second group starts bidding at just above marginal cost. However, with the buy back mechanism this figure is appreciably different, with an initial 60-40 split in favour of the strategic generators, this rises to a 65-35 split in their favour after enforcing a cost-based strategy on the other group

Having noted two very different results between the two mechanisms in terms of the distribution of output, by looking at the average price per MWh that the agents are paid in each case, a clearer picture of what is happening in the market so as to get these results can be obtained.

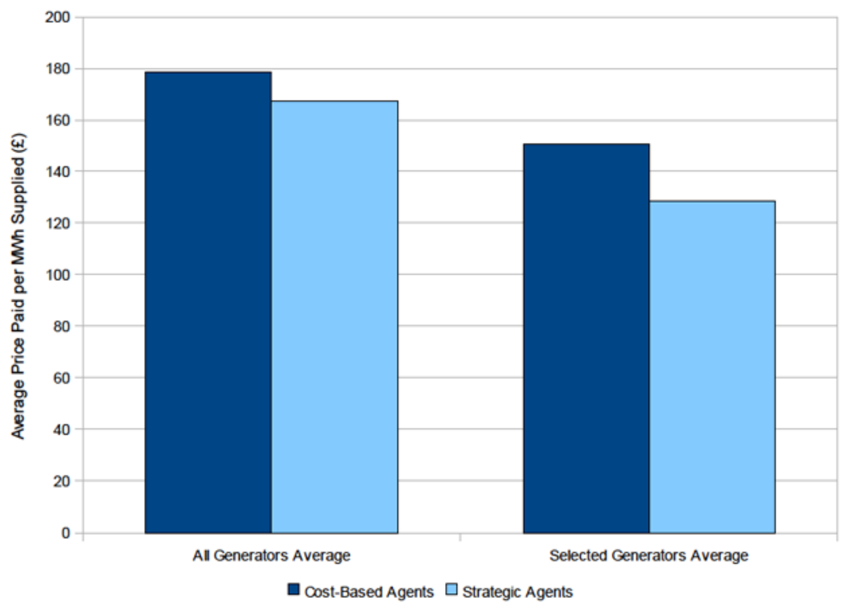


Figure 7.12: Average Price paid per MWh between Competitive and Non-Competitive Agents - Buy Back Case

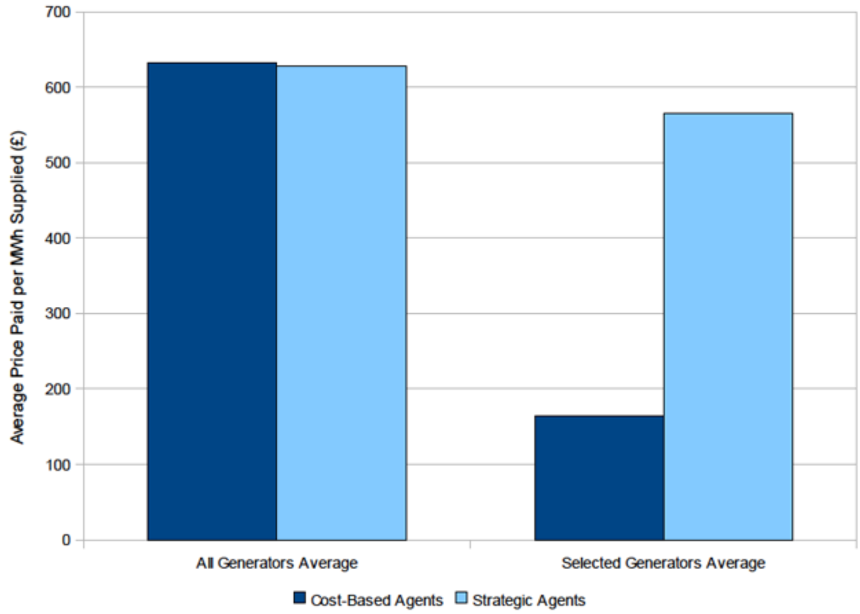


Figure 7.13: Average Price paid per MWh between Competitive and Non-Competitive Agents - Nodal Case

Figure 7.13 shows clearly that the average price obtained by the competitive agents has only fallen slightly between the two cases at a value of approximately 10%, however the average price obtained by the non competitive agents has fallen by approximately 75%.

In the case of the buy back market in figure 7.12, the competitive generators are bidding at a level below their non-competitive counterparts in both cases. The competitive agents drop their price sufficiently to ensure that they are frequently selected and in this case where they are the only ones who can influence the market, they are only able to use that influence to increase their generation.

The results seen in this experiments highlight the difference in the strategies that the agents are able to put into place within the simulated market. The nodal agents seek the potentially more risky higher paying strategies and with the effective co-ordination of the market states are consistently able to find these profits, even in a case where half of the market participants are not attempting the same bidding strategy as the other. Conversely the same agents on the buy back market actively seek the stability of a higher proportional market share, given the likelihood that a sufficiently profitable risky strategy is not available.

7.2.3 Individual vs Corporate

One of the major questions that needs to be analysed is "How much does the market power of the generating companies impact the operation of the market?". To do this, a scenario has been developed where the agents for each of the generation companies are unaware of the other generators that are owned by that company and so are not bidding in a manner to directly increase the collective's profits, but only their own. However the results of the study are directed not at looking at the individuals, but still at the generation companies to see how much the market power impact on their profits versus the standard co-operative measure.

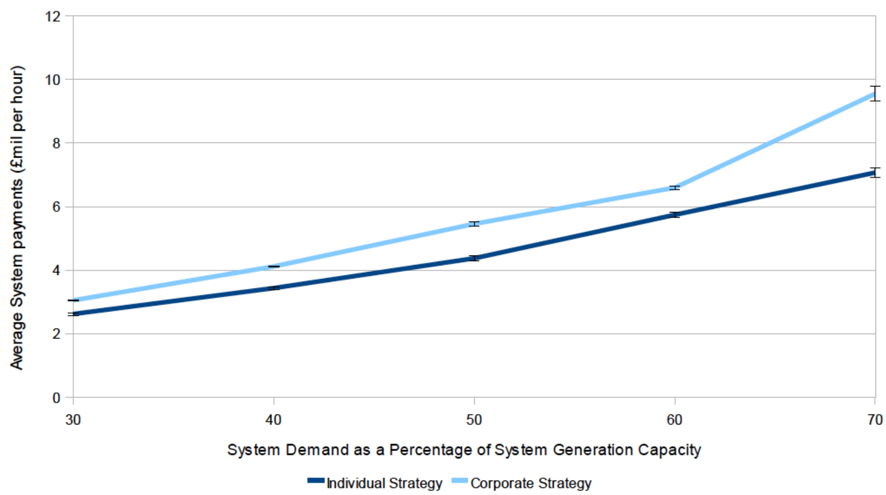


Figure 7.14: Average System Payments for a Buy Back Market on a 29 Node Network with Company and Individual Profit Maximisation

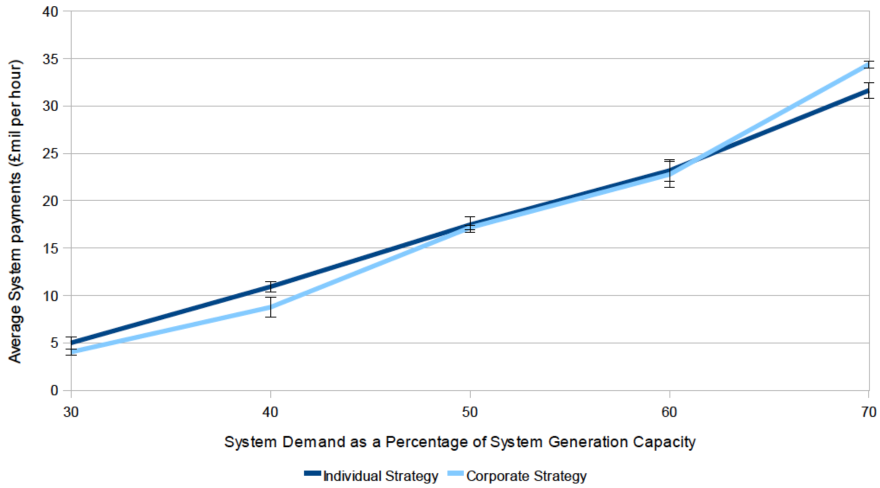


Figure 7.15: Average System Payments for a Nodal Market on a 29 Node Network with Company and Individual Profit Maximisation

The results shown in figures 7.14 and 7.15 show two different scenarios, the first is the case of the buy back market, where the co-operative generators always perform better in pushing for a higher price and eventual payments. This case is exactly as expected since the generators are competing more, and as has been shown with agents using the buy back mechanism, that when the competition increases the price per MW achieved drops.

However the same can not be said for the nodal mechanism, where although the results are close, average within 15%, the individual generators actually appear to perform better than their co-operative counterparts, up until the peak demand level where the co-operative ages are able to push the market slightly further.

Taking into consideration in the case of the nodal mechanism, that there is some error associated by taking the average of the results, the standard error in the individual case would account for an expected variance of 2%, which only does not result in a statistically significant margin of difference in the 50% and the 60% cases (50% $t(8) = 1.028$ $p < 0.334$).

However taking the case of the generator operation proposed in the selected generator case, shown in figure 7.16, then the results show that the co-operative generators are able to obtain a marginally higher level of system payments than the individual generators. these results are more in line with the predicted outcomes.

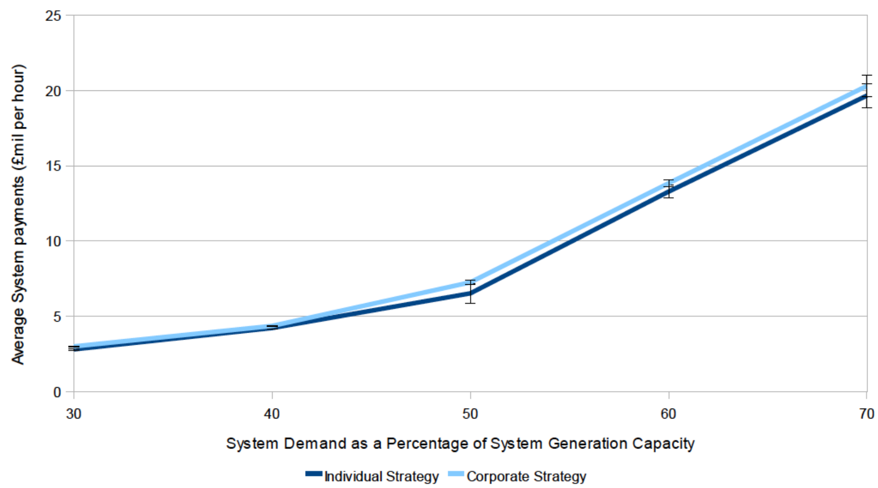


Figure 7.16: Average System Payments for a Nodal Market on a 29 Node Network with Company and Individual Profit Maximisation using Cost-Based and Strategic Generators

In order to understand what is happening, a closer look needs to be made at the distribution of the profits generators receive in these cases in these cases. Figures 7.17 - 7.19 give the average profit levels of each company at three crucial levels in the Nodal market, 40, 50 and 70% demand levels respectively.

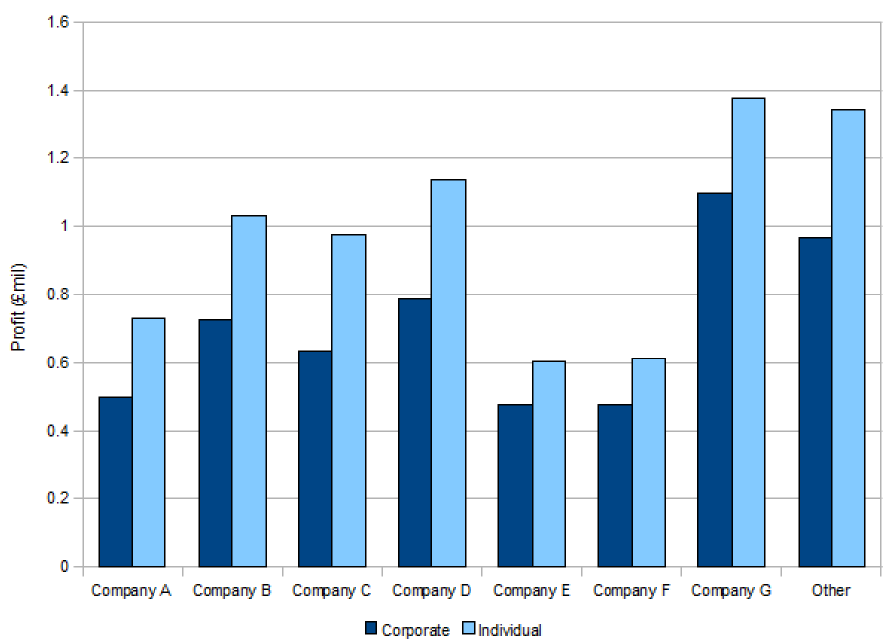


Figure 7.17: Average Profit per Generation Company on a Nodal Market with a Demand Level of 40 Percent of System Generation Capacity

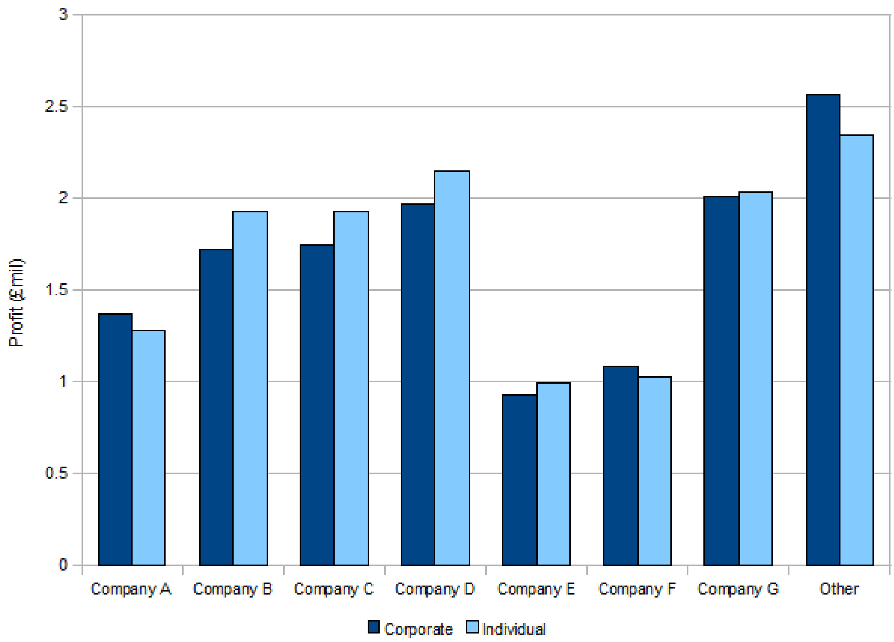


Figure 7.18: Average Profit per Generation Company on a Nodal Market with a Demand Level of 50 Percent of System Generation Capacity

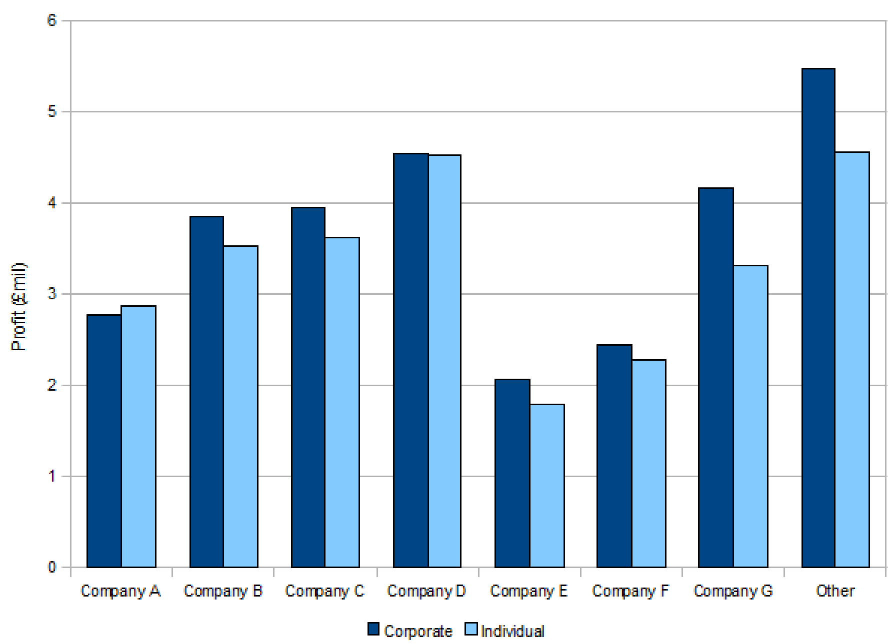


Figure 7.19: Average Profit per Generation Company on a Nodal Market with a Demand Level of 70 Percent of System Generation Capacity

In the 40 percent case, the profits attained by the generators average at 27% lower in the co-operative case than in the individual case, this falls to approximately 2% less profit in the 50% case and then the co-operative obtains 11% more profit at the 70% demand level. The buy back case shown in figures 7.20 - 7.22, shows on average the profits obtained by each of the generators in the 40% demand case is more than 100% higher, however this is not reflected at the 50 and 70 % demand cases.

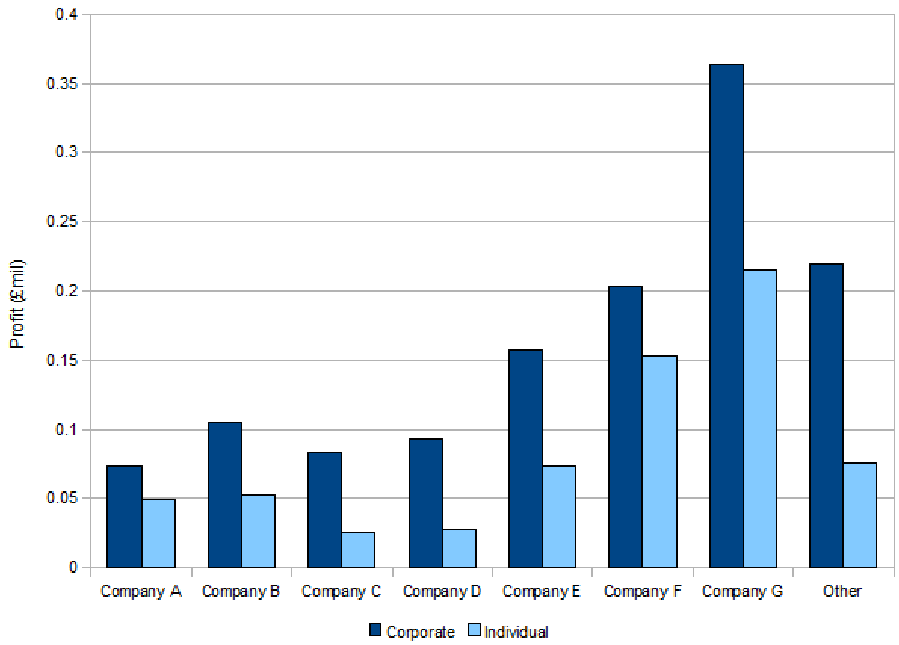


Figure 7.20: Average Profit per Generation Company on a Buy Back Market with a Demand Level of 40 Percent of System Generation Capacity

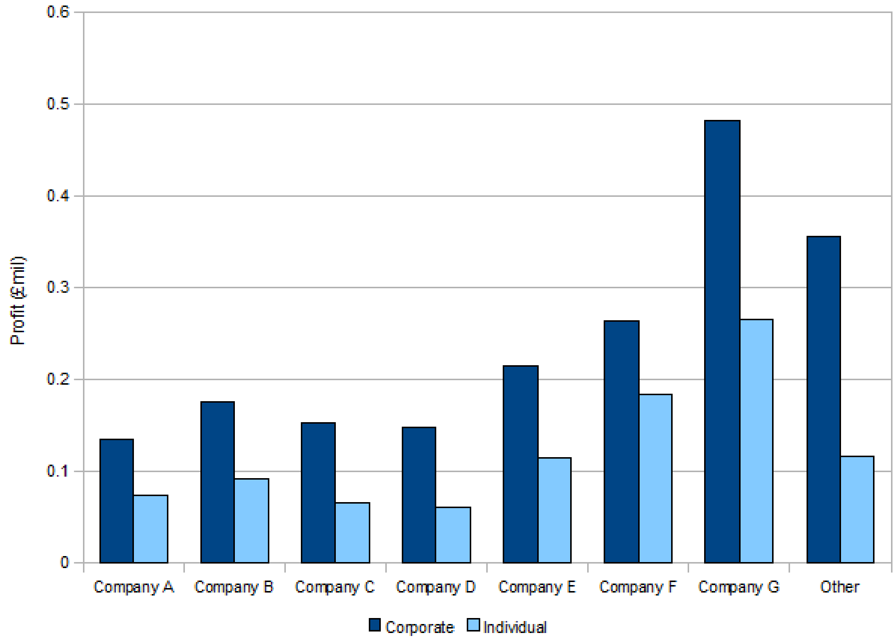


Figure 7.21: Average Profit per Generation Company on a Buy Back Market with a Demand Level of 50 Percent of System Generation Capacity

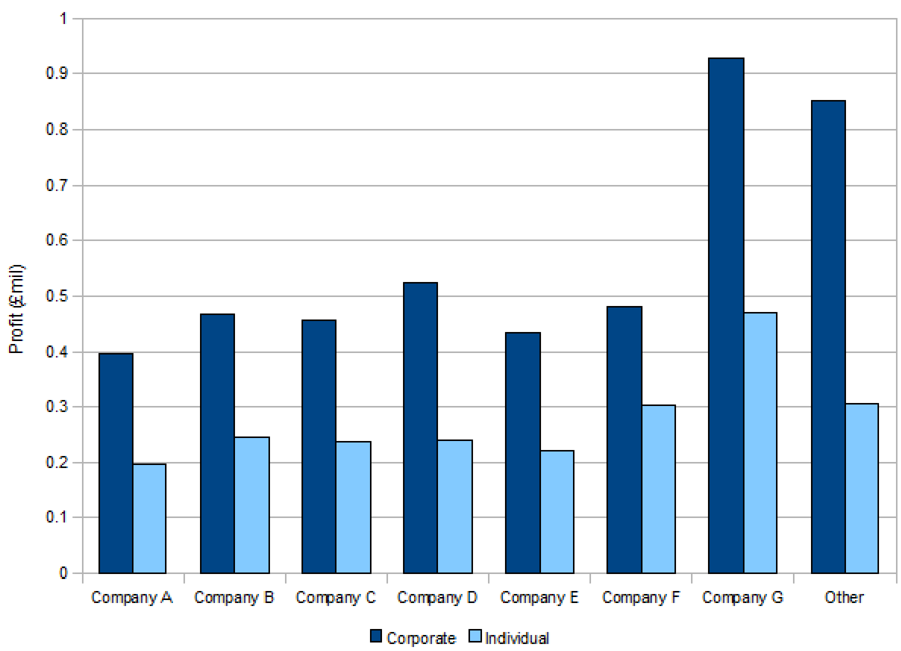


Figure 7.22: Average Profit per Generation Company on a Buy Back Market with a Demand Level of 70 Percent of System Generation Capacity

Even by looking at the revenue and output shares of each of the major companies between the two cases, there is little to obtain in terms of explaining the difference in these results. The proportion of generation by the minor generators, those not part of one of the major companies even seems to increase (Figures 7.23 - 7.25).

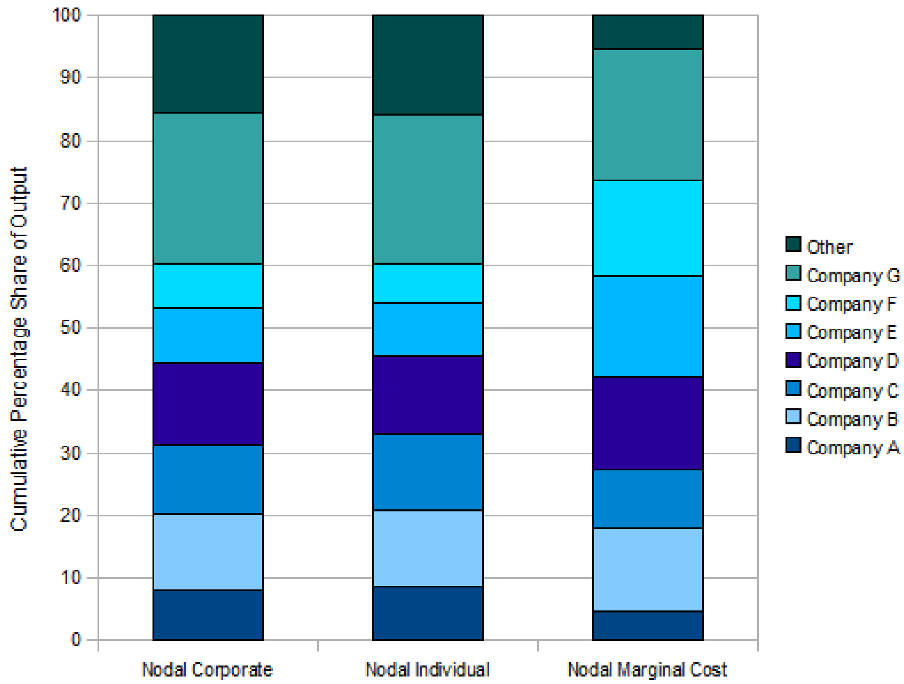


Figure 7.23: Output Distribution by Generation Company on a Nodal Market with a Demand Level of 40 Percent of System Generation Capacity

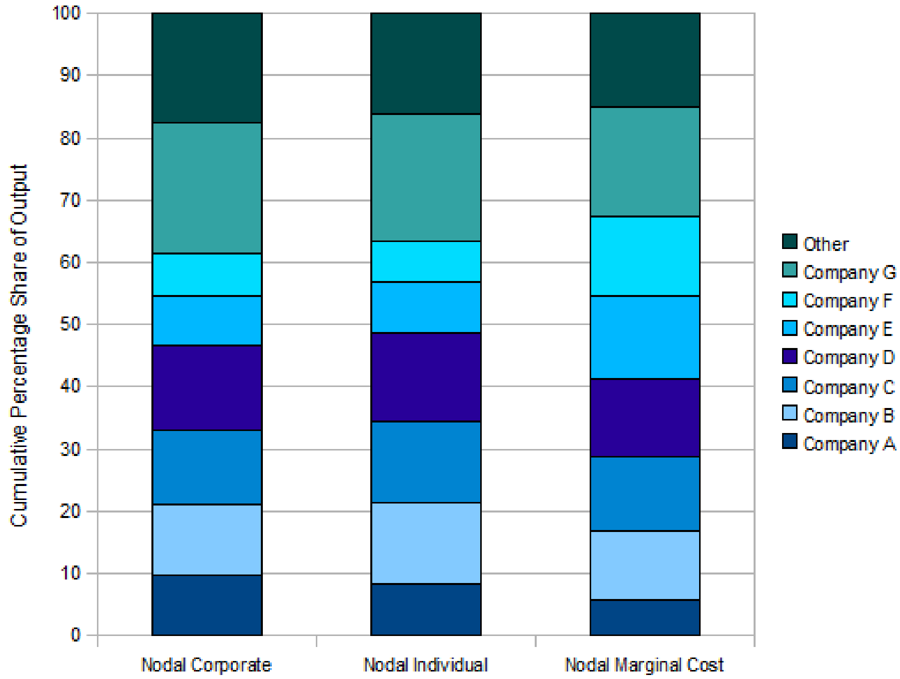


Figure 7.24: Output Distribution by Generation Company on a Nodal Market with a Demand Level of 50 Percent of System Generation Capacity

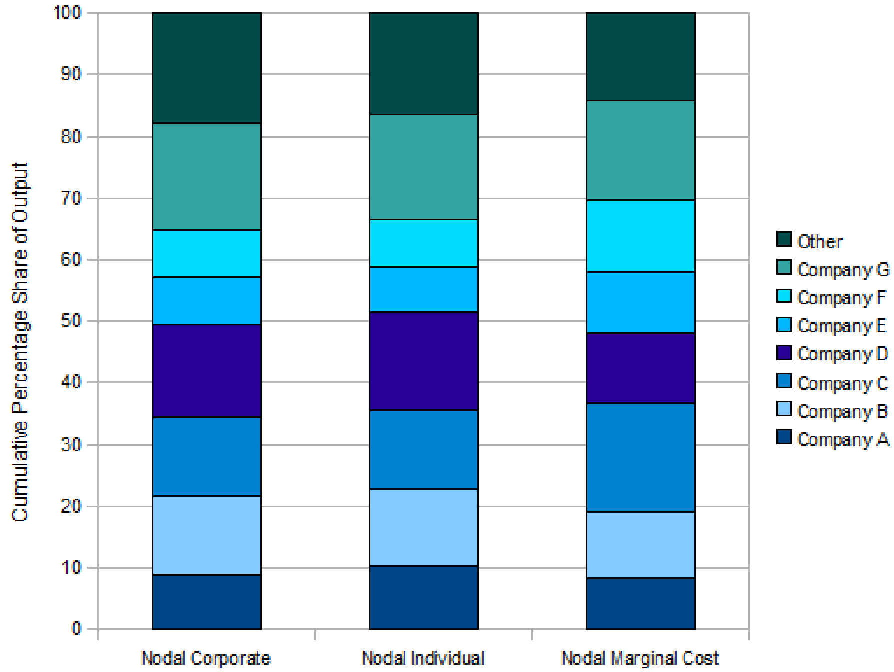


Figure 7.25: Output Distribution by Generation Company on a Nodal Market with a Demand Level of 70 Percent of System Generation Capacity

The reason for this unexpected behaviour comes back to the conceptual thoughts on the agents when explaining why the nodal prices were so much higher than those using the buy back mechanism. From the appearance of the results, it is predicted that the agents act in two slightly different ways. The consistent strand of behaviour appears to be pushing for a higher price, such that the bids are a long way above the levels of marginal cost associated with each generator. However as has been noted previously the market states that are created in every different scenario give a different search space for each of the agents to optimise over, which in this case causes the individual agents to find a stable price above the level of the co-operative generators.

The standard error on the outputs of the average levels of generation in both the corporate and individual cases are 17% and 18% respectively, showing that although there is risk involved in the strategy, often swinging between no generation and high generation, there is little increased risk of the strategies used.

Having looked at a variety of factors that could cause the individual agents to achieve higher profits than the nodal agents in some cases is reasonable to conclude that the strategies that the co-operative agents create form a stable equilibrium at a lower price, where the risk versus reward aspect is perhaps not able to be utilised in as profitable a way that an agent acting for themselves is able to achieve. This is enhanced by the selected generator case, where each action carries a higher risk and so where the individual agents were able to exploit aspects of risk in order to obtain higher levels of profit in the fully competitive case, those same features of the market and search space are no longer present.

The results indicate an interesting position, because the buy back mechanism follows closely with the predictions, showing that not only does the total system payments for the corporate generators exceed those of the individually competing counterparts, but the same is not true for the nodal market, where the agents in the case of acting individually perform better in some cases.

7.3 Discussion

On the small scale there was little evidence to promote the hypothesis that the Nodal market design created higher prices than those in a buy back market, with the opposite holding true when the market contained very little competition. The large scale case study, which was designed to creates a more realistic market environment, shows that the buy back market with the large level of competition creates prices that are comparable to bidding at their cost level plus some percentage of profit, often 10 to 15%. Conversely the Nodal Market is able to reach a market state, where it can consistently average prices in line with the less corporate cases on the small scale.

7.3.1 Constraint Inefficiency in the Nodal Market

There are two hypotheses that can be considered for the results that have been obtained through this work, the first is that the Nodal Market acts inefficiently in a constrained environment due to locational pricing, the second is that the Nodal pricing mechanism effectively creates several small locational markets.

The small scale experimentation results showed that when the lines were constrained they were actively able to push the price up to a level above the buy back mechanism, a trend that is also identifiable on the large scale. An argument could be made that having more constrained lines that are becoming constrained earlier is the cause for the rise in inefficiency of the market. By having a greater number of constrained lines, the number of adjustments that are required to rebalance the market are larger, meaning that there is going to be an increase in price because of the change in generation.

The main criticism with this as an explanation of why the Nodal market is inefficient, is that although the line constraints allow the participants to create higher locational prices than those under similar conditions, the small scale indicated that although there was greater room to game the market than a buy back market, the actual results tended towards a more efficient price for both markets. Under these conditions, it would be expected from the small scale results that the Nodal Market would also tend towards an efficient price, however this is not the case, as the Nodal Market acts in a manner equivalent to having very little competition.

When designing the small scale test cases one aspect that was considered that on a large scale the whole market could act similar to multiple small markets following their interactions. The expectation here is that once a line has become constrained by the cheapest generation results in those generators on the demand side of that constraint creating their own smaller electricity market. These electricity markets then have participation limited to those on the demand side of the constraint that is isolating a particular node or set of nodes.

The question still remains, that if there is the possibility of creating multiple small markets that effectively minimise competition, then why are the high average prices only seen with the Nodal Pricing Mechanism and not with the buy back Mechanism?

7.3.2 Efficiencies of a Uniform Price

In Chapter 1, one of the principle reasons for considering that a buy back pricing mechanism might be more efficient than a nodal Market, was the consideration of how much impact is required to affect the average price per MWh with a Uniform Pricing Structure.

Having shown that on the small scale, when there is a very low level of competition the uniform price appears to be highly exploitable. The reason for this is that the relatively few generators are able to have more of an individual impact on the uniform price than those in a competitive market. Since the uniform price is determined by the price of the last scheduled MW for the initial dispatch, the amount of gaming that is capable in the system is determined by the number of participants. On the small scale, the more agents present, the more more efficient the system price seems to hold true on the large scale, where the average system price is close to the optimal level of marginal cost. Only once the demand has risen above the 60% level do the agents have the opportunity to game the system.

While the Nodal Pricing Mechanism may create lots of small markets as a result of the constraints that allow the agents to force a higher price, the buy back Mechanism still schedules as much generation as possible at the uniform price. The main condition that this creates is that a change in generation in the Nodal market can affect the price of all generation at a node, whereas only the extra generation purchased will be paid at the higher price.

Bakirtzis et. al. conclude in their work that when "no supplier takes advantage of his position , the price under uniform pricing are lower compared to the ones under pay-as-bid". While in this research the agents are actively trying to take advantage of the position that they have, the large scale model shows that there are conditions that allow for the agents to behave in different ways.

It is not possible to state that for all cases the level of competition seen with a large number of agents causes the generators to be restricted in their ability to take advantage of their position. While the Buy Back market appears limited by the level of competition, the Nodal market in some cases is not.

7.4 Summary

The three experiments identify different features that relate to the operation of a wholesale electricity market. The first experiments offer a direct comparison of market operation with no restrictions on operational behaviour. The remaining two experiments propose alternate scenarios in which either some generators act in non-competitive manner or act with concern for their own individual profit over that of a parent company.

Notably the experimental results identify that the hypothesis "A nodal pricing mechanism is more susceptible to the influence of market gaming than a buy back mechanism in a constrained electricity market" seems to be true under these experimental conditions. Under different experimental conditions, the hypothesis also remained true when tested with restrictions on the behaviours of some agents.

Chapter 8

Conclusions

Having completed a study of a simulated electricity market using an evolutionary agent based approach, there are a number of topics that need to be addressed. This chapter will in sections 2 and 3 identify the key findings of the research, section 4 will discuss the limitations of the simulation, with section 5 highlighting aspects that could have been done differently. The chapter closes with a brief summary of future work that could be performed using the simulation as it's basis.

8.1 Market Lessons

The results have shown that both pricing mechanisms can be sufficiently gamed by the agents so as to raise the system price and generate higher profit for the generation companies above marginal cost level.

While both pricing mechanisms show that the market can be gamed by the competing agents, it is the difference in the system payments made and the profits achieved that is most fundamental. Where the uniform based Buy Back system has less exploitable market power when there is a large number of competitors in the market than the Nodal system.

The hypothesis of this research stated that:

"A nodal pricing mechanism is more susceptible to the influence of market gaming than a buy back mechanism in a constrained electricity market"

The results of the experiment clearly back this claim, where in all cases tested by the large scale experiments, the nodal pricing mechanism reached a higher average price per MWh. The main question this raises is, why are the results presented here different from those in other papers on the subject?

The answer to this question comes down to the initial requirements of the agent design, in which the agents were designed to optimise their actions across the entirety of their search space, with minimal constraints on their actions. In doing this they have within the confines of the nodal market been able to consistently push beyond a stable low price in the market to a higher price. At the same time the agents in the Buy Back Market are able to achieve a higher than marginal cost price level for the market participants, but are not able to enforce as high a price as their Nodal counterparts.

8.2 Agent Lessons

While the main focus of this research has been on the market outcomes, the work presented here has also shown how genetic algorithm based agents can be utilised in the analysis of a market.

At the start of this work, three questions were posed of the simulation:

1. How closely does the data set used reflect the real world?
2. How closely does the market set-up reflect the reflect the real world?
3. How effective are the agents in their role within the simulated environment?

By revisiting these questions, it is possible to identify the success of the agents. The development of the large scale data model, and the design of the balancing mechanism and market rules, were both done to answer questions 1 and 2 respectively. By designing the aspects of the simulation to be as accurate as possible, the agents are able to perform their task where the results can be considered reliable.

The interesting aspect of the third question, is that the described role of the agents was to maximise their profits. The results indicate that they were reliably able to achieve this, and thus achieve the third of the stated aims.

Having identified that the simulation and agents performed as expected, it is possible to answer the question:

"Are agents using an evolutionary search methodology ideally suited as tools for market analysis?"

A study into the dynamics and operation of a market should consist of a number of different aspects. This research focuses on attempting to push the operational bounds of the market environment and succeeds in doing so, and the evolutionary agents' ability to search through a greater amount of the potential strategies is key to this. This ability to identify strategies and scenarios that would not otherwise be considered or tested ideally suits them to the task of market analysis.

Despite being well suited to the task, basing the whole of a market analysis on the outcomes of boundary stretching evolutionary would not be advised. An evolutionary based analysis of the potential impact of market power, such as the one shown in this research, should be used in conjunction with a more standardised behavioural based analysis.

8.3 Discussion of Limitations

During each chapter of design, a number of limitations were identified, this section will identify what impact these limitations have had on the research.

The biggest limitation placed on the simulation is the agent's requirement for perfect knowledge to operate. As was stated at the end of chapter 4, without using perfect knowledge the agents would have to estimate the strategies of other generators. Where the estimation of strategies creates a more realistic market setting, the design requirements for the agents to sufficiently overcome the limitation would not only require more processing time. This creates an issue that becomes more prevalent as the model size increases, but more importantly, the loss of optimality in the actions taken by the agents.

The biggest impact this has on the research is that it more specifically defines each agents behaviour, where the reality of the markets would have participants hedging themselves against inherent risk. The results that the nodal market showed are unlikely to be full replicable in a real market environment, however it is still possible that even with a limited knowledge would be able to force the price significantly higher than marginal cost levels.

The other major limiting factor was the enforcement of strategy for the must run generators, while in an actual market they would be able to bid, albeit heavily regulated. It was considered that given a must run schedule for these generators, that if they were allowed to bid, that they would bid at the pice cap, since no matter what they bid they would be run at capacity.

In order to counteract this, they were forced to bid £0 per MWh, which although in some cases might be a realistic bid for a nuclear generator, a value of £0 as a bid can have a knock on effect in the market. This effect was seen in the large scale while analysing the nodal pricing mechanism, where the average of each MWh supplied ended up lower at nodes with nuclear generators than those without.

8.4 Alternative Methods

In considering the limitations and assumptions made during the development of a detailed simulation, there are often other contributing factors that are overlooked and while only minor could affect the outcome.

In addition to the additional generation detail, one of the key simplifications is a lack of demand side control. The simulation does implement a uniform demand reduction system as price rises, however other models such as the AMES project have demand side agents, which are able to better and more accurately control the demand side of the market. By creating demand side agents it might be possible to shift some of the market power away from the generators and onto the demand side agents, potentially reducing the system wide prices.

Despite being more of an imposed limitation, the data for the generators was designed to be fairly simplistic. This is in a way that real generators have a more complex cost calculating structure than the model presented here.

There are two different factors that could be considered when looking at the pricing structures of generators. The main factor is the use of real cost data, where as in all of the experiments presented in this research no realistic cost data was attributed to the generators. Having more realistic cost data would allow for a better comparison with the real market in the UK, which would aid the future application of this research.

The second is locational costing, data used in the model is a predicted cost it makes reference to the technologies and fuel difficult, and in particular there is no notion of the location of the generator affecting price. Given that across Great Britain different regions have different cost this will impact each generator's marginal cost level, where a generator in a more expensive region will have a higher marginal cost to an identical generator in a cheaper region. In some cases a small rise in cost may not impact their strategy, a large increase in price across a relatively small number of generators is capable of changing the market dynamic owing to a change in strategies required.

8.5 Future Work

While this research has provided an in depth study of one factor in the field of electricity markets, there are a number of possible further studies that would be relevant.

8.5.1 Market Extensions

Within the currently implemented simulation and model, there are a number of different questions that can be studied.

Taking a single market design, one of the critical aspects is how does the repeated playing of the game impact the behaviour of the agents. In taking into consideration a longer time period of the market, possibly over a year, a number of additional factors need to be considered.

In the previous section the start-up costs of generators are mentioned as one factor that could have been included to further complete the realism of the simulation. By taking the concept that generators that are not operational need to be started up, a new functionality of the system operator could be implemented to ensure that as much of the capacity of the market is available at all times. This would be a way of studying market power in scenarios such as the Californian Electricity Crisis of 2000.

Along similar lines, other aspects of the market could be tested, such as the potential change that takeovers or mergers might have on the competition in a market. While a merger of two of the large market participants would make for an interesting topic of study, the plans for any such merger is unlikely to be allowed without close scrutiny. While not including the mergers of the major companies, there could be the potential for the acquisition of independent generators by the larger companies that would impact the market dynamic.

8.5.2 Market Designs

The research presented here has produced an insight into two different pricing mechanisms using bilateral trading arrangements. A possible extension to this work would involve looking at additional market rules and regulations for comparative purposes.

An alternative pricing mechanism that was considered during the early stages of this research, was a zonal pricing structure. Rather than the price being decided across the individual nodes of the transmission grid, the grid is divided into zones, where the price is defined by the cost of supplying electricity in that zone.

In addition to the pricing mechanism, an alternative market design such as a pool based system could be developed, this would allow for a direct comparison between the previous implemented market design in Great Britain and the currently implemented one. This would allow for a closer look at the decisions behind the reason to change the market design.

8.5.3 Market Models

During the development of the large market model that was used in the experimentation of this research, a number of different market designs were considered. These could be used either as a method of further studying the impact of the tested market mechanisms, but also the alternatives proposed above.

In Chapter 6, several different designs were considered, including the Nordpool and Belgian models. In addition to these, the Californian model, which has experienced problems with electricity market manipulation in the past would also make for a possible case study.

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Appendix A

Sample DC OPF Equation

A test of a three node network with a network layout as shown in Figure A.1 with network injections of 30MW at Node 0 and a demand of 30MW at Node 1. The expected flows for this sample are 20MW on line 0, 10MW on line 1 and -10MW on line 2.

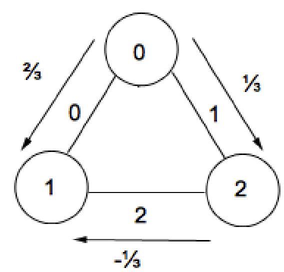

Figure A.1: Sample 3 Node Network

$$\underline{z} = \underline{y}(R^{-1}A(A^T R^{-1} A)^{-1}) \tag{A.1}$$

Where:

$$R = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{A.2}$$

$$A = \begin{bmatrix} -1 & 0 \\ 0 & -1 \\ 1 & -1 \end{bmatrix} \tag{A.3}$$

$$\underline{y} = \begin{bmatrix} 30 \\ -30 \\ 0 \end{bmatrix} \tag{A.4}$$

Each step of the matrix calculation used to calculate the line flows in this example is shown below.

$$R^{-1}A = \begin{bmatrix} -1 & 0 \\ 0 & -1 \\ 1 & -1 \end{bmatrix} \tag{A.5}$$

$$A^T R^{-1} A = \begin{bmatrix} 2 & -1 \\ -1 & 2 \end{bmatrix} \tag{A.6}$$

$$(A^T R^{-1} A)^{-1} = \begin{bmatrix} 0.666 & 0.333 \\ 0.333 & 0.666 \end{bmatrix} \tag{A.7}$$

$$A(A^T R^{-1} A)^{-1} = \begin{bmatrix} -0.666 & -0.333 \\ -0.333 & -0.666 \\ 0.333 & 0.333 \end{bmatrix} \tag{A.8}$$

$$\underline{y}(R^{-1}A(A^T R^{-1} A)^{-1}) = \begin{bmatrix} 20 \\ 10 \\ -10 \end{bmatrix} \tag{A.9}$$

Appendix B

29-Node Data Model

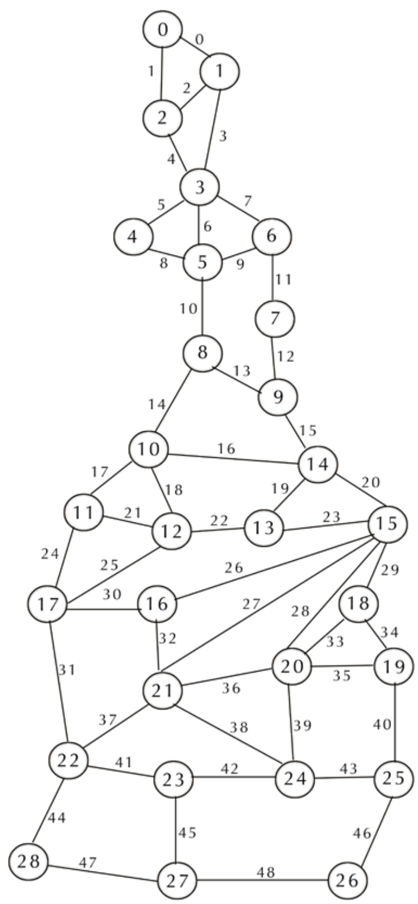

Figure B.1: Grid Layout for 29-Nodel Model

Node ID	Node Peak Demand (MW)	Total Generation at Node (MW)
0	341	1527
1	717	1108
2	62	364
3	431	0
4	202	844
5	2234	4248
6	2244	3631
7	193	1416
8	222	0
9	1749	420
10	317	2987
11	781	0
12	2557	4902
13	3421	7832
14	1596	1934
15	1533	10545
16	2504	0
17	2435	2964
18	2399	1700
19	1291	1942
20	2262	3674
21	7100	4632
22	2436	5733
23	3958	2884
24	9738	3657
25	1323	6958
26	1307	1501
27	2446	2289
28	1852	2306

Table B.1: Peak Nodal Demand

Line ID	Start Node	End Node	Capacity(MW)
0	0	1	1050
1	0	2	264
2	1	2	652
3	1	3	1520
4	2	3	1296
5	3	4	2000
6	3	5	2620
7	3	6	2180
8	4	5	2780
9	5	6	1900
10	5	8	4200
11	6	7	4680
12	7	9	6140
13	8	9	1605
14	8	10	2780
15	9	14	8460
16	10	14	5040
17	10	11	6640
18	10	12	4380
19	14	13	10000
20	14	15	8310
21	11	12	6200
22	12	13	2080
23	13	15	3205
24	11	17	4800
25	12	17	4800
26	15	16	4040
27	15	20	5560
28	15	18	8600
29	16	17	6560

Table B.2: 29-Node Line Data A

Line ID	Start Node	End Node	Capacity(MW)
30	17	22	3960
31	16	21	4200
32	18	20	5810
33	18	19	3180
34	20	19	4560
35	20	21	4560
36	15	21	4200
37	21	22	4560
38	21	24	6550
39	20	24	4560
40	19	25	4560
41	22	23	7180
42	23	24	2480
43	24	25	12500
44	22	28	4020
45	23	27	4420
46	25	26	6200
47	26	27	6140
48	27	28	4560

Table B.3: 29-Node Line Data B

Generator Type	Cost per MW (£)
Type 0	115
Type 1	125
Type 2	105
Type 3	88
Type 4	124
Type 5	125
Type 6	64
Type 7	25
Type 8	90
Type 9	160
Type 10	136
Type 11	64

Table B.4: Cost per Unit for Different Generator Types

Node ID	Type	Maximum Output(MW)
4	Type 7	440
5	Type 5	2028
5	Type 8	933
6	Type 2	2286
6	Type 2	1102
25	Type 3	805
26	Type 3	420

Table B.5: Company A Generators

Node ID	Type	Maximum Output(MW)
0	Type 8	965
1	Type 3	1108
2	Type 8	261
4	Type 8	281
6	Type 2	123
12	Type 1	1987
13	Type 1	1986
15	Type 3	735
21	Type 2	228
22	Type 2	363
23	Type 3	1234
25	Type 3	700
27	Type 3	900

Table B.6: Company B Generators

Node ID	Type	Maximum Output(MW)
5	Type 10	45
12	Type 3	1380
15	Type 3	395
15	Type 3	900
21	Type 1	964
21	Type 1	2021
25	Type 1	1966
25	Type 0	1355
24	Type 3	408
24	Type 3	860
24	Type 4	144

Table B.7: Company C Generators

Node ID	Type	Maximum Output(MW)
18	Type 3	1700
19	Type 3	420
20	Type 3	665
22	Type 2	2058
22	Type 1	1665
23	Type 3	1550
23	Type 4	100
25	Type 1	1131
27	Type 2	158
27	Type 4	145
27	Type 0	1036
28	Type 3	905
24	Type 0	1245

Table B.8: Company D Generators

Node ID	Type	Maximum Output(MW)
10	Type 3	229
15	Type 3	260
15	Type 3	665
15	Type 3	1285
20	Type 3	905
20	Type 3	405
22	Type 3	245

Table B.9: Company E Generators

Node ID	Type	Maximum Output(MW)
12	Type 3	515
14	Type 3	1835
15	Type 3	1100
17	Type 7	1644
17	Type 7	360
21	Type 1	1018
28	Type 4	140

Table B.10: Company F Generators

Node ID	Type	Maximum Output(MW)
15	Type 1	2000
15	Type 1	1987
20	Type 3	819

Table B.11: Company G Generators

Node ID	Type	Maximum Output(MW)
5	Type 6	515
7	Type 6	1835
10	Type 6	1100
19	Type 6	1644
26	Type 6	360
28	Type 6	1018

Table B.12: Company H Generators

Node ID	Type	Maximum Output(MW)
0	Type 8	562
2	Type 8	103
4	Type 8	123
5	Type 8	168
6	Type 2	120
7	Type 8	201
9	Type 2	420
10	Type 2	155
10	Type 9	105
12	Type 2	210
12	Type 3	810
13	Type 1	3906
13	Type 1	1940
14	Type 3	99
15	Type 2	1218
17	Type 11	960
19	Type 9	315
20	Type 3	880
21	Type 3	401
22	Type 3	552
22	Type 3	850
25	Type 3	800
25	Type 9	201
27	Type 4	50
24	Type 3	1000

Table B.13: Other Generators